# Evolving Neural Networks for Statistical Decision Theory

Michal Valko[1]    Mgr. Radoslav Harman PhD.[2]

[1]Department of Applied Informatics
Faculty of Mathematics, Physics and Informatics
Comenius University

[2]Department of Applied Mathematics and Statistics
Faculty of Mathematics, Physics and Informatics
Comenius University

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
   - Hypothesis Testing of Regularity

# 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

# Outline

# 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

# Master Thesis Goals

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

# Master Thesis Goals

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

# Master Thesis Goals

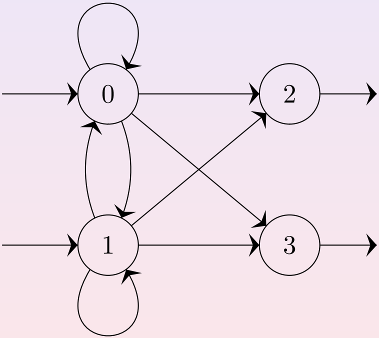
1. Explore statistical decisioning in NNs
2. Analyze the abilities of simple network structures
3. Try to evolve the networks useful for statistical decisioning of mean rates and regularities
4. Methods: JASTAP and GA's

# Master Thesis Goals

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

# Outline

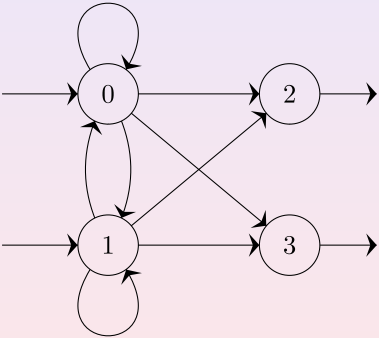
# What is JASTAP?




## Characteristics

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

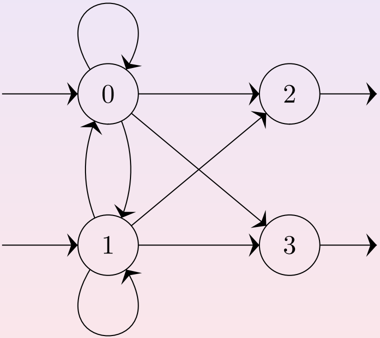
# What is JASTAP?




## Characteristics

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

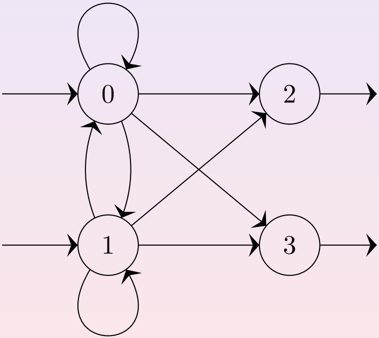
# What is JASTAP?




## Characteristics

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

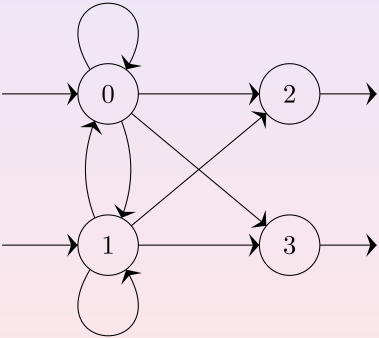
# What is JASTAP?




## Characteristics

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

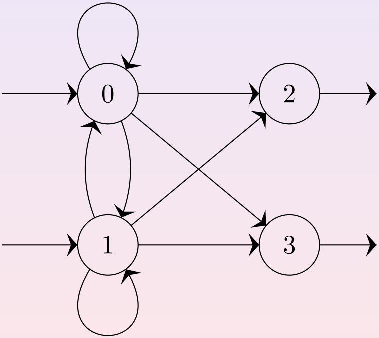
# What is JASTAP?




## Characteristics

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

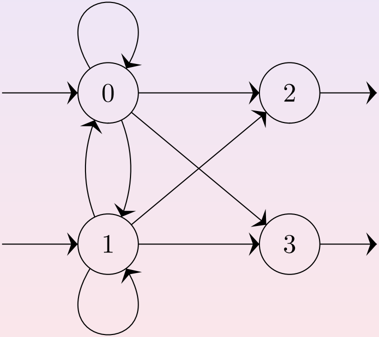
# What is JASTAP?




## Characteristics

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

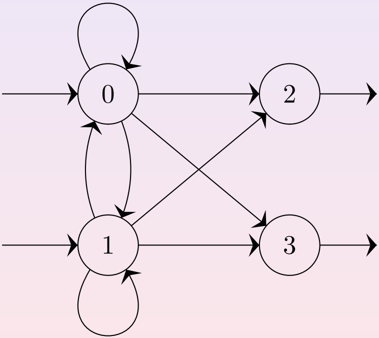
# What is JASTAP?




## Characteristics

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

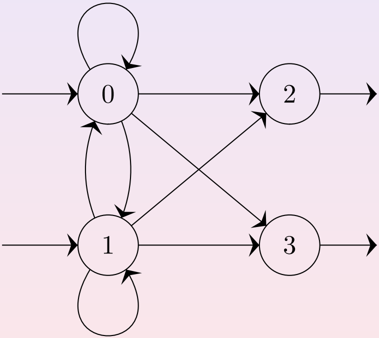
# What is JASTAP?




## Characteristics

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

# What is JASTAP?



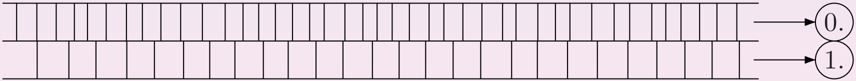

## Characteristics

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

# Information Processing

## Encoding

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



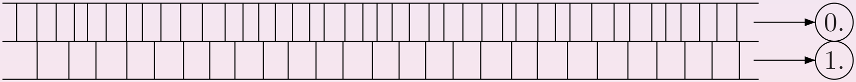

## PSP Definition

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

# Information Processing

## Encoding

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



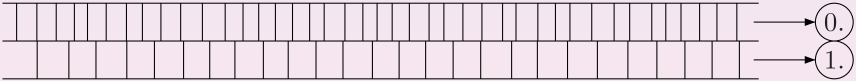

## PSP Definition

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

# Information Processing

## Encoding

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



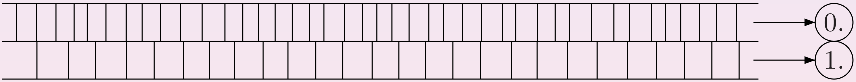

## PSP Definition

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

# Information Processing

## Encoding

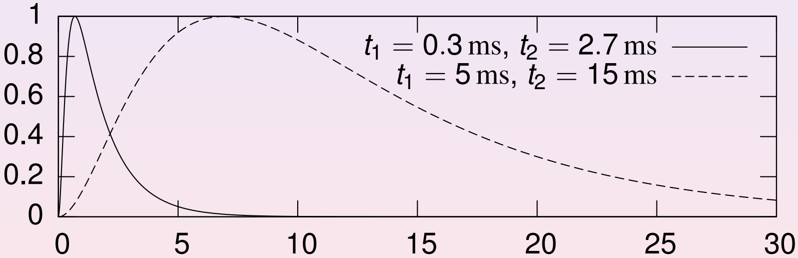
- JASTAP works with temporal code
- information is coded in inter–spike intervals




## PSP Definition

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

# Postsynaptic Potential



# Outline

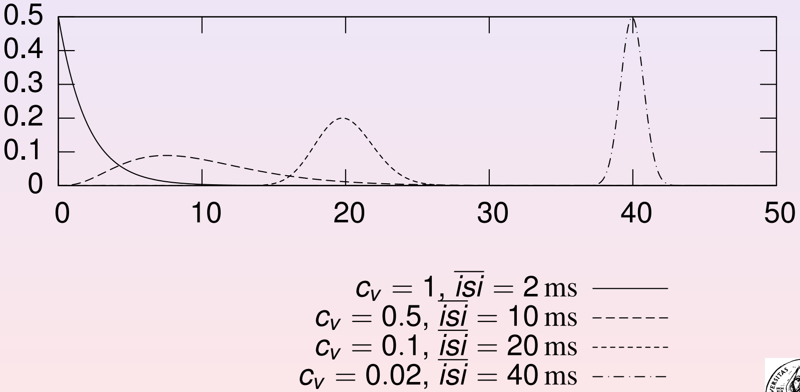
# Gamma Distribution

## Definition

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

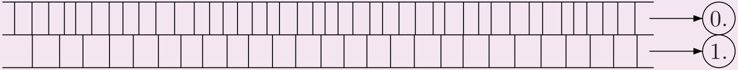
$$f(z) = \frac{z^{\alpha-1} e^{-\frac{z}{\beta}}}{\beta^{\alpha}\Gamma(\alpha)} \quad \alpha, \beta > 0, z \geq 0, \text{and we denote it as } \mathscr{G}(\alpha, \beta)$$

# Gamma Distribution



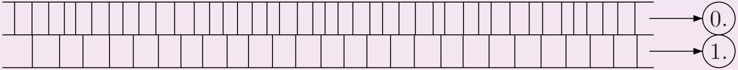
# Outline

# How it works?

1. input temporal code is generated from random Gamma distribution drawns
2. 

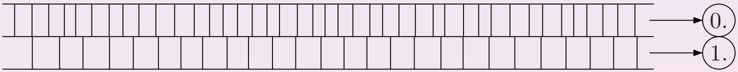
3. input is processed by the network
4. if any of the output neurons fires, it is taken as a decision

# How it works?

1. input temporal code is generated from random Gamma distribution drawns
2. 

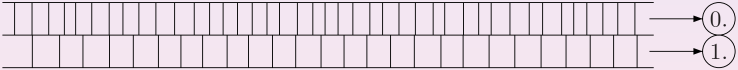
3. input is processed by the network
4. if any of the output neurons fires, it is taken as a decision

# How it works?

1. input temporal code is generated from random Gamma distribution drawns
2. 

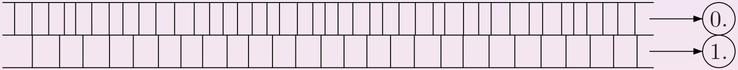
3. input is processed by the network
4. if any of the output neurons fires, it is taken as a decision

# How it works?

1. input temporal code is generated from random Gamma distribution drawns
2. 

3. input is processed by the network
4. if any of the output neurons fires, it is taken as a decision

# How it works?

1. input temporal code is generated from random Gamma distribution drawns
2. 

3. input is processed by the network
4. if any of the output neurons fires, it is taken as a decision

# 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

# 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, $I_{min} := 1\,\mathrm{ms}$, $I_{max} := 10\,\mathrm{ms}$ |

# 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, $I_{\min} := 1\,\mathrm{ms}$, $I_{\max} := 10\,\mathrm{ms}$

# 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, $I_{min} := 1\,\mathrm{ms}$, $I_{max} := 10\,\mathrm{ms}$ |

# 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, $I_{\min} := 1\,\mathrm{ms}$, $I_{\max} := 10\,\mathrm{ms}$ |

# 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, $I_{\mathrm{min}} := 1\,\mathrm{ms}$, $I_{\mathrm{max}} := 10\,\mathrm{ms}$ |

# 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, $I_{\min} := 1\,\mathrm{ms}$, $I_{\max} := 10\,\mathrm{ms}$ |

# 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, $I_{min} := 1\,\mathrm{ms}$, $I_{max} := 10\,\mathrm{ms}$ |

# 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, $I_{\text{min}} := 1\,\text{ms}$, $I_{\text{max}} := 10\,\text{ms}$ |

# Evolution Set Up

## Genetic Algorithm

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

# Evolution Set Up

## Genetic Algorithm

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

# Evolution Set Up

## Genetic Algorithm

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

# Evolution Set Up

## Genetic Algorithm

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

# Evolution Set Up

## Genetic Algorithm

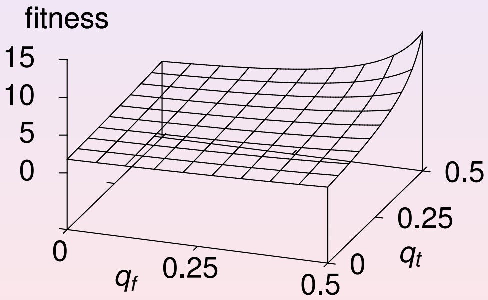
- Gray binary coding
- recombination: multipoint crossover
- mutation: $p$–scaled
- 2 phases: second is for *fine–tuning* from the *seed*
- fitness function → crucial issue

# Evolution Set Up

## Genetic Algorithm

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

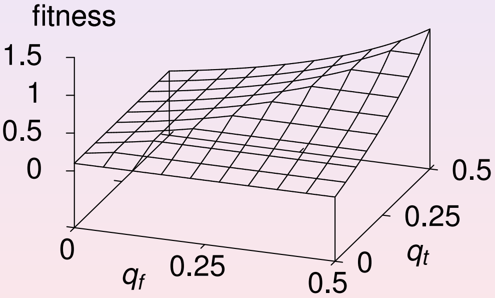
# Fitness Functions: Overall Ratio




**overall ratio**

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

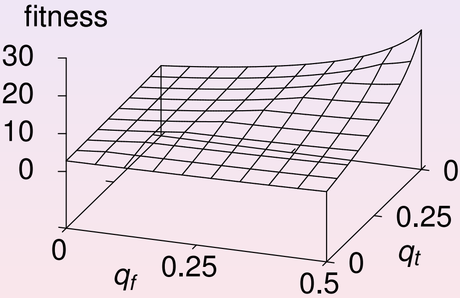
# Fitness Functions: One Side Minimum

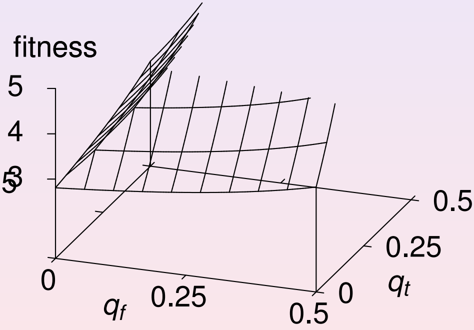



**one side minimum**

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

# Fitness Functions: Combined

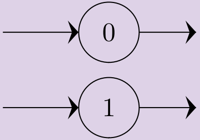


# Outline

# Theoretical Strategies: Description

## copy machine

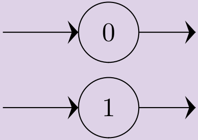



## event counting

it makes the decision that the more frequent input is the one with the more events observed

# Theoretical Strategies: Description

### copy machine




### event counting

it makes the decision that the more frequent input is the one with the more events observed

# Theoretical Strategies: Defining the Bounds

### copy machine

| 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 % |
| 10 ms | 30 ms | 75.00 % |
| 10 ms | 20 ms | 66.67 % |

### event counting

| lower $\overline{isi}$ | higher $\overline{isi}$ | ratio |
|---|---|---|
| 30 ms | 40 ms | 72.45 % |
| 20 ms | 40 ms | 94.51 % |
| 10 ms | 40 ms | 99.99 % |
| 20 ms | 30 ms | 83.97 % |
| 10 ms | 30 ms | 99.91 % |
| 10 ms | 20 ms | 98.83 % |

# Theoretical Strategies: Defining the Bounds

## copy machine

| 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 % |
| 10 ms | 30 ms | 75.00 % |
| 10 ms | 20 ms | 66.67 % |

## event counting

| lower $\overline{isi}$ | higher $\overline{isi}$ | ratio |
|---|---|---|
| 30 ms | 40 ms | 72.45 % |
| 20 ms | 40 ms | 94.51 % |
| 10 ms | 40 ms | 99.99 % |
| 20 ms | 30 ms | 83.97 % |
| 10 ms | 30 ms | 99.91 % |
| 10 ms | 20 ms | 98.83 % |

# Theoretical Strategies: Defining the Bounds

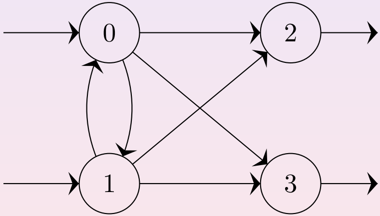
## copy machine

| 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 % |
| 10 ms | 30 ms | 75.00 % |
| 10 ms | 20 ms | 66.67 % |

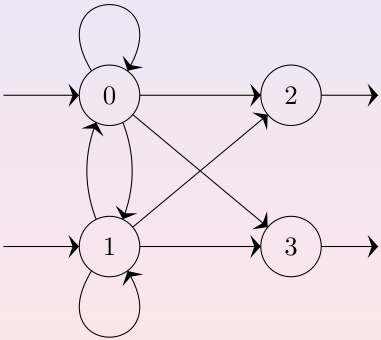
## event counting

| lower $\overline{isi}$ | higher $\overline{isi}$ | ratio |
|---|---|---|
| 30 ms | 40 ms | 72.45 % |
| 20 ms | 40 ms | 94.51 % |
| 10 ms | 40 ms | 99.99 % |
| 20 ms | 30 ms | 83.97 % |
| 10 ms | 30 ms | 99.91 % |
| 10 ms | 20 ms | 98.83 % |

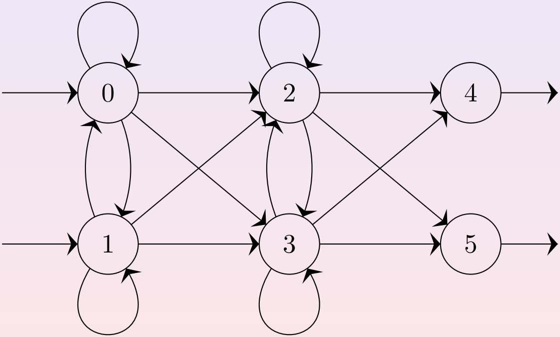
# Network Structures: $A$



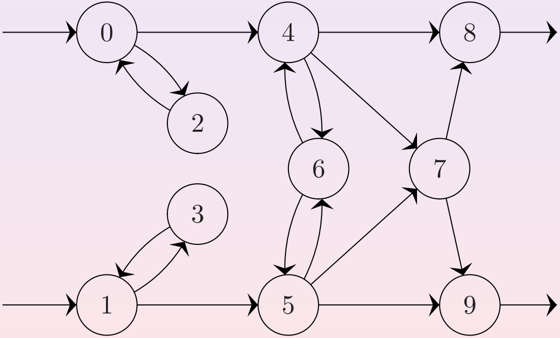
# Network Structures: *B*



# Network Structures: $C$



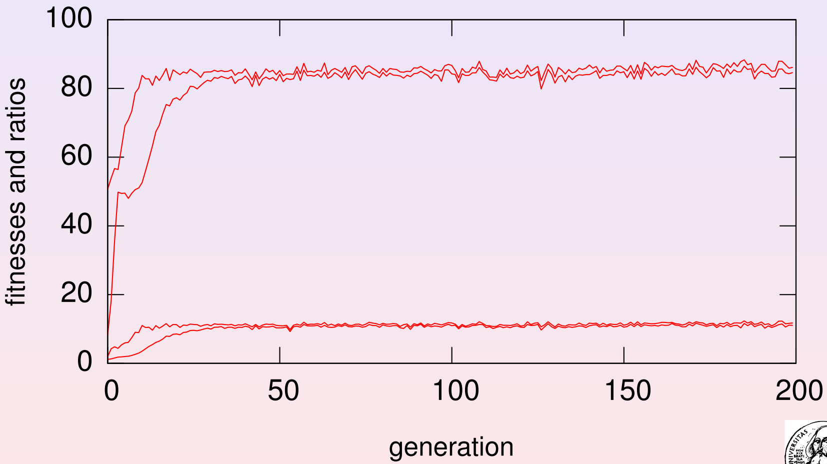
# Network Structures: *D*



# 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 |

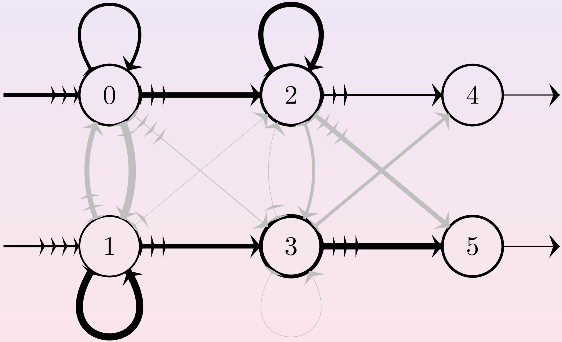
# Evolution curves: $\overline{isi}$ 10 vs. 20 ms, $c_v = 1$



# Comparison: Different $c_v$s (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$10 ms, 40 ms$\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

# Results

## Strategies

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

# Results

## Strategies

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

# Results

## Strategies

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

# Results

## Strategies

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

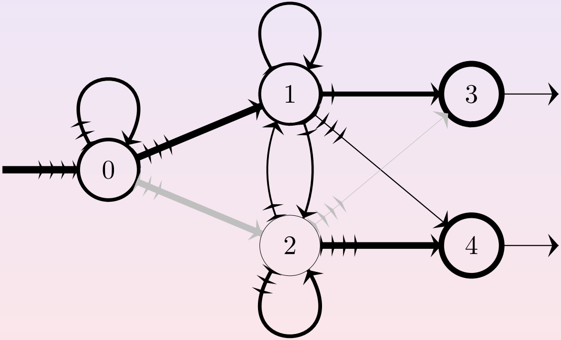
# Results

## Strategies

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

# Outline

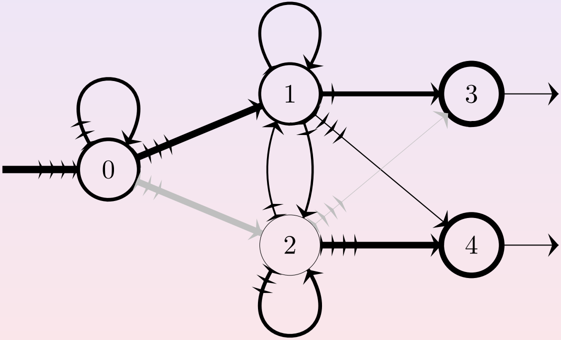
# Network Structure for Hypothesis Testing




**Strategies**

- gap detection
- perfect timing

# Network Structure for Hypothesis Testing




## 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 % |

# Outline

# Results

| 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

# Results

| low | high | $10\,\mathrm{ms}$ | $20\,\mathrm{ms}$ | $30\,\mathrm{ms}$ | $40\,\mathrm{ms}$ | $\langle 10, 40\rangle$ |
|---|---|---|---|---|---|---|
| 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

# Results

| 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

# Results

| 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

# 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

# Results

| $H_0$ | 10 ms | 20 ms | 30 ms | 40 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

# Results

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

## One Neuron Strategies

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

# Results

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

## One Neuron Strategies

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

# Results

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

## One Neuron Strategies

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

# Results

| $H_0$ | 10 ms | 20 ms | 30 ms | 40 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

# Summary

## Conclusions

- JASTAP is able to model decision making.
- We have found decision makers for comparing and statistical testing of mean and $c_v$ of Gamma distributions
- Results are amenable to analysis.
- Several strategies emerged during evolution, that helped networks to decide.

# Summary

## Conclusions

- JASTAP is able to model decision making.
- We have found decision makers for comparing and statistical testing of mean and $c_v$ of Gamma distributions
- Results are amenable to analysis.
- Several strategies emerged during evolution, that helped networks to decide.

# Summary

## Conclusions

- JASTAP is able to model decision making.
- We have found decision makers for comparing and statistical testing of mean and $c_v$ of Gamma distributions
- Results are amenable to analysis.
- Several strategies emerged during evolution, that helped networks to decide.

# Summary

## Conclusions

- JASTAP is able to model decision making.
- We have found decision makers for comparing and statistical testing of mean and $c_v$ of Gamma distributions
- Results are amenable to analysis.
- Several strategies emerged during evolution, that helped networks to decide.

# Summary

## Conclusions

- JASTAP is able to model decision making.
- We have found decision makers for comparing and statistical testing of mean and $c_v$ of Gamma distributions
- Results are amenable to analysis.
- Several strategies emerged during evolution, that helped networks to decide.

# Summary

## Further work

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

# Summary

## Further work

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

# Summary

## Further work

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

# Summary

## Further work

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

# Summary

## Further work

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

# Obsah dodatku

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

**Mgr. Radoslav Harman, PhD.**

Department of Applied Mathematics and Statistics
Faculty of Mathematics, Physics and Informatics
Comenius University

**Ing. Igor Farkaš, PhD.**

Department of Applied Informatics
Faculty of Mathematics,
Physics and Informatics
Comenius University

# 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?

## Odpoveď

- . . .
- Jančo, Stavrovský, Pavlásek
- **JA**nčo, **STA**vrovský, **P**avlásek

# 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?

## Odpoveď

- . . .
- Jančo, Stavrovský, Pavlásek
- **JA**nčo, **STA**vrovský, **Pa**vlásek

# 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?

## Odpoveď

- ...
- Jančo, Stavrovský, Pavlásek
- **JA**nčo, **STA**vrovský, **P**avlásek

# 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?

## Odpoveď

- ...
- Jančo, Stavrovský, Pavlásek
- **JA**nčo, **STA**vrovský, **P**avlásek

# 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?

## Odpoveď

- ...
- Jančo, Stavrovský, Pavlásek
- **JA**nčo, **STA**vrovský, **P**avlásek

# Oponentská otázka č. 2

## Otázka

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)
- $\Gamma(z) = \int_0^\infty t^{z-1}\, e^{-t}\, dt$
- $\Gamma(n+1) = n\,\Gamma(n) = \cdots = n!\,\Gamma(1) = n!$
- $\Gamma(a)$ je hodnota funkcie $\Gamma$ v bode $a$

# Oponentská otázka č. 2

## Otázka

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)
- $\Gamma(z) = \int_0^\infty t^{z-1}\, e^{-t}\, dt$
- $\Gamma(n+1) = n\,\Gamma(n) = \cdots = n!\,\Gamma(1) = n!$
- $\Gamma(a)$ je hodnota funkcie $\Gamma$ v bode $a$

# Oponentská otázka č. 2

## Otázka

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)
- $\Gamma(z) = \int_0^\infty t^{z-1}\, e^{-t}\, dt$
- $\Gamma(n+1) = n\,\Gamma(n) = \cdots = n!\,\Gamma(1) = n!$
- $\Gamma(a)$ je hodnota funkcie $\Gamma$ v bode $a$

# Oponentská otázka č. 2

## Otázka

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)
- $\Gamma(z) = \int_0^\infty t^{z-1}\, e^{-t}\, dt$
- $\Gamma(n+1) = n\Gamma(n) = \cdots = n!\,\Gamma(1) = n!$
- $\Gamma(a)$ je hodnota funkcie $\Gamma$ v bode $a$

# Oponentská otázka č. 2

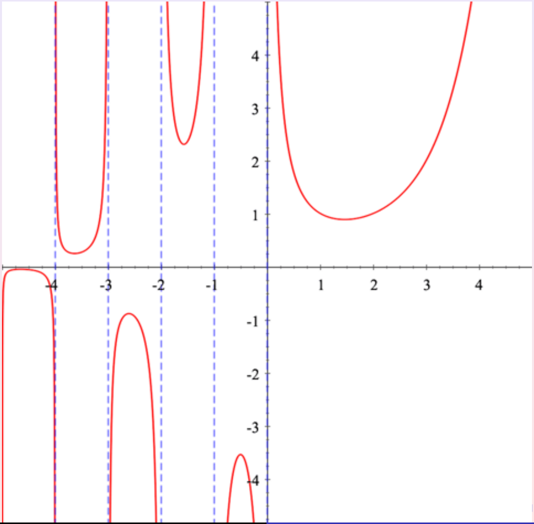
## Otázka

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)
- $\Gamma(z) = \int_0^\infty t^{z-1} e^{-t} \, dt$
- $\Gamma(n+1) = n\Gamma(n) = \cdots = n!\,\Gamma(1) = n!$
- $\Gamma(a)$ je hodnota funkcie $\Gamma$ v bode $a$

# Oponentská otázka č. 2



# 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. . .

# 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...

# 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 |

# 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

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

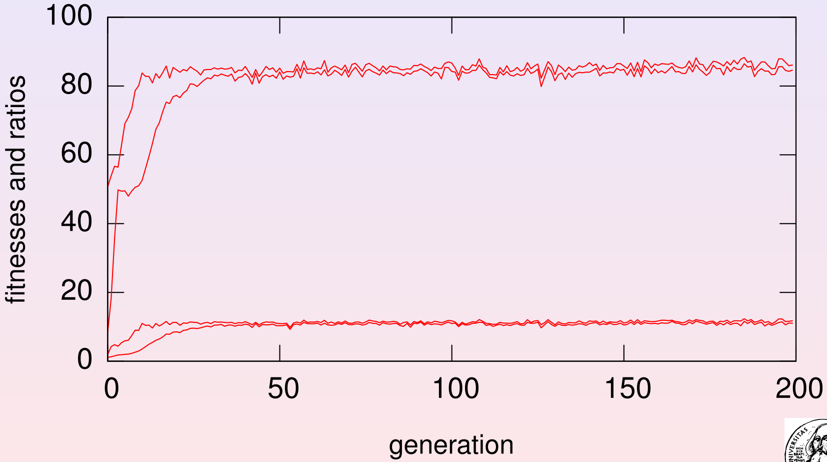
## Otázka

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

## Odpoveď

Pozrime si dotyčný graf. . .

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



# 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

- 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.

# Oponentská otázka č. 5

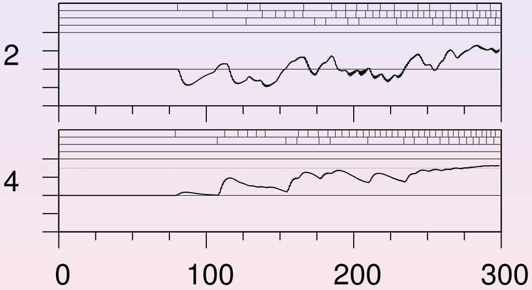
## Otázka

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.

# Oponentská otázka č. 5




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.

# 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.

# Voľná diskusia