Politechnika Wrocławska

KAPITAŁ LUDZKI
NARODOWA STRATEGIA SPÓJNOŚCI

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EUROPEJSKI
FUNDUSZ SPOŁECZNY

On-line Bayesian Context Change Detection in Web Service Systems

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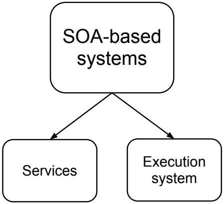
Agenda

1. Problem background
2. Change detection problem statement
3. Approaches for solving the problem
4. Bayesian Model
5. Algorithm for change detection
6. Simulation environment
7. Results and discussion

Problem background

SOA-based systems

- **SOA-based systems**: systems that implement Service Oriented Architecture, i.e., an architectural style whose goal is to achieve loose coupling among interacting software components called *services*.



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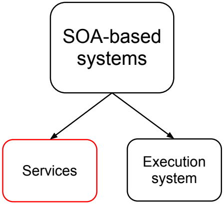
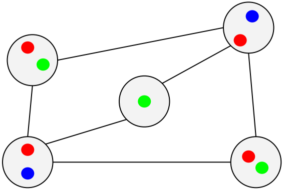
- **Services**: self-describing, stateless, modular applications that are distributed across the Web and which provide functionalities and are described by quality attributes (QoS).





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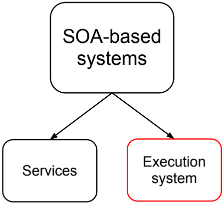
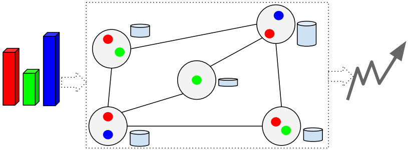
- **Execution system**:
  - network of virtual machines;
  - distributed computational resources;
  - *input*: streams of requests;
  - *output*: system performance, e.g., latency.





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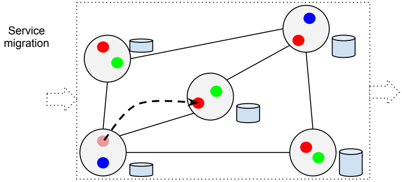

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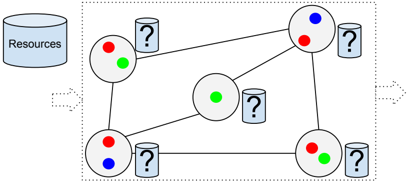

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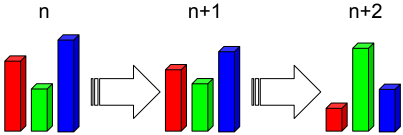

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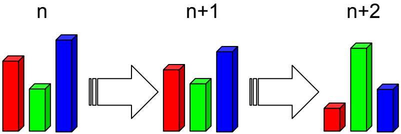

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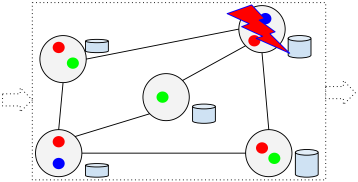

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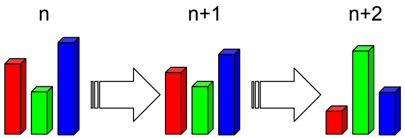

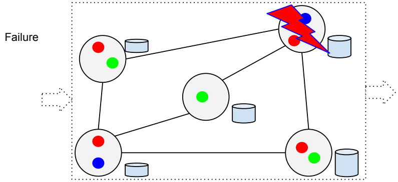

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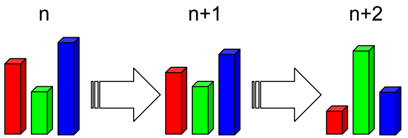
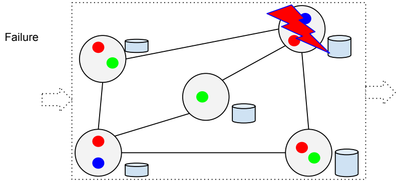


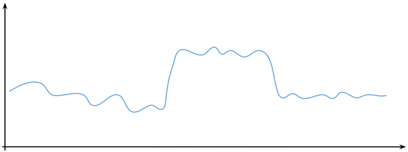


- Hence, there is a need to propose an **adaptive approach** for resource allocation.
- Resource re-allocation: if a *change* in the **input** (or **output**) is reported, then calculate new resource allocation.

Change detection problem

Overview

- **Change detection**: identifies changes in the probability distribution of a stochastic process.



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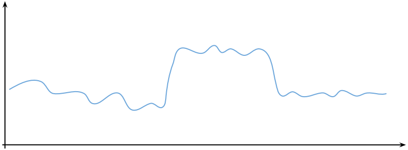

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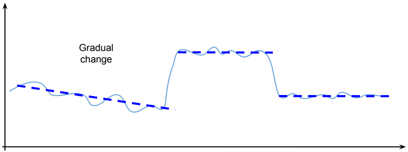

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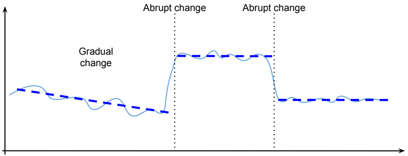

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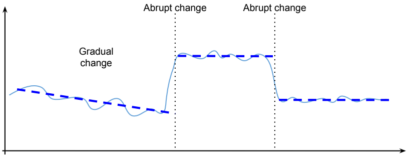

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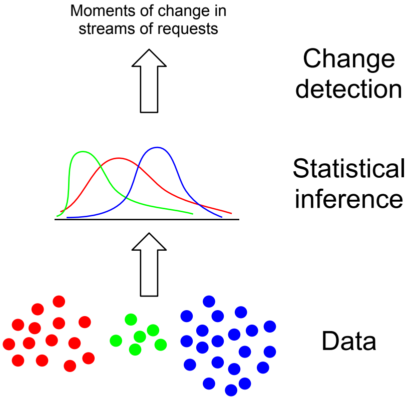

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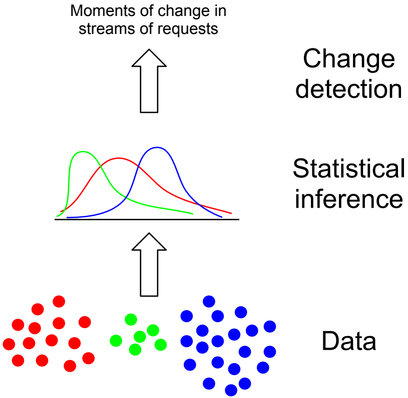
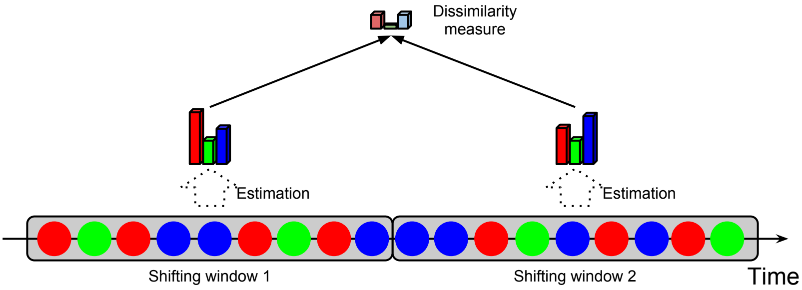


Frequentist approach



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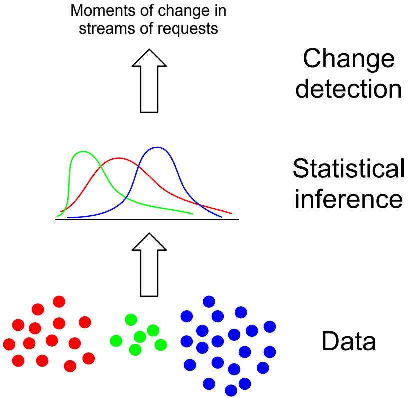

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Likelihood functions for models

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$$p(\mathcal{D}_n^L | \mathcal{M}_0, \boldsymbol{\theta}_0) = p(\mathcal{D}_n^L | \boldsymbol{\theta}_0) \tag{1}$$

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2. If there is one context change in $\mathcal{D}_n^L$ at $t < n$, then we say that data are generated from a model $\mathcal{M}_1$ and its likelihood function is as follows

$$p(\mathcal{D}_n^L | \mathcal{M}_1, \boldsymbol{\theta}_1, t) = p(\mathcal{D}_t^{L-n+t} | \boldsymbol{\theta}_1^1)\ p(\mathcal{D}_n^{n-t} | \boldsymbol{\theta}_1^2) \tag{2}$$

   where $\boldsymbol{\theta}_1 = (\boldsymbol{\theta}_1^1\ \boldsymbol{\theta}_1^2)^{\mathrm{T}}$ – parameters of $\mathcal{M}_1$, $\boldsymbol{\theta}_1^1$ are parameters for partition before context change, and $\boldsymbol{\theta}_1^2$ – parameters after context change.

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where $p(\boldsymbol{\theta}_0|\mathcal{M}_0)$ – *a priori* probability distribution of parameters. Next, the model evidence of $\mathcal{M}_1$ is the following (using the independence of $\boldsymbol{\theta}_1^1, \boldsymbol{\theta}_1^2, t$)

$$\begin{aligned} p(\mathcal{D}_n^L|\mathcal{M}_1) = \iint p(\mathcal{D}_n^L|\mathcal{M}_1, \boldsymbol{\theta}_1, t)\ p(\boldsymbol{\theta}_1^1|\mathcal{M}_1)\times \\ \times\ p(\boldsymbol{\theta}_1^2|\mathcal{M}_1)\ p(t|\mathcal{M}_1)\ \mathrm{d}\boldsymbol{\theta}_1\ \mathrm{d}t, \end{aligned} \tag{4}$$

where $p(\boldsymbol{\theta}_1^1|\mathcal{M}_1)$, $p(\boldsymbol{\theta}_1^2|\mathcal{M}_1)$, $p(t|\mathcal{M}_1)$ – *a priori* probability distributions of parameters.

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For such assumptions we can approximate the model evidence by the Bayesian Information Criterion (BIC)

$$\ln p(\mathcal{D}_n^L|\mathcal{M}) \approx \ln p(\mathcal{D}_n^L|\hat{\boldsymbol{\theta}}) - \frac{K}{2}\ln L, \tag{5}$$

where $\hat{\boldsymbol{\theta}}$ is the maximum likelihood estimator of $\boldsymbol{\theta}$.

Bayesian approach

Bayes factor

To compare both models, we calculate the Bayes factor (assuming equal probabilities over models):

$$B_{10} = \frac{p(\mathcal{D}_n^L|\mathcal{M}_1)}{p(\mathcal{D}_n^L|\mathcal{M}_0)}. \tag{6}$$

B_{10}	$\ln(B_{10})$	Evidence in favor of $\mathcal{M}_1$
$1-3$	$0-1.1$	Weak
$3-10$	$1.1-2.3$	Substantial
$10-100$	$2.3-4.6$	Strong
>100	>4.6	Decisive

Algorithm description

Algorithm 1: Change detection using approximated Bayes factor

Input : $\mathcal{D}$, L, $\mathcal{M}_0$, $\mathcal{M}_1$

Output: Moments of context change $\tau_1, \ldots, \tau_M$

$n \longleftarrow 1$, $m \longleftarrow 0$, $\tau_0 \longleftarrow 0$;

while $n < \text{card}\{\mathcal{D}\}$ **do**

  Calculate $\ln p(\mathcal{D}_n^L|\mathcal{M}_0)$ and $\ln p(\mathcal{D}_n^L|\mathcal{M}_1)$;

  Calculate $\ln B_{10}$;

  if $\ln B_{10} > \sigma$ **then**

    if $\big((n - \lceil L/2 \rceil) - \tau_m\big) \geqslant \lceil L/2 \rceil$ **then**

      $m := m + 1$;

      $\tau_m \longleftarrow n - \lceil L/2 \rceil$;

    end

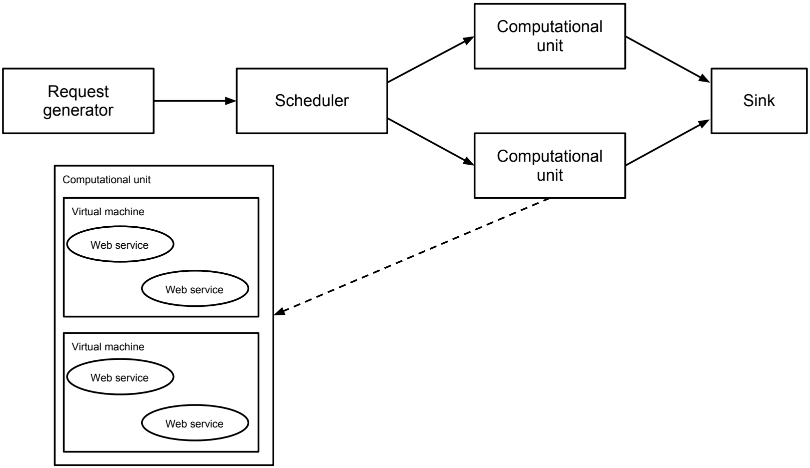
  end

  $n := n + 1$;

end

Simulator

Structure



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- Processing delays for web servers are equal **0.0004 seconds** and for virtual machines are equal **0.0008 seconds**

According to the technical report: ***Lite Technologies, Web server performance comparison: Litespeed 2.0 vs.***.

Simulator

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- The simulation model was implemented in discrete events simulation environment **Arena**.

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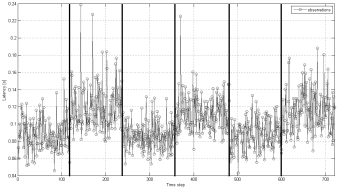
Description

- The aim of the experiment is to compare the performance of frequentist approaches with Bayesian approach for change detection problem.
- Following dissimilarity measures were considered:
  - **Bhattacharyya**
  - **Kullback-Leibler**
  - **Lin-Wong**
  - **modified Lin-Wong**
- **Average latency** in request responses was considered as a quality rate for entire system.
- The simulation model was implemented in discrete events simulation environment **Arena**.
- Algorithms for change detection were implemented in **Matlab**.

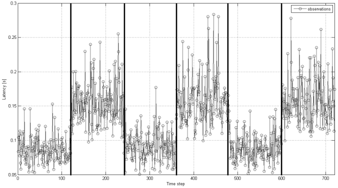
Experiment

Considered scenarios (1)

1. *Slight context change*. The context is changed periodically (5 times per simulation) and change is gained by increasing the intensity parameters of Poisson process three times.



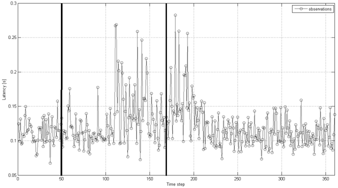
2. *Significant context change*. The context is changed periodically (5 times per simulation) and change is gained by increasing the intensity parameters of Poisson process six times.



Experiment

Considered scenarios (2)

3. *Processors failure (anomaly)*.
Anomaly is gained by failure of 4 processors on first virtual machine.



Experiment

Results for slight context change simulation

Measure	Correctly detected (max. 5)	Incorrectly detected
Bhattacharyya ($L = 25$, $\sigma = 0.2$)	3.2	0.2
Kullback-Leibler ($L = 25$, $\sigma = 1$)	3.8	0.8
Lin-Wong ($L = 25$, $\sigma = 0.15$)	2.8	0.7
mod. Lin-Wong ($L = 25$, $\sigma = 0.02$)	2.9	0.9
Bayesian approach ($L = 25$)	3	0.2

Experiment

Results for significant context change simulation

Measure	Correctly detected (max. 5)	Incorrectly detected
Bhattacharyya ($L = 25$, $\sigma = 0.2$)	4.6	0.1
Kullback-Leibler ($L = 25$, $\sigma = 1$)	4.8	0.2
Lin-Wong ($L = 25$, $\sigma = 0.15$)	4.6	0.3
mod. Lin-Wong ($L = 25$, $\sigma = 0.02$)	4.6	0.2
Bayesian approach ($L = 25$)	5	0

Experiment

Results for processors failure simulation

Measure	Correctly detected (max. 2)	Incorrectly detected
Bhattacharyya ($L = 25$, $\sigma = 0.2$)	1	0.3
Kullback-Leibler ($L = 25$, $\sigma = 1$)	0.7	0.3
Lin-Wong ($L = 25$, $\sigma = 0.15$)	1.1	0.1
mod. Lin-Wong ($L = 25$, $\sigma = 0.02$)	1	0.1
Bayesian approach ($L = 25$)	1.1	0.1

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- The best results for slight context changes were gained using Bhattacharyya measure.

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- Bayesian approach performed slightly better for *Significant context change* and *Processors failure (anomaly)* scenarios.
- The number of incorrectly detected changes using Bayesian model was the lowest for all considered scenarios.
- The best results for slight context changes were gained using Bhattacharyya measure.
- Bayesian approach, in comparison to the frequentist approach, does not demand defining additional parameters beside shifting window's size.