

# MockSAS: Facilitating the Evaluation of MAB in SAS

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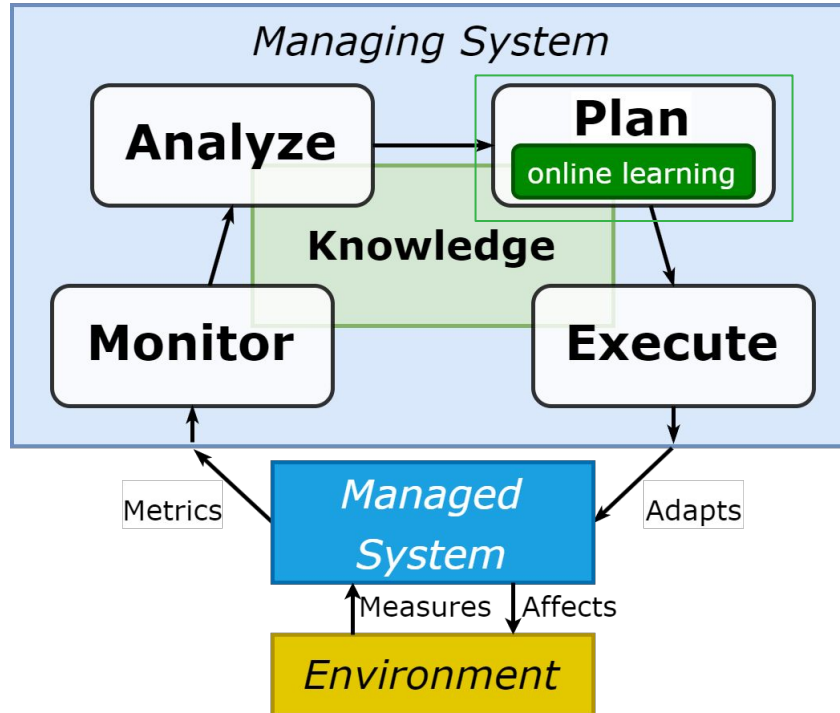
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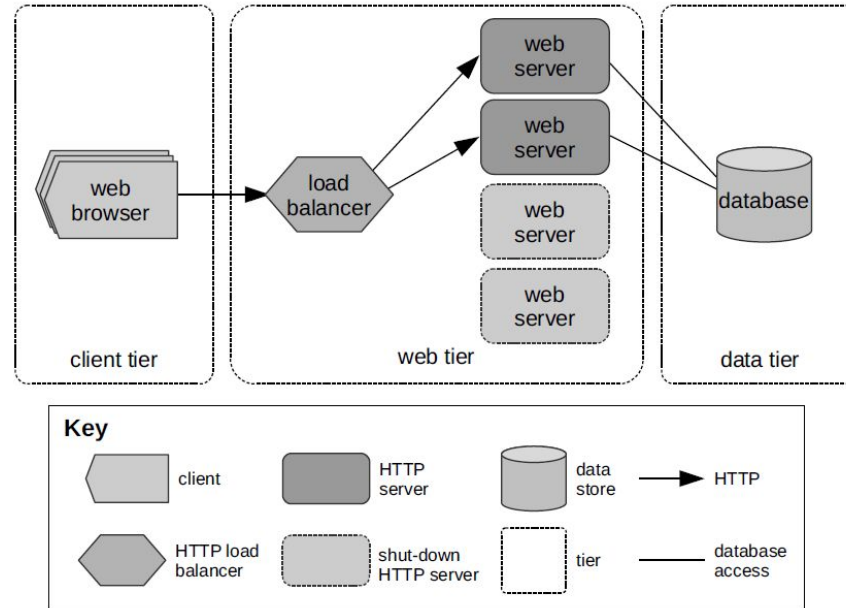
**Charles University in Prague**



# Self-Adaptive Systems and Online Learning



# SWIM: Simulator for Web Infrastructure and Management<sup>1</sup>



<sup>1</sup>Moreno, Gabriel A., Bradley Schmerl, and David Garlan. "Swim: an exemplar for evaluation and comparison of self-adaptation approaches for web applications." *2018 SEAMS*. IEEE, 2018.



# Multi-armed Bandits

Arms:

$$A = \{a_1, a_2, \dots, a_k\}$$

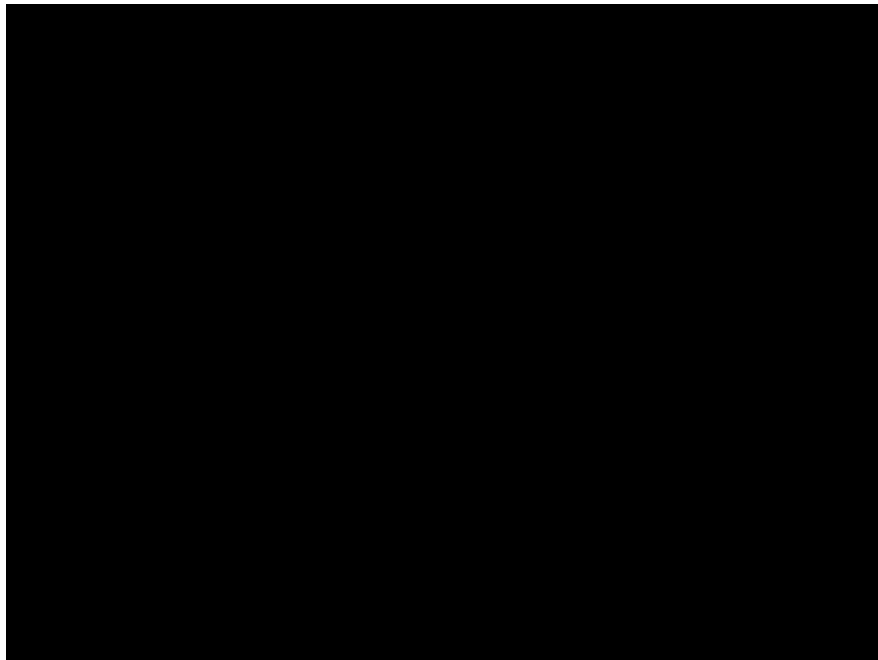
Horizon:  $n$ , total number of rounds

Context:

$$C_{t \in [n]} = \{R(a_1), R(a_2), \dots, R(a_k)\}$$

Regret:

$$\mu^* n - \sum_{j=1}^K \mu_j \mathbb{E}[T_j(n)] \quad \text{where } \mu^* = \max_{i=1, \dots, K} \mu_i$$



UCB Tuned



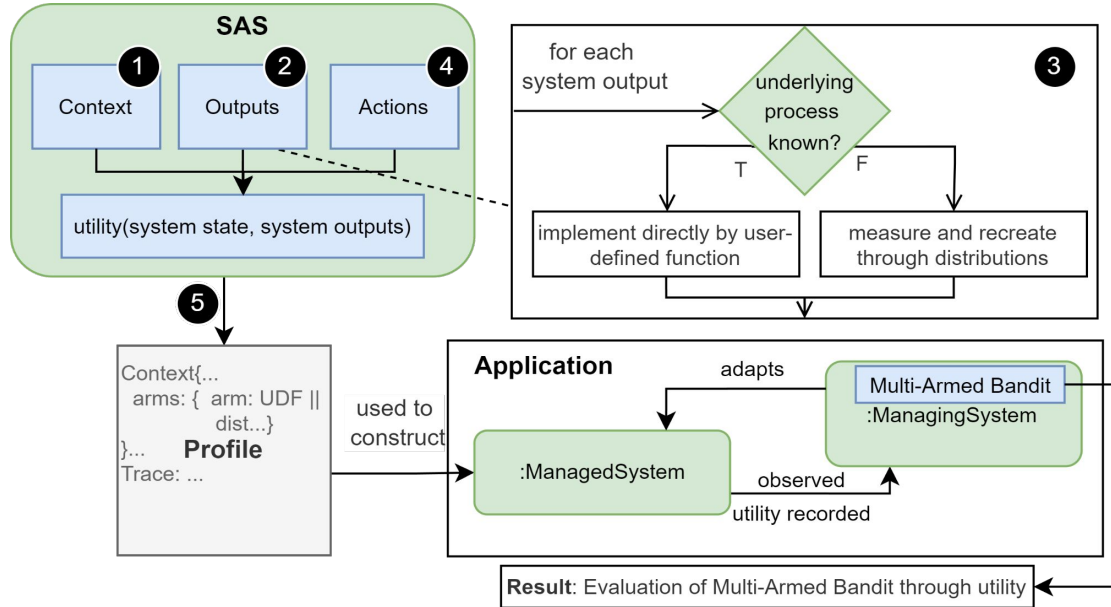
# Problems in Evaluating MAB Policies

- Operating environments are unpredictable, and may contain unknown unknowns
- Statistically significant evaluations cost a lot of time when run on 'real' systems
- Reproducing system states and extrapolating new ones is tedious manual work

**A reusable and extensible method for more time-efficient evaluation of MAB policies with SAS**



# Approach: MockSAS



1. Determine the system context(s) to be profiled.
2. Identify which outputs influence the calculation of the reward.
3. Of the identified outputs, determine which require profiling.
4. Identify the arms (adaptation actions) per context whose effects on the reward should be measured.
5. For each arm in each context, collect sufficient values of the profiled outputs to be able to identify their distribution.



# Example

```
60Requests {  
  features: { rq_rate: uniform(54,66) }
```

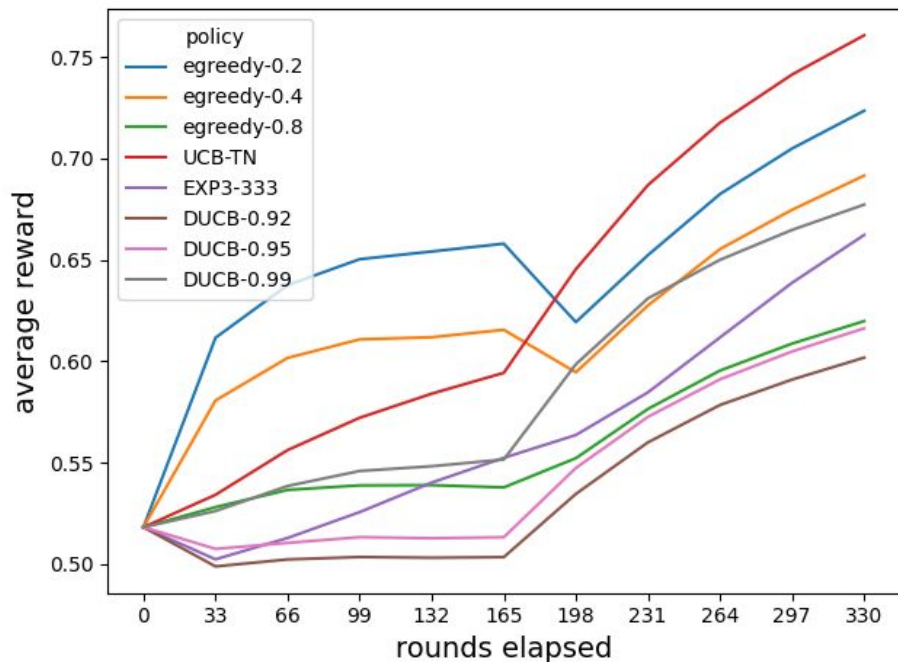
```
  arms: {  
    3Servers: utilitySWIM(rq_rate, normal(.064,.009)...  
    6Servers: utilitySWIM(rq_rate, normal(.039,.001)...)  
    8Servers: utilitySWIM(rq_rate, normal(.039,.001)...)  
    ...  
  }}  
}}
```

```
80Requests {  
  features: { rq_rate: uniform(72,88) }
```

```
  arms: {  
    3Servers: utilitySWIM(rq_rate, normal(1.68,1.44)...)  
    6Servers: utilitySWIM(rq_rate, normal(.041,.001)...)  
    8Servers: utilitySWIM(rq_rate, normal(.039,.001)...)  
    ...  
  }}  
}}
```

```
Trace: (60Requests, 166) (80Requests,166)
```

# (Subset of) Results



| Policy Name | Mean Reward | Median Reward | Average Ranking | Percentage Matching SWIM |
|-------------|-------------|---------------|-----------------|--------------------------|
| UCB-TN      | 0.77        | 0.76          | 1.13            | 86.67%                   |
| egreedy-0.2 | 0.73        | 0.73          | 2.03            | 76.67%                   |
| egreedy-0.4 | 0.69        | 0.69          | 3.1             | 73.33%                   |
| DUCB-0.99   | 0.68        | 0.68          | 4.07            | 23.33%                   |
| EXP3-333    | 0.66        | 0.66          | 4.7             | 26.67%                   |
| egreedy-0.8 | 0.62        | 0.62          | 6.47            | 56.67%                   |
| DUCB-0.95   | 0.62        | 0.62          | 6.6             | 60.00%                   |
| DUCB-0.92   | 0.6         | 0.6           | 7.9             | 0.00%                    |





# Looking Ahead

- Comparing more online learning solutions across paradigms (not just reinforcement learning)
- Applying MockSAS to more SAS.
- Automating the profiling process further through distribution detection etc.

Code can be found at:

<https://github.com/EGAlberts/MockSAS>

[https://github.com/EGAlberts/MASCed\\_bandits](https://github.com/EGAlberts/MASCed_bandits)

<https://github.com/EGAlberts/swim>