Learning Prediction Suffix Trees with Winnow

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Introduction

Sequential prediction

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Our task: Is a program behaving normally?

- Monitor a program and take appropriate actions based on the actual system calls and the predicted ones
- Deviations may signify a bug, a security problem, etc.

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Known alphabet e.g. {A, C, G, T} or $\{-1, +1\}$ or {open(), read(), …} or …

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PSTs (aka Context Trees) are popular models for this task [Pereira & Singer, 1999, Ron et al., 1996, Willems et al., 1995]

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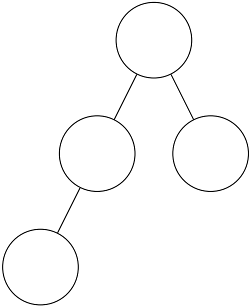
Now, a PST is a binary tree



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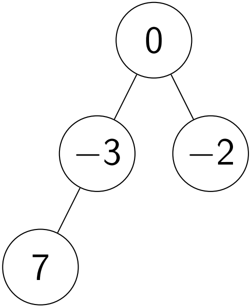

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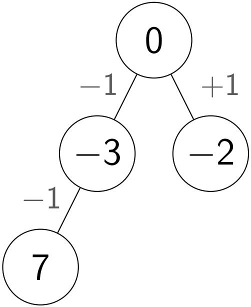

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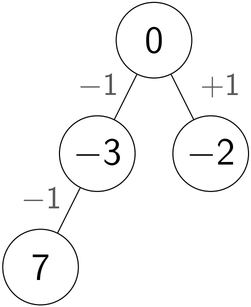

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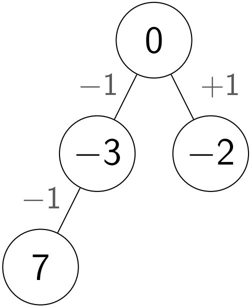

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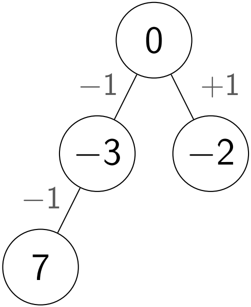

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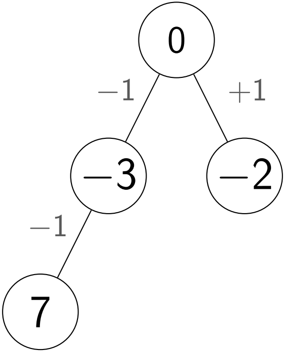
Earlier symbols are discounted more than recent ones

Example

Discounting: Values discounted by $\left(\frac{1}{2}\right)^{\text{depth}}$



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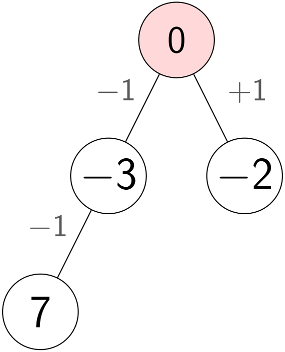

Input Sequence: $\ldots, +1$

Decision: 0

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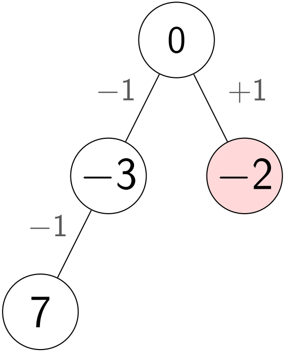

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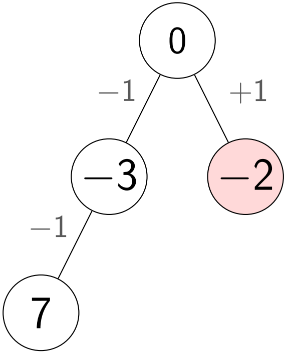

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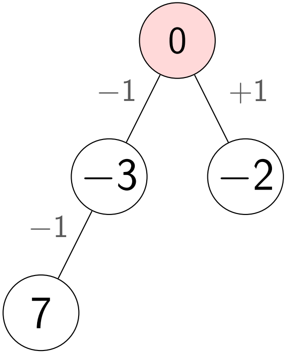

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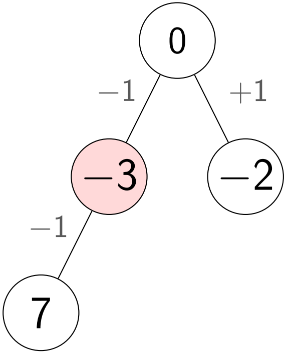

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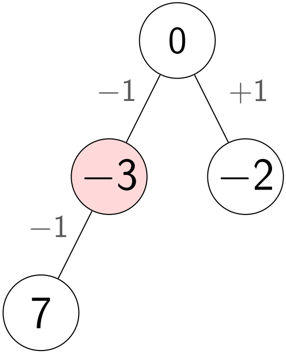

Input Sequence: $\ldots, +1, \mathbf{-1}$

Decision: $0 + \frac{1}{2} \cdot -3 = -\frac{3}{2} \xrightarrow{\textit{sign}} -1$

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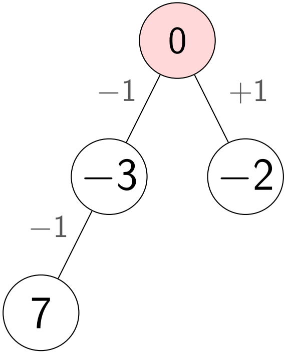

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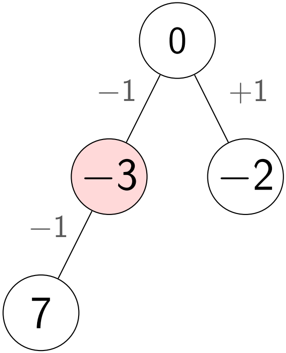

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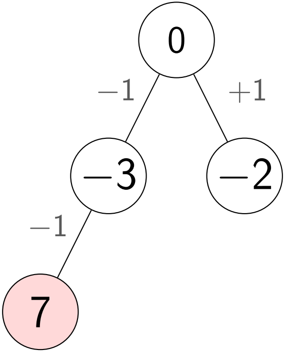

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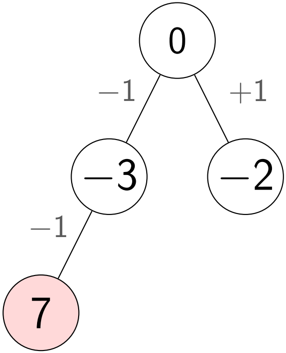

Input Sequence: $\ldots, -\mathbf{1}, -1$

Decision: $0 + \frac{1}{2} \cdot -3 + \frac{1}{4} \cdot 7 = \frac{1}{4} \xrightarrow{\textit{sign}} +1$

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Online setting

Balanced Winnow

$\theta_1 \leftarrow 0$

for $t = 1, \ldots, T$ **do**

$$w_{t,i} \leftarrow \frac{e^{\theta_{t,i}}}{\sum_j e^{\theta_{t,j}}}$$

$\hat{y}_t \leftarrow \langle w_t, x_t \rangle$

if $y_t \hat{y}_t \leq 0$

$\theta_{t+1} \leftarrow \theta_t + \alpha y_t x_t$

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Important

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$[x_{t,1}^+, \ldots, x_{t,d}^+, -x_{t,1}^+, \ldots, -x_{t,d}^+]$

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Known fact

Let $\theta_t = [\theta_t^+, \theta_t^-]$ then
$\langle w_t, x_t \rangle \propto \sum_i \sinh(\theta_{t,i}^+) x_{t,i}^+$

$\sinh(\theta_{t,i}^+) = 0$ iff $\theta_{t,i}^+ = 0$

Learning a PST

Winnow can learn good θ_t^+ values for the tree

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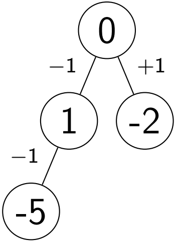
Winnow/Perceptron update quickly leads to large trees

Illustration

Input: $\ldots, -1, +1, -1, +1, -1, ?$



$$x^+_{t,s} = \begin{cases} \left(\frac{1}{2}\right)^{|s|} & \text{if } s \text{ is a suffix} \\ 0 & \text{otherwise} \end{cases}$$

Decision:

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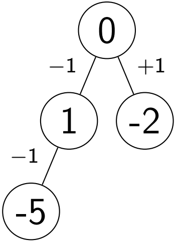

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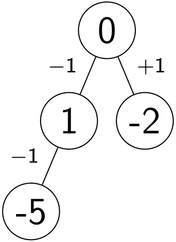

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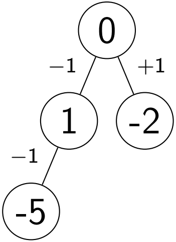

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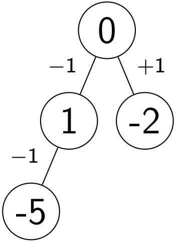

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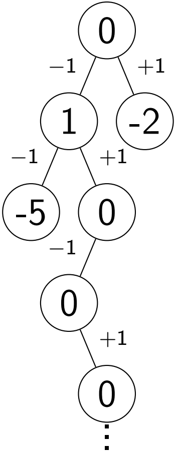

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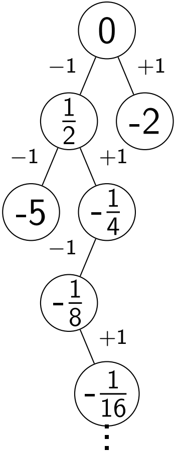

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- d_t will be growing slowly if necessary

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New update: $\theta_{t+1} = \theta_t + \alpha y_t x_t + \alpha n_t$

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d_t is set to guarantee $P_t \leq |J_t|^{2/3}$. Suffices to set

$$d_t = \left\lceil \log_\beta \left(\sqrt[3]{P_{t-1}^3 + 2P_{t-1}^{3/2} + 1} - P_{t-1} \right) - 1 \right\rceil$$

Theorems

Mistake Bound

Let there be a tree u ($||u||_1 = 1, u_i \geq 0$) which over the input sequence $y_1, y_2, \ldots, y_T$ attains loss $L = \sum_{t=1}^{T} \max(0, \delta - y_t \langle u, x_t \rangle)$, then our algorithm's mistakes M_T will be at most

$$\max\left\{\frac{2L}{\delta} + \frac{8\log T}{\delta^2}, \frac{64}{\delta^3}\right\}$$

Theorems

Mistake Bound and Growth Bound

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$$\max\left\{\frac{2L}{\delta} + \frac{8\log T}{\delta^2}, \frac{64}{\delta^3}\right\}$$

Moreover, by setting $\beta = 2^{-1/3}$, the learned tree will have at most $\log_2(M_T) + 4$ levels

Proof Sketch

Growth bound is straightforward

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Mistake bound via potential function

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$$\Phi(w_t) = \sum_i u_i \log \frac{u_i}{w_{t,i}} \geq 0$$

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Mistake bound via potential function

$$\Phi(w_t) = \sum_i u_i \log \frac{u_i}{w_{t,i}} \geq 0$$

Upper bound $\Phi(w_1)$ and lower bound decrease in potential with each mistake:

$$\Delta\Phi = \underbrace{\text{effect of full update}}_{\geq f(\alpha,\delta,\text{loss of } u)} - \text{effect of noise}$$

Proof Sketch II

Potential: $\Phi(w_1)$ ⊢———⊣ 0

Noise P_t :

Example	Correct Prediction
x_1	

Progress due to classic update

Net progress

Effect of noise

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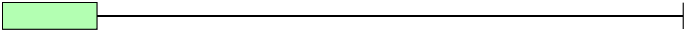

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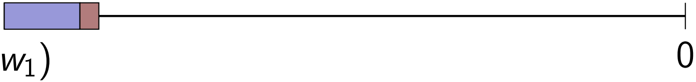

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Noise P_t :

Example	Correct Prediction
x_1	✗
x_2	

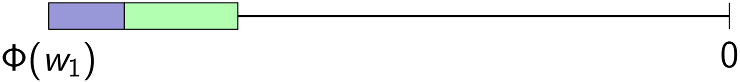
Progress due to classic update

Net progress

Effect of noise

Proof Sketch II

Potential:



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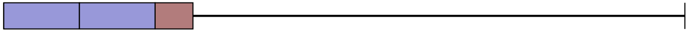
Potential: 

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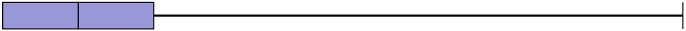
Potential: 

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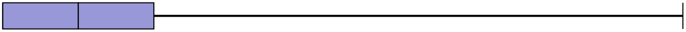

$\Phi(w_1)$ 0

Noise P_t :

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Noise P_t :

Example	Correct Prediction
x_1	✗
x_2	✗
x_3	✓
x_4	

Progress due to classic update

Net progress Effect of noise

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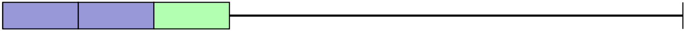

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Noise P_t :

Example	Correct Prediction
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x_3	✓
x_4	✗

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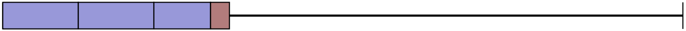
Proof Sketch II

Potential:



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Net progress

Effect of noise

Proof Sketch III

length of $\boxed{} \leq \Phi(w_1)$

Proof Sketch III

length of $\square \leq \Phi(w_1)$

length of $\square$ $-$length of $\square \leq \Phi(w_1)$

Proof Sketch III

length of $\leq \Phi(w_1)$

$$\underbrace{\text{length of }}_{\geq \text{min } \text{ size} \times \text{mistakes}} - \text{length of } \leq \Phi(w_1)$$

Proof Sketch III

$$\text{length of } \square \leq \Phi(w_1)$$

$$\underbrace{\text{length of } \square}_{\geq \min \square \text{ size} \times \text{mistakes}} - \underbrace{\text{length of } \square}_{\leq \text{mistakes}^{2/3}} \leq \Phi(w_1)$$

Proof Sketch III

$$\text{length of } \square \leq \Phi(w_1)$$

$$\underbrace{\text{length of } \square}_{\geq \min \square \text{ size} \times \text{mistakes}} - \underbrace{\text{length of } \square}_{\leq \text{mistakes}^{2/3}} \leq \Phi(w_1)$$

$$\min \square \text{ size} \cdot \text{mistakes} - \text{mistakes}^{2/3} \leq \Phi(w_1)$$

Results

3 programs, 120 sequences of system calls

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Winnow makes fewer mistakes and grows smaller trees for all 120 sequences

Related Work

Much work on PSTs [Willems et al., 1995], [Ron et al., 1996], [Pereira & Singer, 1999]. . . but with assumptions on the tree structure e.g. a priori bounds on the tree's depth

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[Shalev-Shwartz & Tewari, 2009] get sparse solutions from any p-norm algorithm

Summary

Introduced an online learning algorithm to learn PSTs

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On our task, it made fewer mistakes and grew smaller trees than other state-of-the-art algorithms.

References I

Dekel, O., Shalev-Shwartz, S., & Singer, Y. (2004).
The power of selective memory: Self-bounded learning of prediction suffix trees.
Advances in Neural Information Processing Systems, 17.

Pereira, F., & Singer, Y. (1999).
An Efficient Extension to Mixture Techniques for Prediction and Decision Trees.
Machine Learning, *36*, 183–199.

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Ron, D., Singer, Y., & Tishby, N. (1996).

The Power of Amnesia: Learning Probabilistic Automata with Variable Memory Length.

Machine Learning, *25*, 117–149.

Shalev-Shwartz, S., & Tewari, A. (2009).

Shochastic Methods for ℓ_1 Regularized Loss Minimization.

Proceedings of the 26th ICML.

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Willems, F., Shtarkov, Y., & Tjalkens, T. (1995).

The context-tree weighting method: basic properties.

IEEE Transactions on Information Theory, *41*, 653–664.

Differences with [Dekel et al., 2004]

Features: $\beta = 2^{-1/3}$ vs. $\beta = 2^{-1/2}$

P_t: $\sum ||n_i||_\infty$ vs. $\sum ||n_i||_2$

Tolerance: $P_t \leq M_t^{2/3}$ vs. $P_t \leq \frac{1}{2}\sqrt{M_t}$

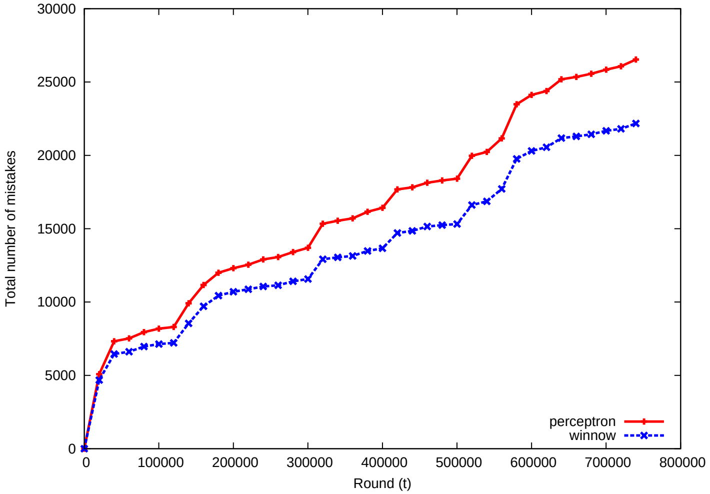
Tweaking [Dekel et al., 2004]

Setting $\beta = 2^{-1/3}$: big trees many mistakes (overfit)

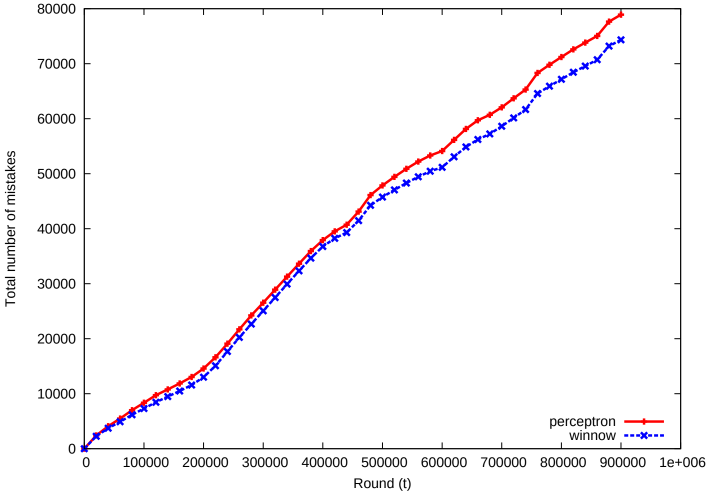
Setting $P_t \leq M_t^{2/3}$: small trees many mistakes (underfit)

Doing both: few mistakes, medium sized trees (less overfit)

More Results



More Results



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