

Problem Statement

A typical workflow of IT service management (ITSM) involves a mixture of **human engineers**, **process** and **information technology**.

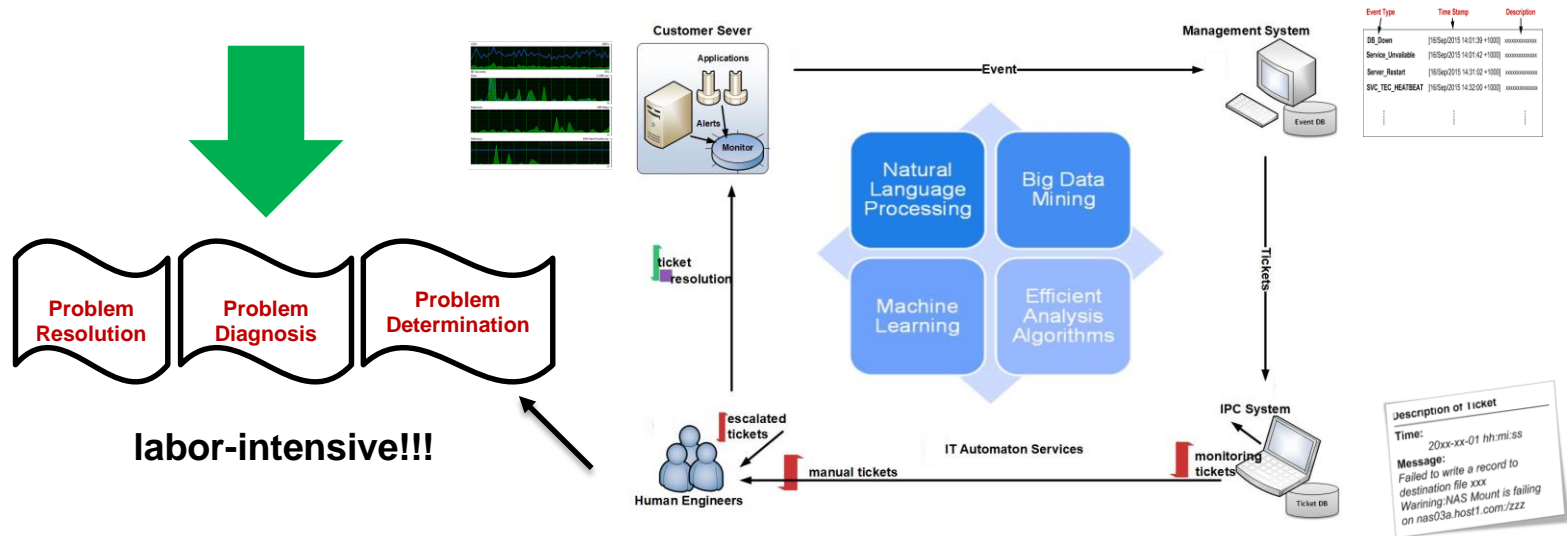


Figure 1: A Typical Workflow of IT Service Management

Problem Statement

IT automation services (ITAS) [1] plays an important role in IT service management.

- **An automation is a scripted resolution.**

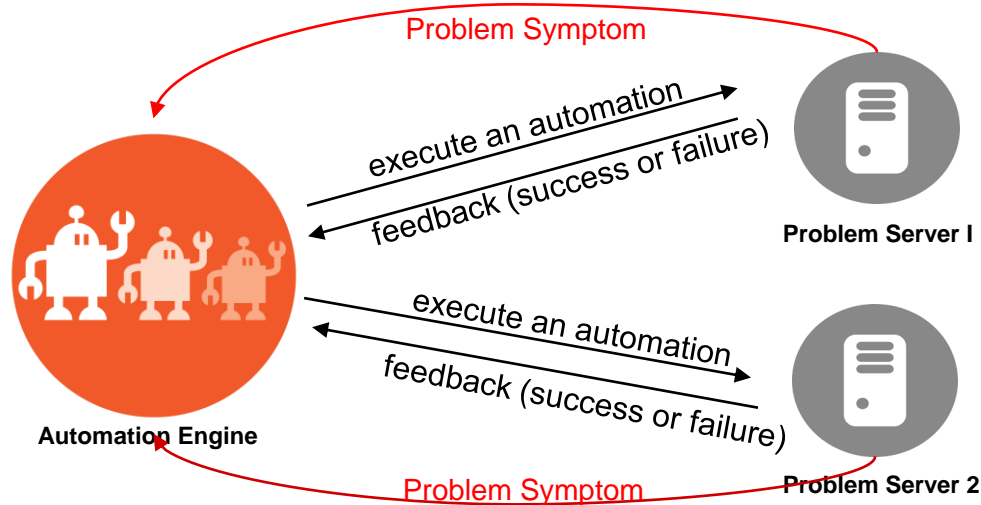


Figure 2: An overview of IT automation services.

Challenges

- Challenge 1: How do we appropriately solve the well-known **cold-start** problem [2] in IT automation services?
- Challenge 2: How do we utilize the **interactive feedback** to adaptively optimize the recommending strategies of the enterprise automation engine to enable a quick problem determination by IT automation services?

ALERT_KEY	cpc_cpuutil_gntw_win_v3			AUTOMATON_NAME				CPC:WIN:GEN:R:W:System Load Handler
OPEN_DTTM	CLIENT_ID	HOSTNAME	ORIGINAL SEVERITY	OSTYPE	COMPONENT	SUBCOMPONENT	AUTO RESOLVED	
2016-04-30 12:43:07	136	LEXSBWS01 VH	2	WIN	WINDOWS	CPU	1	feedback
TICKET SUMMARY	CPU Workload High. CPU 1, busy 99% time.			TICKET RESOLUTION	The CPU Utilization was quite reduced, hence closing the ticket.			

Table 3: A sample ticket in ITSM and its corresponding automation

Challenges

- Challenge 3: How do we efficiently improve the performance of recommendation using the explicit **automation hierarchies** of IT automation services [3]?

For example, a ticket is generated due to a failure of the DB2 database.

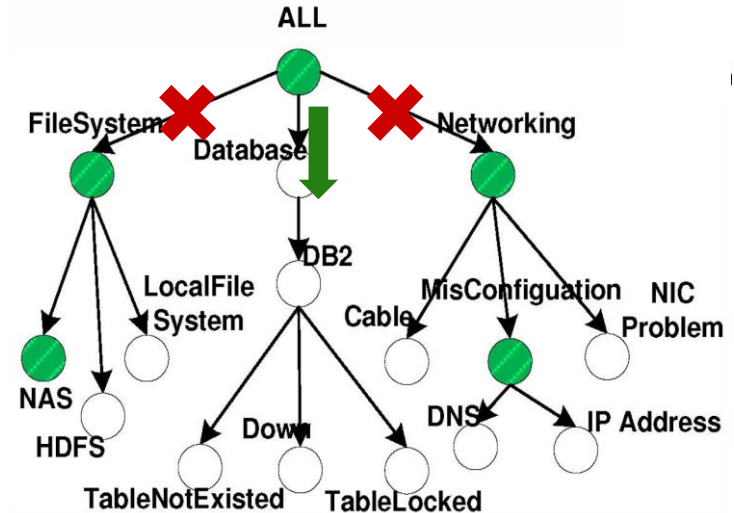


Figure 3: An example of taxonomy in IT tickets.

Related Work

➤ Multi-armed Bandit Algorithms

- ϵ -greedy, UCB, Thompson sampling, LinUCB [4].
- Used to balance the tradeoff between *exploration* and *exploitation* in interactive recommender systems, i.e., movies recommendation, news recommendation, etc.

➤ Multi-armed Bandit problem with Dependent Arms [5, 6, 7, 8]

- Use the taxonomy to explore the dependencies among arms in the context-free bandit setting. [6]
- Learn the item hierarchy by a small number of user profiles. [7]
- Propose a generative model to automatically learn the dependencies among arms. [8]

[4] Li, Lihong, et al. "A contextual-bandit approach to personalized news article recommendation" In WWW. ACM, 2010.

[5] S. Pandey, D. Agarwal, and V. Chakrabarti, D.and Josifovski. Bandits for taxonomies: A model-based approach. In SDM, pages 216-227. SIAM, 2007.

[6] S. Pandey, D. Chakrabarti, and D. Agarwal. Multi-armed bandit problems with dependent arms. In ICML, pages 721-728. ACM, 2007.

[7] Y. Yue, A. Hong, and C. Guestrin. Hierarchical exploration for accelerating contextual bandits. arXiv preprint arXiv:1206.6454, 2012.

[8] Qing Wang, Chunqiu Zeng, Wubai Zhou, Tao Li, S. S. Iyengar, Larisa Shwartz, Genady Ya. Graharnik, "Online Interactive Collaborative Filtering Using Multi-armed Bandit with Dependent Arms", In the IEEE Transactions on Knowledge and Data Engineering (TKDE) (under revision), 2017.

Online IT Automation Recommendation Modeling

In IT automation recommendation modeling,

- **Arms:** $A = \{\mathbf{a}^{(1)}, \dots, \mathbf{a}^{(N)}\}$ denotes a set of **automations** (i.e., scripted resolutions) feasible in ITAS.
- **Observed information:** The contextual information (i.e., the ticket symptom) of a reported ticket at time t is represented as a feature vector $\mathbf{x}_t \in \mathbf{X}$, where \mathbf{X} denotes the *d-dimensional* feature space.
- **Instant feedback:** Every recommended automation ($\mathbf{a}^{(i)} = \pi(\mathbf{x}_t) \in A$ at time t , which is selected by a policy π has a corresponding feedback $r_{k,t}$ (i.e., reward) indicating whether or not the ticket has been successfully resolved. The total reward received by the policy π after T iterations is:

$$R_\pi = \sum_{t=1}^T r_{\pi(\mathbf{x}_t)}.$$

- **The goal** is to identify the optimal policy π^* for maximizing the total reward after T iterations.

$$\pi^* = \operatorname{argmax}_{\pi} E(R_\pi) = \operatorname{argmax}_{\pi} \sum_{t=1}^T E(r_{\pi(\mathbf{x}_t)} | t)$$

Online IT Automation Recommendation Modeling

At each time $t = [1, \dots, T]$, based on the historical observation, the reward $r_{k,t}$ is typically modeled as a linear combination of the feature vector x_t as follows:

$$r_{k,t} = x_t^T \theta_k + \xi_k$$

a d-dimension feature vector

an observation noise, $\xi_k \sim N(0, \sigma_k^2)$.

a d-dimension coefficient vector

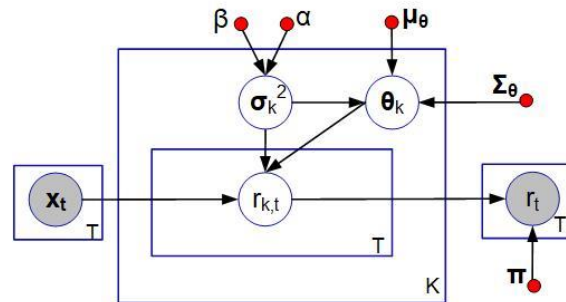
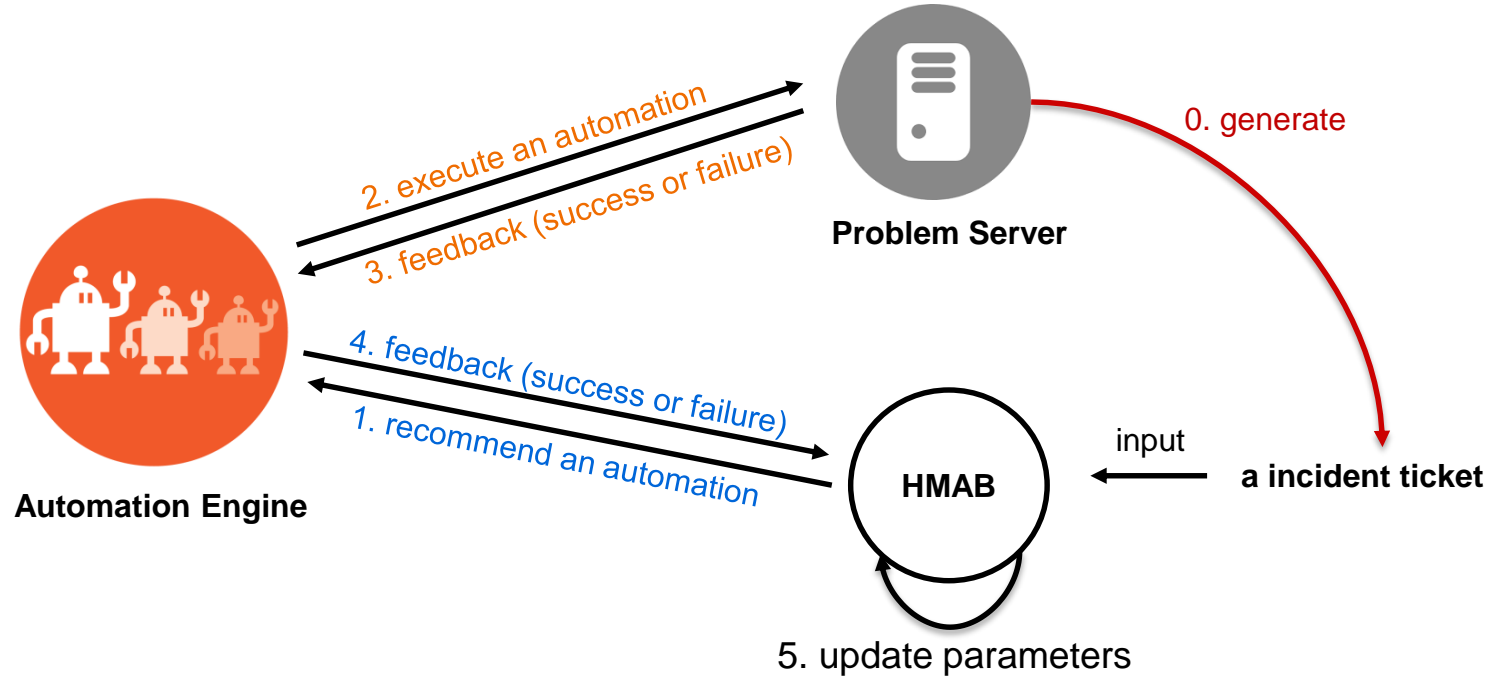


Figure 4: A graphic model of contextual MAB [8]

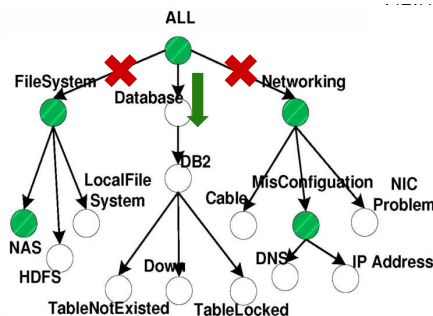
Hierarchical IT Automation Recommendation Modeling



Hierarchical IT Automation Recommendation Modeling

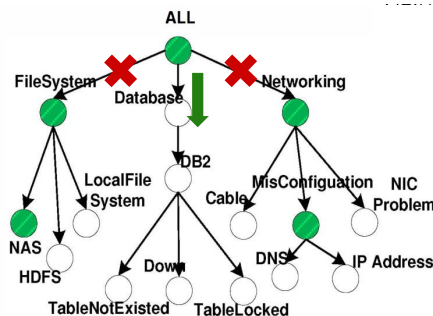
Let H denote the taxonomy. Given a node $a^{(i)} \in H$, $pa(a^{(i)})$ and $ch(a^{(i)})$ are used to represent the parent and children sets, respectively.

- A leaf node of H represents an automation, $ch(a^{(i)})$ is empty.
- A non-leaf node is a category or a subcategory.
- In our model, the automation recommendation is reduced to **the selection of a path** in H from root to a leaf node (**explore the feature space from the coarse to fine level**), and multiple nodes along the path are sequentially selected by policy π based on the contextual information x_t at time t .



Hierarchical IT Automation Recommendation Modeling

PROPERTY 3.2. Given the contextual information \mathbf{x}_t at time t , if a policy π selects a node $a^{(i)}$ in the hierarchy \mathcal{H} and receives positive feedback (i.e., success), the policy π receives positive feedback as well by selecting the nodes in $pth(a^{(i)})$.



$\pi^* =$

$$\arg \max_{\pi} \sum_{t=1}^T \left(\sum_{\substack{a^{(i)} \in \pi_{\mathcal{H}}(\mathbf{x}_t|t), \\ ch(a^{(i)}) \neq \emptyset}} E_{\theta_{\pi(\mathbf{x}_t|ch(a^{(i))})}} (\mathbf{x}_t^T \theta_{\pi(\mathbf{x}_t|ch(a^{(i))})} | t) \right)$$

The policy π selects an arm from the children set of $a^{(i)}$ given the contextual information \mathbf{x}_t at time t .

Solution and Algorithm

- The reward $r_{k,t}$ depends on $\mathbf{x}_t, \theta_k, \sigma_k^2$.

$$p(r_{k,t}|\mathbf{x}_t, \theta_k, \sigma_k^2) \sim N(\mathbf{x}_t^T \theta_k, \sigma_k^2)$$

- We assume θ_k and σ_k^2 follow a conjugate prior distribution (*Normal Inverse Gamma, NIG distribution*) as follows:

$$p(\sigma_k^2|\alpha_k, \beta_k) \sim \mathcal{IG}(\alpha_k, \beta_k)$$

$$p(\theta_k|\mu_{\theta_k}, \Sigma_{\theta_k}, \sigma_k^2) \sim \mathcal{N}(\mu_{\theta_k}, \sigma_k^2 \Sigma_{\theta_k})$$

- After recommend an automation $a^{(p)}$ at time t , the observed feedback will be used to update the hyper parameters $\alpha_{k,t}, \beta_{k,t}, \mu_{\theta_{k,t}}, \Sigma_{\theta_{k,t}}$ of each node along the selected path $pth(a^{(p)})$.

$$\Sigma_{\theta_{k,t}} = (\Sigma_{\theta_{k,t-1}}^{-1} + \mathbf{x}_t \mathbf{x}_t^T)^{-1}$$

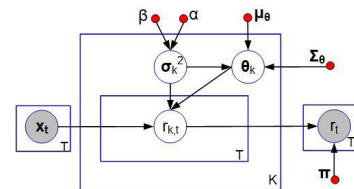
$$\mu_{\theta_{k,t}} = \Sigma_{\theta_{k,t}} (\Sigma_{\theta_{k,t-1}}^{-1} \mu_{\theta_{k,t-1}} + \mathbf{x}_t r_{k,t})$$

$$\alpha_{k,t} = \alpha_{k,t-1} + \frac{1}{2}$$

$$\beta_{k,t} = \beta_{k,t-1} +$$

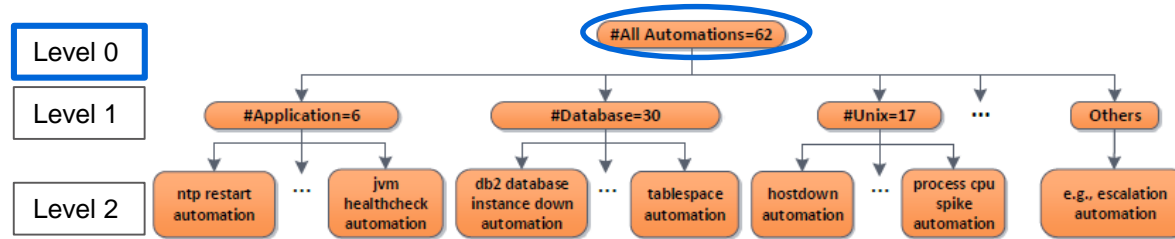
$$\frac{1}{2} [r_{k,t}^2 + \mu_{\theta_{k,t-1}}^T \Sigma_{\theta_{k,t-1}}^{-1} \mu_{\theta_{k,t-1}} - \mu_{\theta_{k,t}}^T \Sigma_{\theta_{k,t}}^{-1} \mu_{\theta_{k,t}}]$$

- Developing with different strategies (i.e., Thompson sampling, LinUCB), we have HMAB-TS and HMAB-LinUCB.



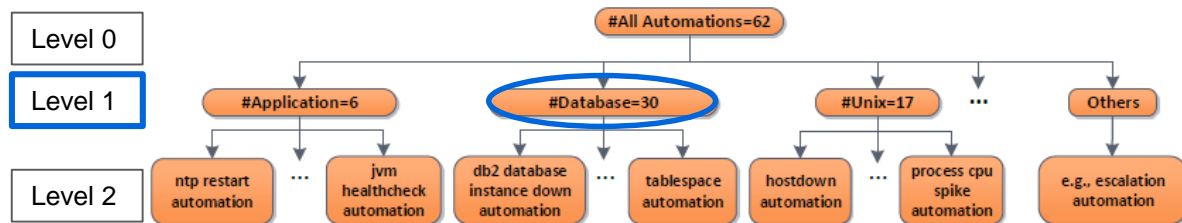
Example: Hierarchical Multi-armed Bandit Algorithm

At time $t = [1, \dots, T]$:



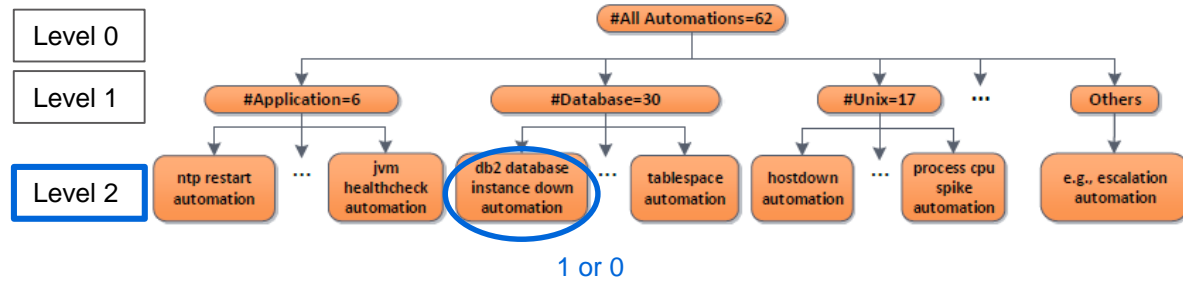
Example: Hierarchical Multi-armed Bandit Algorithm

At time $t = [1, \dots, T]$:



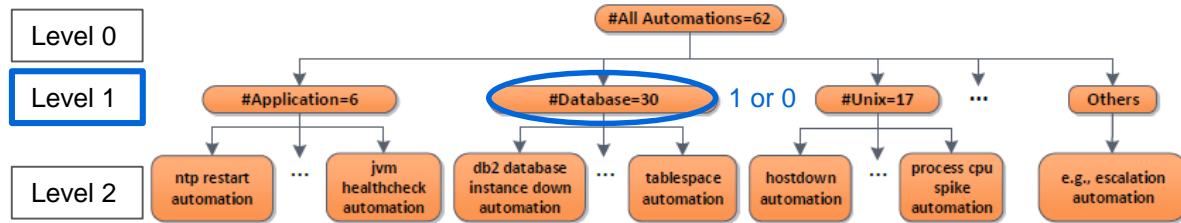
Example: Hierarchical Multi-armed Bandit Algorithm

At time $t = [1, \dots, T]$:



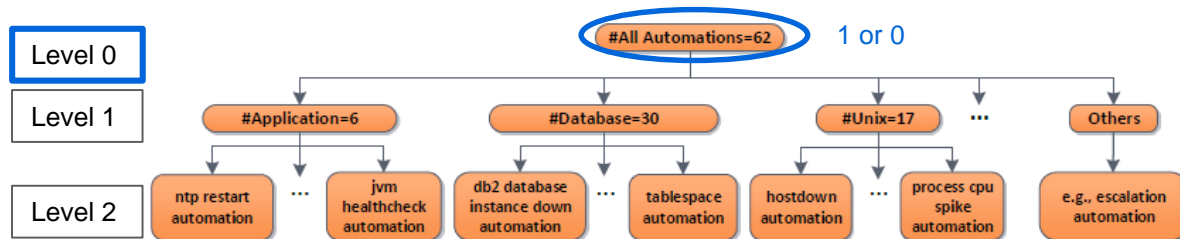
Example: Hierarchical Multi-armed Bandit Algorithm

At time $t = [1, \dots, T]$:



Example: Hierarchical Multi-armed Bandit Algorithm

At time $t = [1, \dots, T]$:



Experiment

➤ Data Set

- Experimental tickets are collected by **IBM Tivoli Monitoring system** covering from July 2016 to March 2017 with the size of $|D| = 116,429$.
- Each ticket is represented as a binary feature vector \mathbf{x} with dimension 1,182.
- The dataset contains 62 automations.
- A three-layer hierarchy H is given by domain experts.

➤ Evaluation Method

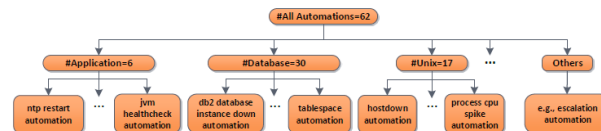
- Replayer method. [8]

➤ Baselines

- ϵ -greedy, Thompson sampling, LinUCB

➤ Our methods

- HMAB- ϵ -greedy, HMAB-TS, HMAB-LinUCB



Experiment

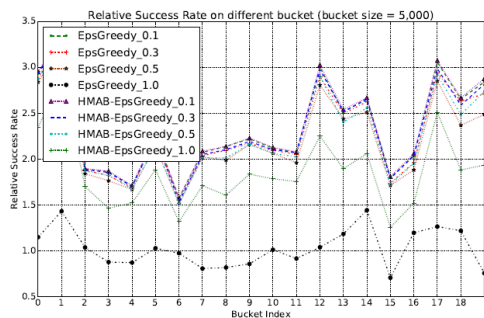


Figure 5: The Relative Success Rate of EpsGreedy and HMAB-EpsGreedy on the dataset is given along each time bucket with diverse parameter settings.

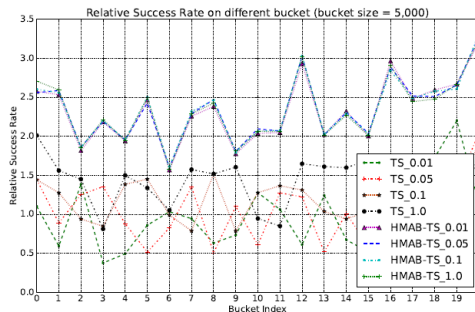


Figure 6: The Relative Success Rate of TS and HMAB-TS on the dataset is given along each time bucket with diverse parameter settings.

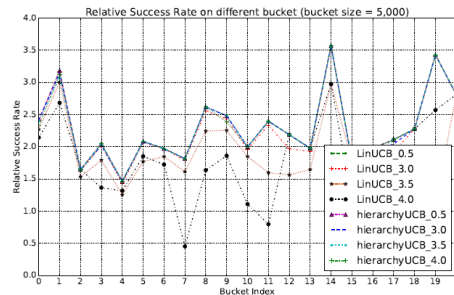


Figure 7: The Relative Success Rate of LinUCB and HMAB-LinUCB on the dataset is given along each time bucket with diverse parameter settings.

A Comparative Case Study

The recommendation for **escalated tickets** can be regarded as a *cold-start problem* due to the lack of the corresponding automations.

ALERT_KEY	ac2_dbinact_grzc_std	AUTOMATON NAME	Escalation Handler
TICKET SUMMARY	Database fin91dmo status is inactive.	TICKET RESOLUTION	The database is down. It has been restarted, hence closing the ticket.
RECOMMENDED CATEGORY	(%)	RECOMMENDED AUTOMATON	
DATABASE	57.13	(1) database instance down automation; (2) db2 database inactive automation; (3) mysql database offline automation.	
UNIX	20.12	(1) asm space check diskgroup dbautomation; (2) hostdown automation; (3) certification expiration automation.	
APPLICATION	17.71	(1) ntp restart automation; (2) mq manager down automation.	
OTHERS	5.04	(1) system load automation; (2) others.	

Figure 8: The exploration by HMAB-TS of a cold-start ticket case.

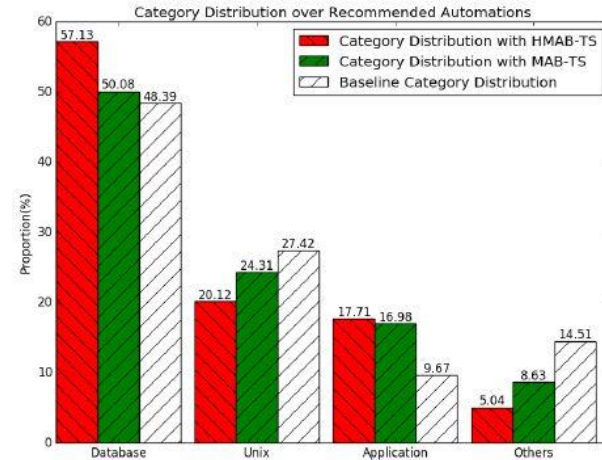


Figure 9: The comparison of category distribution on the recommended automations.

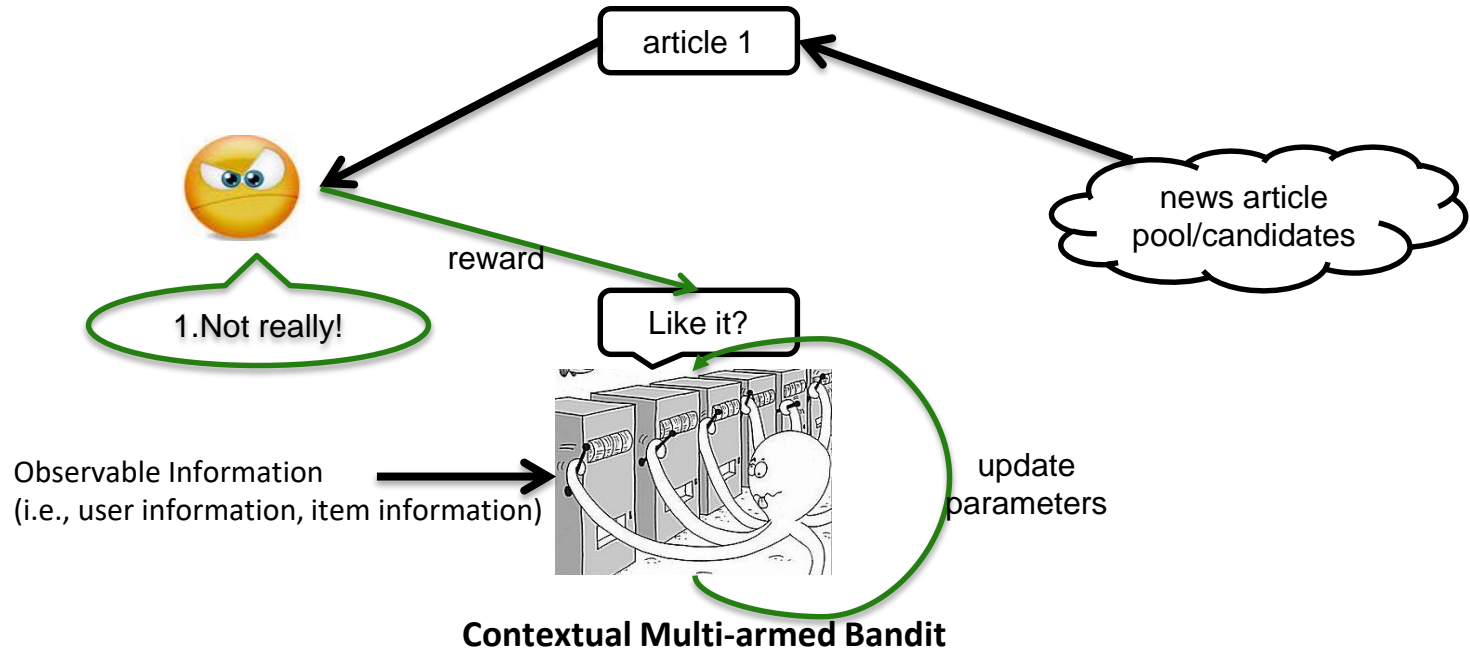
Conclusion

- A new online learning algorithm for IT automation recommendation
 - Solve the cold-start problem.
 - Utilize the interactive feedback for continuous improvement.
 - Integrate the hierarchical information to model the dependencies among arms.
- The effectiveness and efficiency of our proposed methods are verified on a large dataset of tickets from IBM Global Services.
- Future work
 - Ticket representation

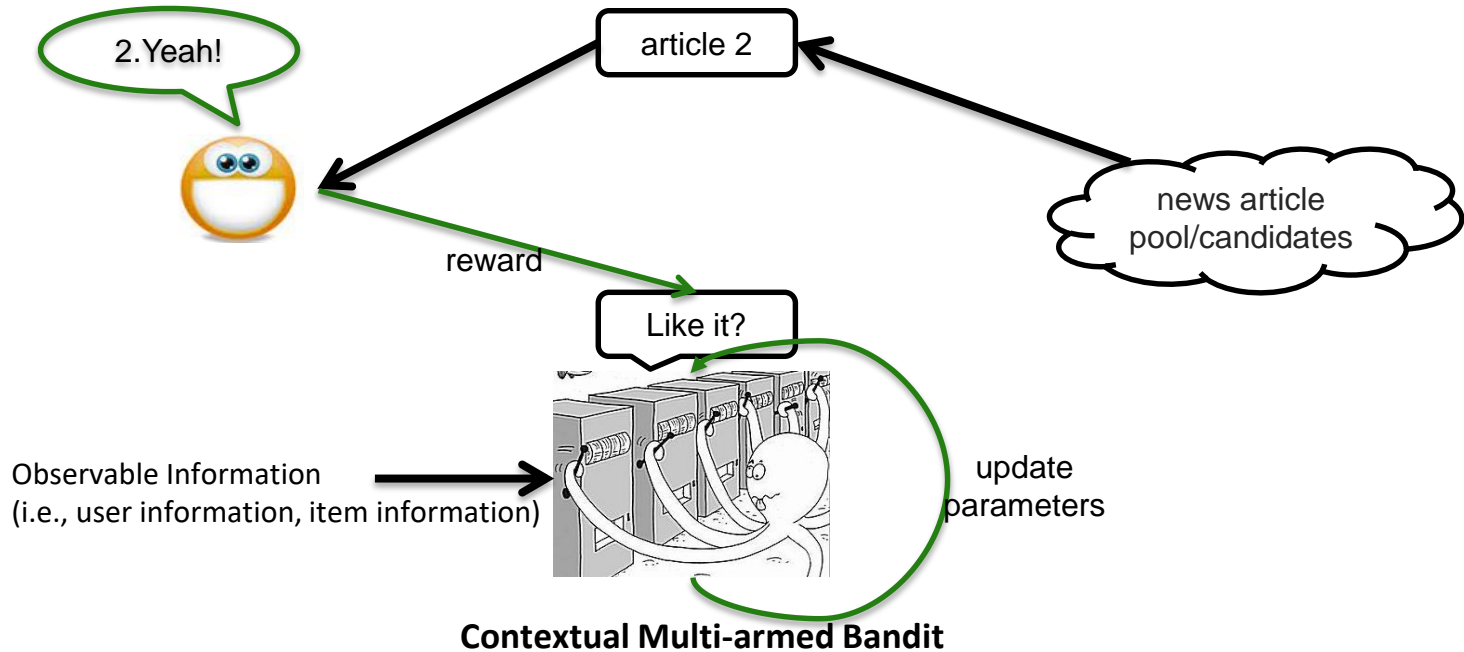
Q & A



Example: News Recommendation



Example: News Recommendation



Online IT Ticket Automation Recommendation Using Hierarchical Multi-armed Bandit Algorithms



Qing Wang¹, Tao Li¹,
S. S. Iyengar¹

Larisa Shwartz²

Genady Ya. Grabanrnik³

¹School of Computing and Information Science, Florida International University Miami, FL, USA

²Cognitive Service Management, IBM T.J. Watson Research Center Yorktown Heights, NY, USA

³Dept. Math & Computer Science, St. John's University, Queens, NY, USA

Outline

- Introduction
- Problem Statement & Challenges
- Related Work
- Online IT Automation Recommendation Modeling
- Solution and Algorithm
- Experiment
- Conclusion

Introduction

- IT service management (**ITSM**) refers to all the activities that are performed to **plan**, **deliver**, **operate** and **control** the IT services, which are provided to customers.
- Many ITSM products are booming from different companies. Aiming at providing **higher quality** and **more complex** services, service providers are increasingly employing machine learning and data mining techniques to automate or optimize their services.

