Evolving Neural Networks for Statistical Decision Theory

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Master Thesis Defense, 2005

Outline

1. Introduction
   - Master Thesis Goals
2. Methods
   - JASTAP — Biologically Plausible NN Model
   - Inter–spike Intervals
   - Decisioning With NNs
   - Evolution
3. Decision Problems
   - More Frequent Input
   - Hypothesis Testing of Frequency
   - More Regular Input
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1. Explore statistical decisioning in NNs
2. Analyze the abilities of simple network structures
3. Try to evolve the networks useful for statistical decisioning of mean rates and regularities
4. Methods: JASTAP and GA's

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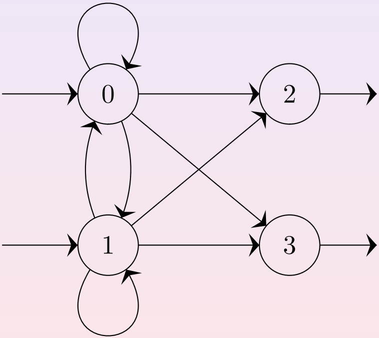

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- spiking neuron model
- respects physiological aspects of a real neuron
- weights, thresholds, latencies, PSP's, firing rates

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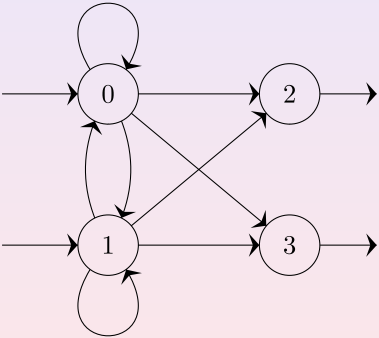

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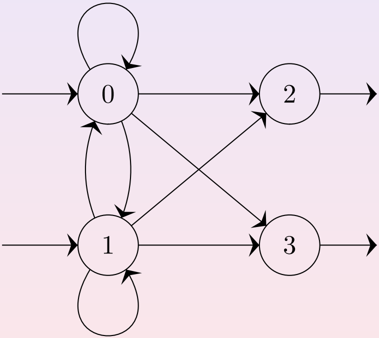

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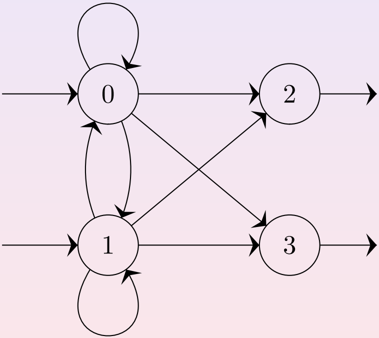

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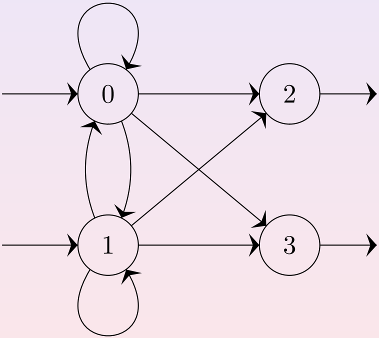

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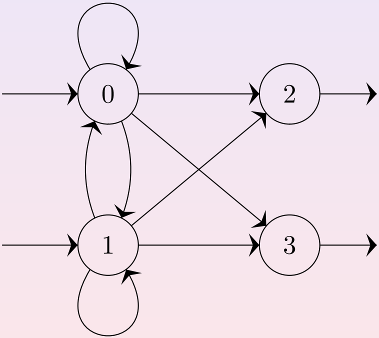

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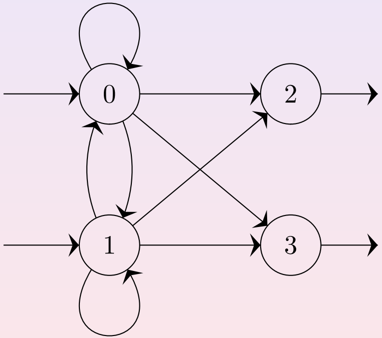

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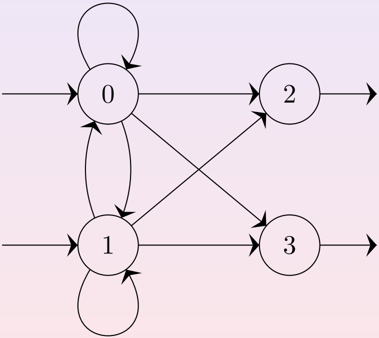

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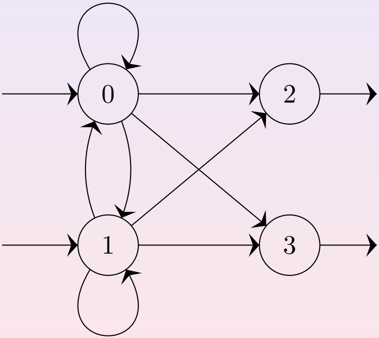

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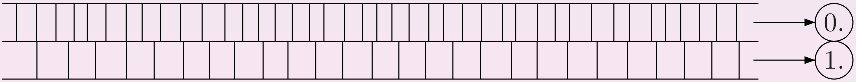
Information Processing

Encoding

- JASTAP works with temporal code
- information is coded in inter–spike intervals



PSP Definition

$$\mathrm{PSP}(t) = k \cdot \left(1 - \mathrm{e}^{-\frac{t}{t_1}}\right)^2 \cdot \mathrm{e}^{-\frac{2t}{t_2}}$$

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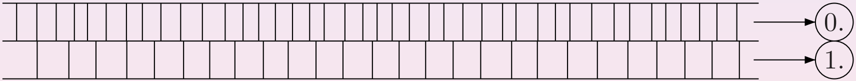

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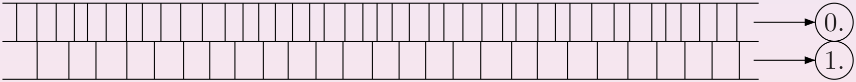

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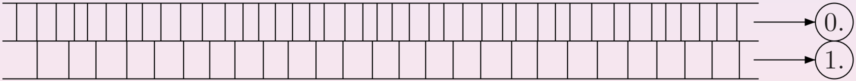

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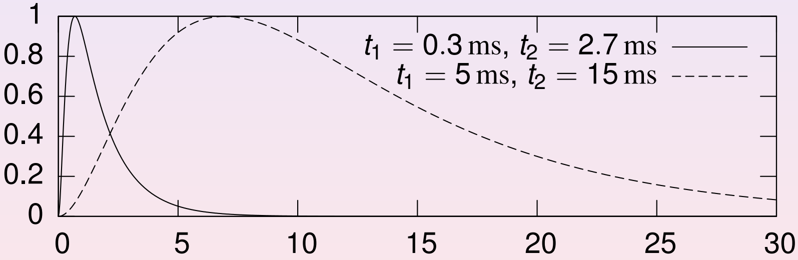
Postsynaptic Potential



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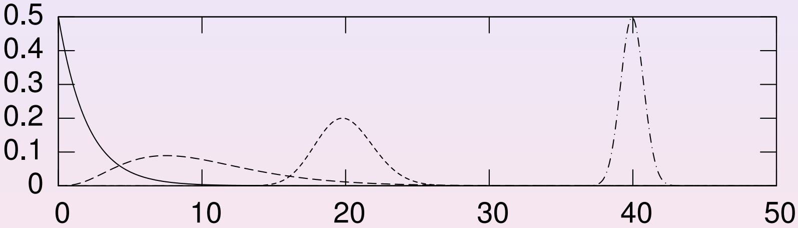
Gamma Distribution

Definition

A random variable Z has the Gamma distribution, if the probabilistic density function of Z is

$$f(z) = \frac{z^{\alpha-1}\mathrm{e}^{-\frac{z}{\beta}}}{\beta^{\alpha}\Gamma(\alpha)} \quad \alpha, \beta > 0, z \geq 0, \text{ and we denote it as } \mathscr{G}(\alpha, \beta)$$

Gamma Distribution



$$c_v = 1, \overline{isi} = 2\,\mathrm{ms}$$
$$c_v = 0.5, \overline{isi} = 10\,\mathrm{ms}$$
$$c_v = 0.1, \overline{isi} = 20\,\mathrm{ms}$$
$$c_v = 0.02, \overline{isi} = 40\,\mathrm{ms}$$

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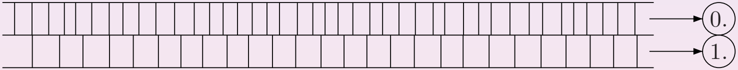
2. 

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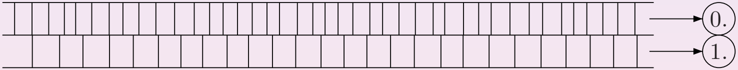
2. 

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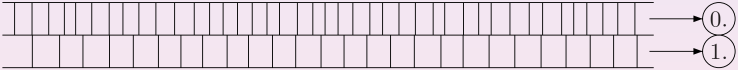
2. 

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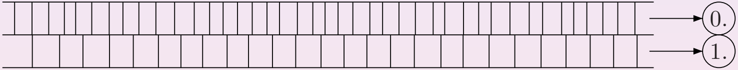
2. 

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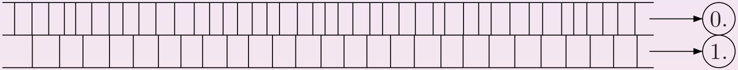
2. 

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Evolution Set Up

What to evolve?

weights	absolutely
latencies	important for time–related patterns
PSP shapes	expands the search space, slower decay chosen
thresholds	no comment
fire rates	not evolved, $I_{\min} := 1\,\mathrm{ms}$, $I_{\max} := 10\,\mathrm{ms}$

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- Gray binary coding
- recombination: multipoint crossover
- mutation: p–scaled
- 2 phases: second is for *fine–tuning* from the *seed*
- fitness function → crucial issue

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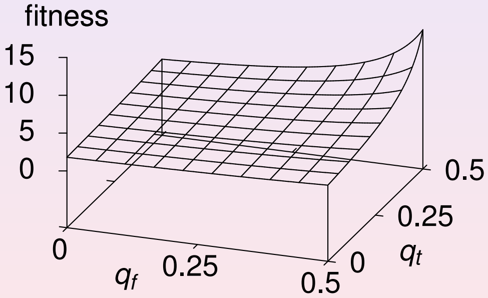
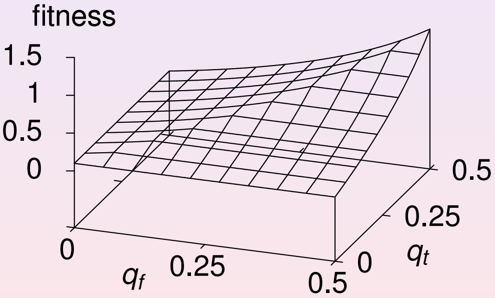
Fitness Functions: Overall Ratio



overall ratio

$$1/(1+\varepsilon-q_t-q_f)$$

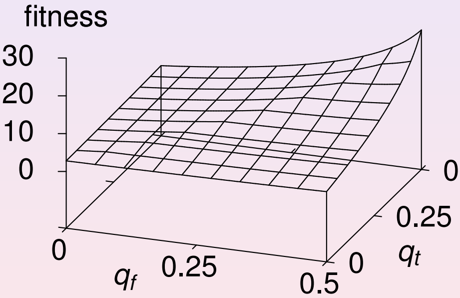
Fitness Functions: One Side Minimum

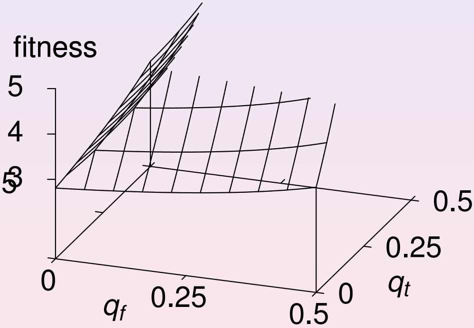


one side minimum

$1/(1 - \min(q_t, q_f)) - 1$

Fitness Functions: Combined





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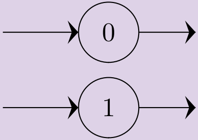

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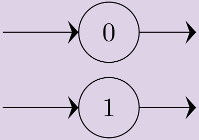

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Theoretical Strategies: Defining the Bounds

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lower $\overline{isi}$	higher $\overline{isi}$	ratio
30 ms	40 ms	57.14 %
20 ms	40 ms	66.67 %
10 ms	40 ms	80.00 %
20 ms	30 ms	60.00 %
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30 ms	40 ms	72.45 %
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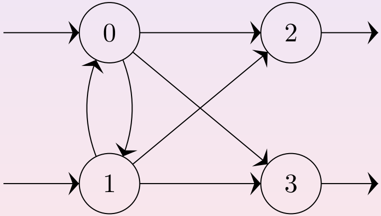
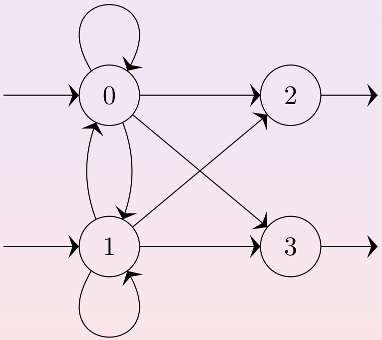
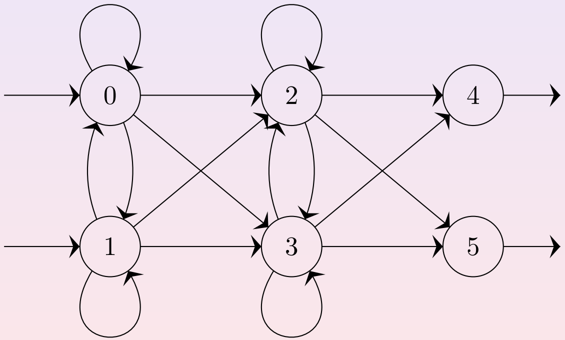


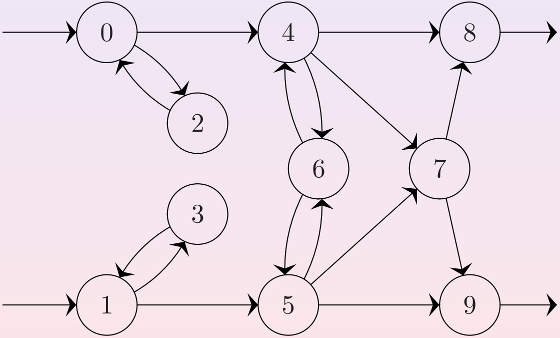
Network Structures: *B*



Network Structures: C



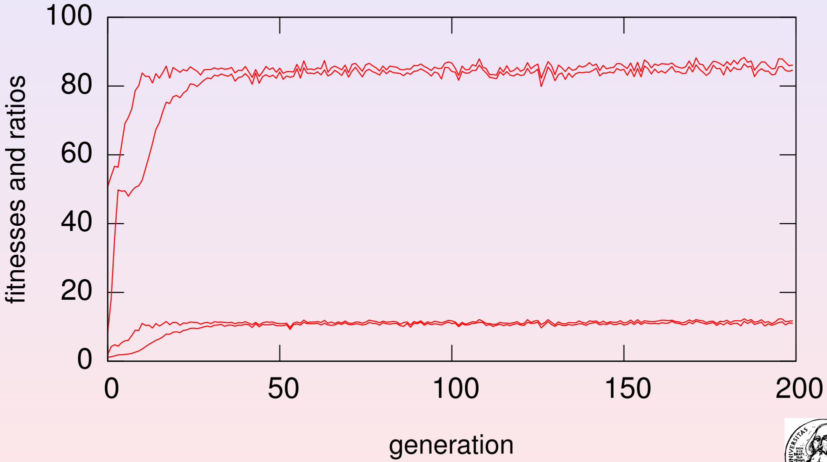
Network Structures: *D*



Network Structures: Comparison

low $\overline{isi}$	high $\overline{isi}$	copy	A	B	C	D	event
30 ms	40 ms	57.14	60.12	62.18	59.03	61.31	72.45
20 ms	40 ms	66.67	88.11	87.56	87.67	81.32	94.51
10 ms	40 ms	80.00	99.81	99.65	99.25	99.58	99.99
20 ms	30 ms	60.00	66.92	71.52	69.65	67.27	83.97
10 ms	30 ms	75.00	99.35	99.19	99.14	98.08	99.91
10 ms	20 ms	66.67	95.04	92.74	94.12	91.75	98.83
$\langle 10\,\mathrm{ms}, 40\,\mathrm{ms}\rangle$		60.22	66.66	66.68	68.48	65.75	79.68

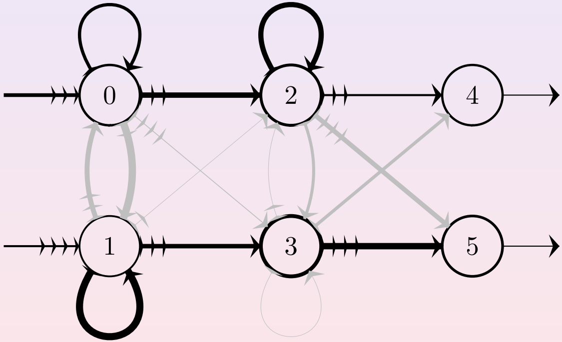
Evolution curves: $\overline{isi}$ 10 vs. 20 ms, $c_v = 1$



Comparison: Different c_vs (in %)

low $\overline{isi}$	high $\overline{isi}$	0.02	0.1	0.5	1	$\langle 0, 1\rangle$
30 ms	40 ms	100.00	100.00	77.17	63.26	73.29
20 ms	40 ms	100.00	100.00	98.07	87.67	95.61
10 ms	40 ms	100.00	100.00	99.99	99.69	99.85
20 ms	30 ms	100.00	99.96	90.78	70.94	87.62
10 ms	30 ms	100.00	100.00	99.94	99.14	99.77
10 ms	20 ms	100.00	100.00	99.85	94.25	98.60
$\langle 10\,\mathrm{ms}, 40\,\mathrm{ms}\rangle$		98.02	92.51	78.15	72.00	66.01

Example: evolved network for $\overline{isi}$: 20 vs. 30 ms, $c_v = 1$



Results

Strategies

- information paths
- competing
- redundancy handling
- copy machine principle
- activity routing

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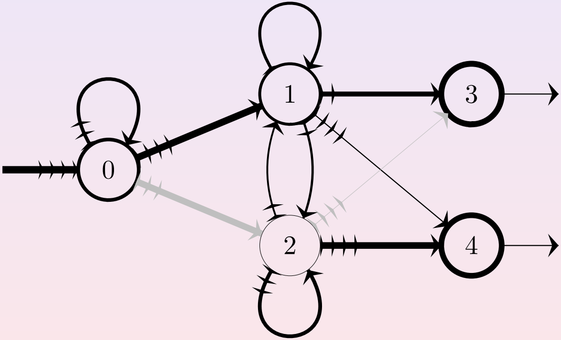
Outline

1. Introduction
   - Master Thesis Goals
2. Methods
   - JASTAP — Biologically Plausible NN Model
   - Inter–spike Intervals
   - Decisioning With NNs
   - Evolution
3. Decision Problems
   - More Frequent Input
   - Hypothesis Testing of Frequency
   - More Regular Input
   - Hypothesis Testing of Regularity

Network Structure for Hypothesis Testing



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- gap detection
- perfect timing

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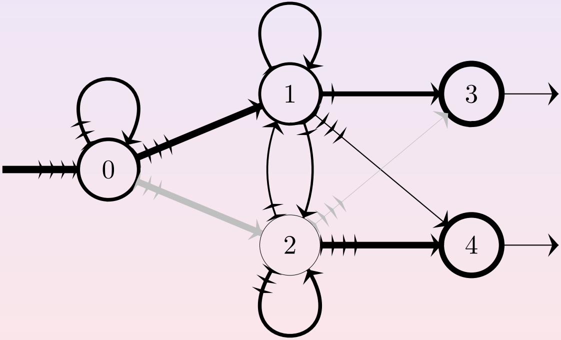

Strategies

- gap detection
- perfect timing

Results: $\overline{isi} \in_R \langle 10\,\mathrm{ms}, 40\,\mathrm{ms}\rangle$, $300\,\mathrm{ms}$

H_0	$c_v = 0.02$	$c_v = 0.1$	$c_v = 0.5$	$c_v = 1$	$\langle 0, 1\rangle$
$\overline{isi} < 20\,\mathrm{ms}$	98.57 %	94.72 %	89.48 %	57.20 %	73.91 %
$\overline{isi} < 25\,\mathrm{ms}$	99.00 %	95.04 %	85.59 %	60.66 %	73.78 %
$\overline{isi} < 30\,\mathrm{ms}$	98.97 %	94.64 %	67.53 %	56.86 %	74.21 %

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low	high	10 ms	20 ms	30 ms	40 ms	$\langle 10, 40 \rangle$
0.02	0.50	99.93 %	99.75 %	98.90 %	98.74 %	74.52 %
0.02	1.00	99.95 %	99.61 %	97.99 %	98.32 %	88.85 %
0.50	1.00	83.05 %	76.55 %	77.44 %	64.32 %	67.08 %
$\langle 0.00, 1.00 \rangle$		70.99 %	67.85 %	67.78 %	63.96 %	55.07 %

Strategies

- close events
- distant events

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H_0	$10\,\mathrm{ms}$	$20\,\mathrm{ms}$	$30\,\mathrm{ms}$	$40\,\mathrm{ms}$	$\langle 10, 40\rangle$
$c_v < 0.5$	83.04 %	76.28 %	76.20 %	74.99 %	66.31 %

One Neuron Strategies

- memory in latency
- from regularity to frequency
- irregularity stopping

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Further work

- Enhance the evolution.
- Evolve the topologies.
- Evolve *PSP*s and firing rates.
- Speed preferences, faster decision makers.

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Obsah dodatku

4. Dodatok
   - Školiteľský posudok
   - Oponentský posudok
   - Odovede na otázky oponenta
   - Voľná diskusia

Mgr. Radoslav Harman, PhD.

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Comenius University

Ing. Igor Farkaš, PhD.

Department of Applied Informatics
Faculty of Mathematics,
Physics and Informatics
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Oponentská otázka č. 1

Otázka

Autor si zvolil model JASTAP, no patrilo by sa aspoň v referenciách spomenúť, že existuje celá škála iných, etablovaných, biologicky prijateľných modelov neurónu (pozri napr. prehľadový článok Izhikevich E., IEEE Trans. on Neural Networks, 15(5), 2004). Okrem toho, čo znamená tá skratka?

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Niektoré symboly neboli vysvetlené, napr. str. 8: predpokladám, že k=1; pracuje sa v princípe v modeli aj s inou hodnotou k? Str. 10: Čo je $\Gamma(a)$ pri gamma distribúcii f(z)?

Odpoveď

- k je normovacia konštanta konštanta, je hodnota je 1/(maximálna hodnota PSP)
- $\Gamma(z) = \int_0^\infty t^{z-1}\, e^{-t}\, dt$
- $\Gamma(n+1) = n\,\Gamma(n) = \cdots = n!\,\Gamma(1) = n!$
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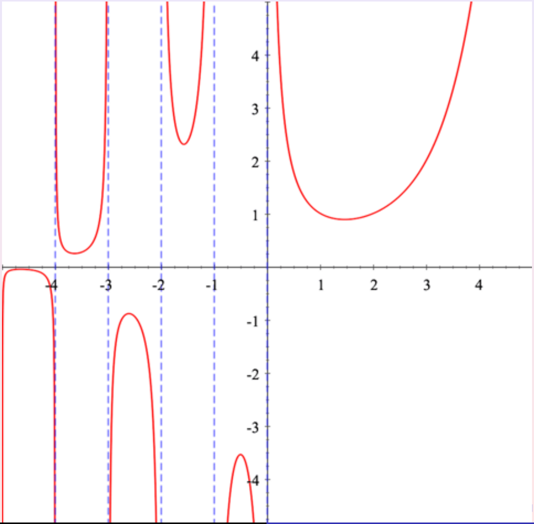

Oponentská otázka č. 3

Otázka

Rozdiely medzi jednotlivými modelmi AD (tab.4.3, 4.4) vyzerajú byť minimálne. Otázka je, či sú štatisticky signifikantné. Pomohli by tu štatistické testy?

Odpoveď

Pozrime si znova tabuľku. . .

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Odpoveď

Pozrime si znova tabuľku...

Oponentská otázka č. 3

vyššie $\overline{isi}$	nižšie $\overline{isi}$	A	B	C	D	rozdiel
30 ms	40 ms	60.12	62.18	59.03	61.31	2.06
20 ms	40 ms	88.11	87.56	87.67	81.32	6.79
10 ms	40 ms	99.81	99.65	99.25	99.58	0.40
20 ms	30 ms	66.92	71.52	69.65	67.27	4.60
10 ms	30 ms	99.35	99.19	99.14	98.08	1.27
10 ms	20 ms	95.04	92.74	94.12	91.75	3.29
$\langle 10\,\mathrm{ms}, 40\,\mathrm{ms}\rangle$		66.66	66.68	68.48	65.75	2.73

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Odpoveď

Je pravdou, že testovanie jedincov kvôli ohodnoteniu počas simulácií bolo iba 50 testami z rýchlostostných dôvodov. V tabuľke sú však uvedené výsledky vypočítané z 10 000 testov a chyby sú na úrovni stotín.

Oponentská otázka č. 4

Otázka

Obr. 4.3: krivka pre *avg* kopíruje tú pre *best*. Očakával by som, že ako priemer bude *avg* hladká.

Odpoveď

Pozrime si dotyčný graf. . .

Oponentská otázka č. 4

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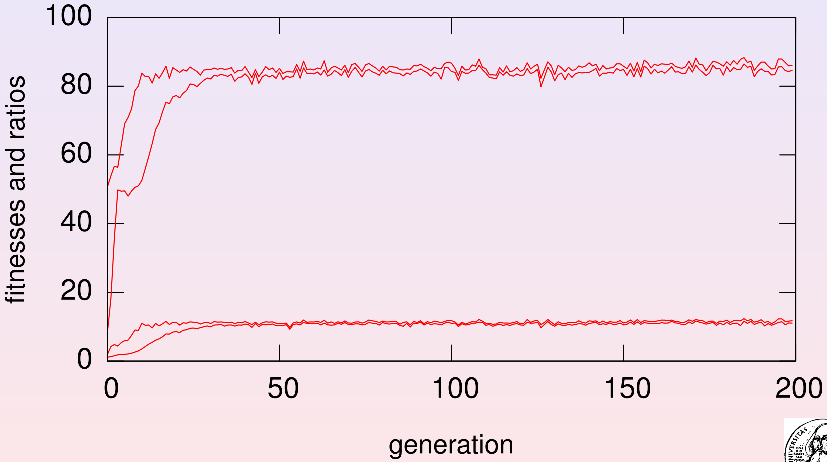
Odpoveď

Pozrime si dotyčný graf. . .

Evolution curves: $\overline{isi}$ 10 vs. 20 ms, $c_v = 1$



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Obr. 4.3: krivka pre *avg* kopíruje tú pre *best*. Očakával by som, že ako priemer bude *avg* hladká.

Odpoveď

- skoky v grafe súvisia z generovaním úplne novej trénovacej sady pre každú generáciu
- na nehladkosť má vplyv aj elitizmus
- čiarkovaný priebeh v tlačenej verzii DP

Oponentská otázka č. 5

Otázka

Z textu som nedokázal vydedukovať, čo znamenajú tie impulzy (prečo 4 línie), napr. obr. 4.4.

Odpoveď

Línie nad neurónmi znamenajú vstupy zo synáps. Štyri sú preto lebo zobrazované štruktúry majú štyri vstupy. Ak je neurón zároveň vstupným, prvá *línia* znázorňuje vonkajší vstup.

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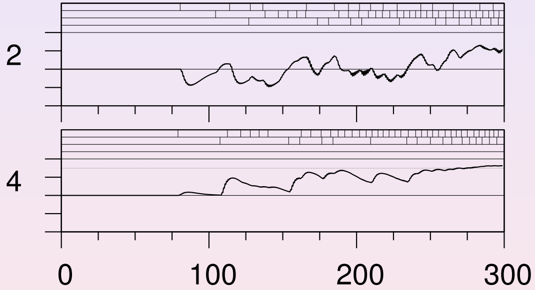

Obrázok: gap detection — a *yes* decision

Oponentská otázka č. 6

Otázka

Autor rieši biologicky relevantný problém biologicky relevantnými prostriedkami, avšak použil “fylogenetický” prístup (GA) na riešenie “ontologického” problému (učenie). Je to odôvodniteľné problémom návrhu vhodného tradičného algoritmu učenia (napr. na báze Hebbovho učenia), hoci tento prístup by bol zrejme viac biologicky prijateľný ako GA.

Odpoveď

Je to presne tak, ale cieľom bolo skôr nájsť štruktúry schopné rozhodovania než zistiť ako takéto štruktúry vznikli.

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Voľná diskusia