HOCHSCHULE
MITTWEIDA
University of Applied Sciences

Cognitive Science and Machine Learning

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Agenda

What is Cognitive Bias?

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Introduction

1. Bias created by human cognition
2. Has an active role in decision making
3. Not always logical
4. Notation: $B(q|p)$,
   How strongly one belives q occurs after observing p

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What is Cognitive Bias?

Types of cognitive bias we use

Symmetry Bias

Example: ‘If the weather was rainy, then the ground is wet’
$(p \implies q)$
$\implies$ ‘Only if the ground is wet, then the weather was rainy a while ago’ [1]
$(q \implies p)$

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Mutual Exclusivity Bias

Example: 'If you do not clean your room, then you will not be allowed to play' $(p \implies q)$

$\implies$ 'If I clean up my room, then my mom will allow me to play' [2] $(\neg p \implies \neg q)$

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What is Cognitive Bias?

Illogical bias

p: 'The shoe is white'
q: 'A star is printed on it'
$p \implies q$: 'If the shoe is white, then a star is printed on it' [3]

Symmetry Bias

$q \implies p$: 'If a star is printed on a shoe, then the shoe is white' [3]

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$\neg p \implies \neg q$: 'If the shoe is not white, then a star is not printed on it' [3]

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What is Cognitive Bias?

Properties and biases

- **Symmetry Bias (S):** $B(q|p) \sim B(p|q)$
- **Mutual Exclusitivity Bias (MX):** $B(q|p) \sim B(\neg q|\neg p)$
- **The law of excluded middle (XM):** $B(q|p) \sim 1 - B(\neg q|p)$
- **Estimation relativity (ER):** $B(q|p) \sim 1 - B(q|\neg p)$

Note: Adapted from [4]

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ML Implementation

ML Implementation

Interpretation

	q	$\neg q$
p	a	b
$\neg p$	c	d

Table: Co-occurence frequency [5]

	$L(x) = L(w^x)$	$L(x) \neq L(w^x)$
$L(w_i) = L(w^x)$	a	b
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Table: ML implementation of the co-occurence frequency table [5]

- x: sample
- w_i: i^{th} prototype
- w_x: winner prototype of sample x
- $L(y)$: label of y

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Updating learning rates

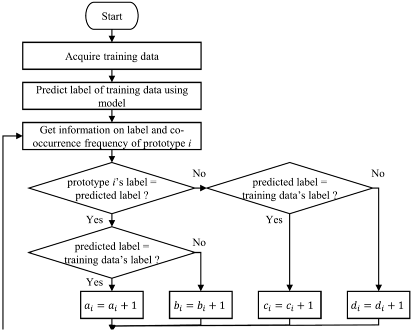

Figure: Learning rate update flowchart part 1 [4]

ML Implementation

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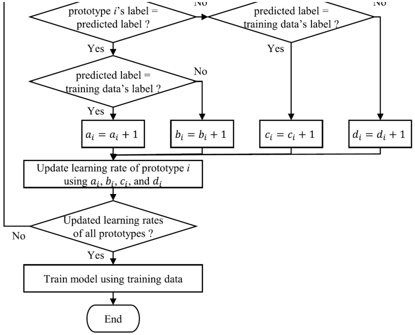

Figure: Learning rate update flowchart part 2 [4]

ML Implementation

Updating learning rates

- $R_i(a_i, b_i, c_i, d_i, t)$: Causal relationship between events for i^{th} prototype at time t
- $\epsilon_i(t) = 1 - R_i(t)$: Local learning rate of i^{th} prototype at time t
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Optimizers

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Loose Symmetry (LS)

- $R_i^{\mathrm{LS}}(t) = \dfrac{a_i(t)+\frac{b_i(t)}{b_i(t)+d_i(t)}d_i(t)}{a_i(t)+\frac{b_i(t)}{b_i(t)+d_i(t)}d_i(t)+b_i(t)+\frac{a_i(t)}{a_i(t)+c_i(t)}c_i(t)}$ [4, 5]
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- Has better results than other cognitive bias optimizers in tested datasets [4]

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Loose Symmetry under Rarity (LSR)

- Assumption: The events p and q are small, hence the correlation of any two events is unlikely, $d(t) \rightarrow \infty$ [2]
- Example: The correlation between any random event and you starting you car in the morning [2]
- $R_i^{\text{LSR}}(t) = \lim_{d_i(t)\rightarrow\infty} R_i^{\text{LS}}(t)$
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- Compare the performance cognitive models with OGVLQ model
- OGLVQ model stands for optimized GLVQ [6]
- For balanced dataset, use accuracy as score
- For Imbalanced dataset, use F1 score as score
- Prototype selection is optimized for OGLVQ

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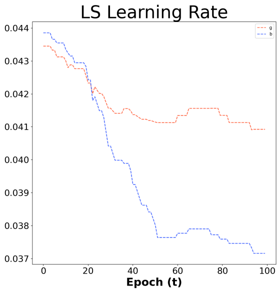
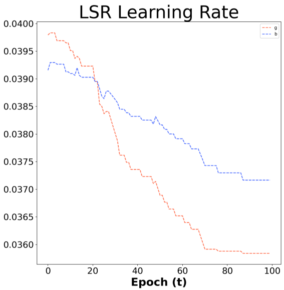
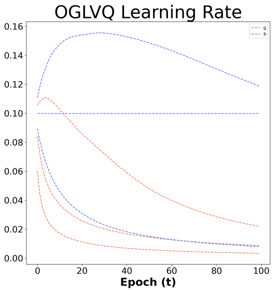
Dataset: Ionosphere dataset [7]







Be careful with y-axis, since they do not share common size

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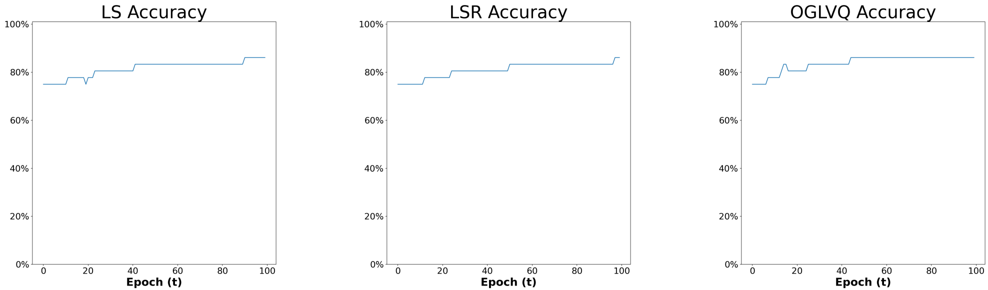

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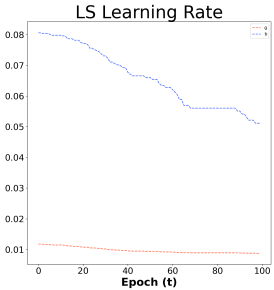

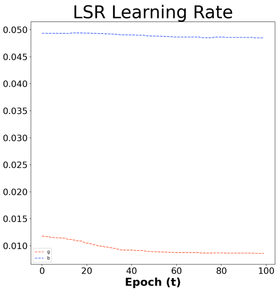

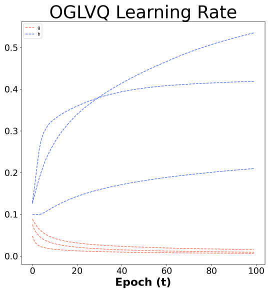

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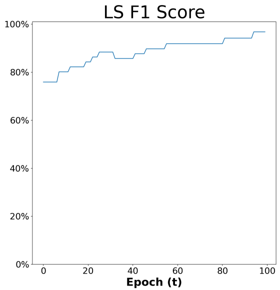

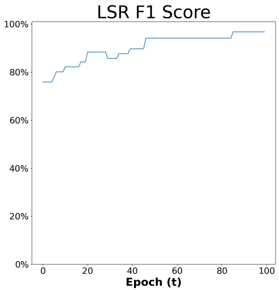

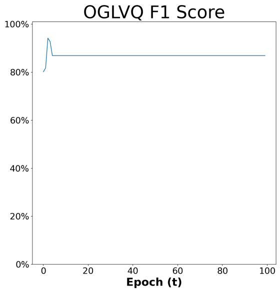

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Further

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Bibliography I

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Thank You

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