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

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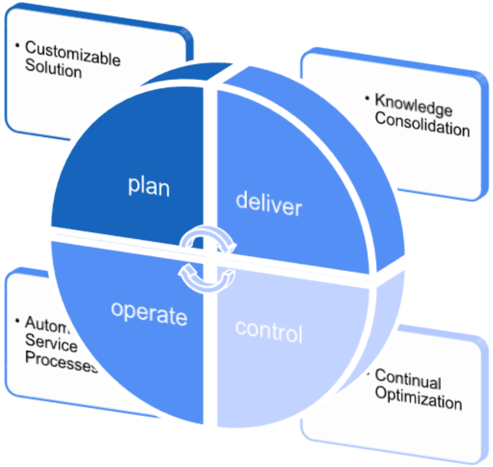
Outline

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

Introduction

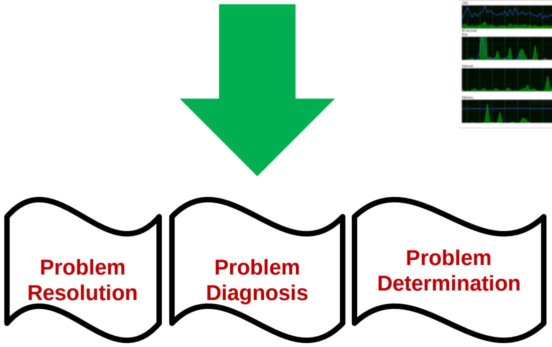
- IT service management (**ITSM**) refers to all the activities that are performed to **plan**, **deliver**, **operate** and **control** the IT services, which are provided to customers.

- 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.



Problem Statement

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



labor-intensive!!!

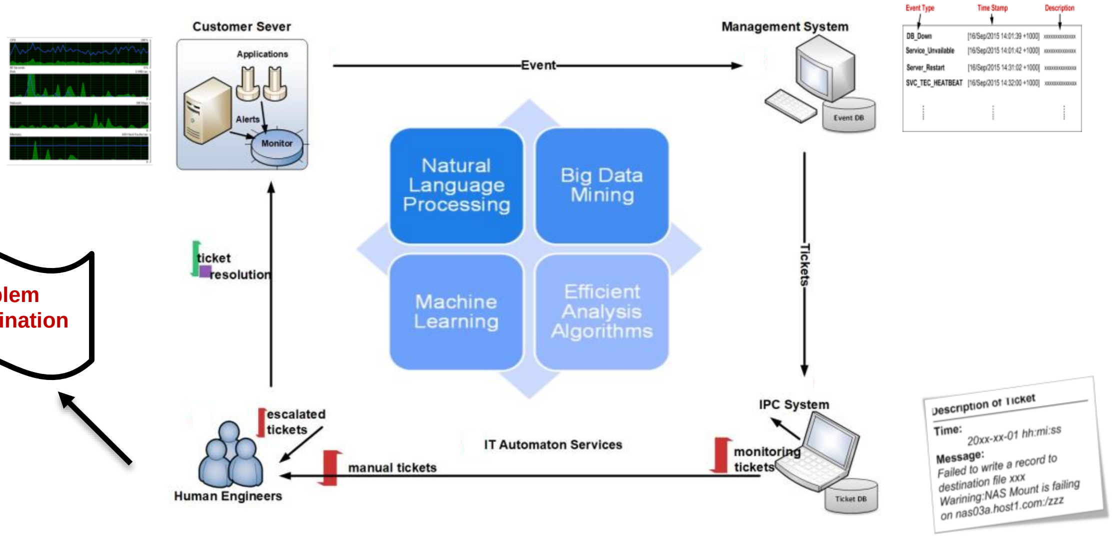


Figure 1: A Typical Workflow of IT Service Management

Problem Statement

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

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

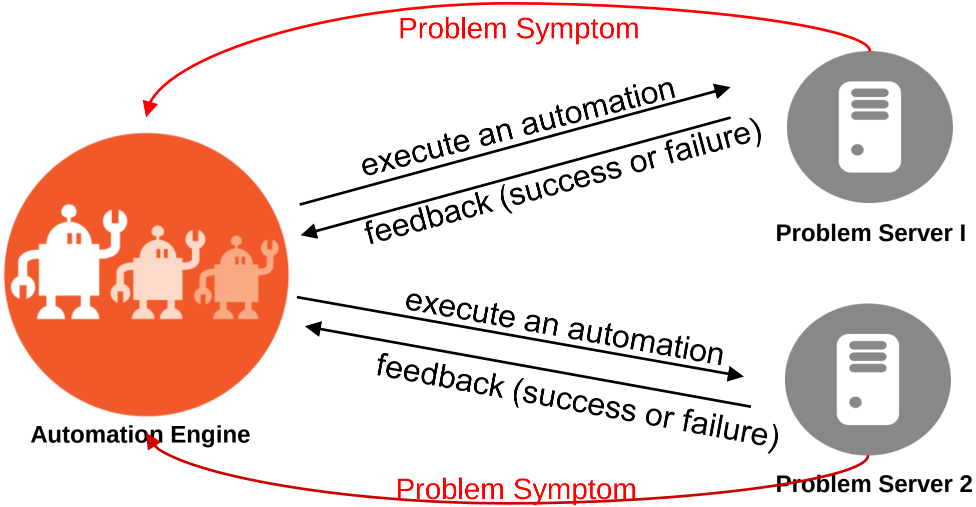


Figure 2: An overview of IT automation services.

[1] IBM Enterprise IT Automation Services. www.redbooks.ibm.com/redpapers/pdfs/redp5363.pdf.

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	COMPONET	SUBCOMP OMET	AUTO RESOVLED
2016-04-30 12:43:07	136	LEXSBWS01 VH	2	WIN	WINDOWS	CPU	1
TICKET SUMMARY	CPU Workload High. CPU 1, busy 99% time.		TICKET RESOLUTION		The CPU Utilization was quite reduced, hence closing the ticket.		

feedback

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

[2] C. Zeng, Q. Wang, S. Mokhtari, and T. Li. Online context-aware recommendation with time varying multi-armed bandit. In SIGKDD, pages 2025-2034. 2016.

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.

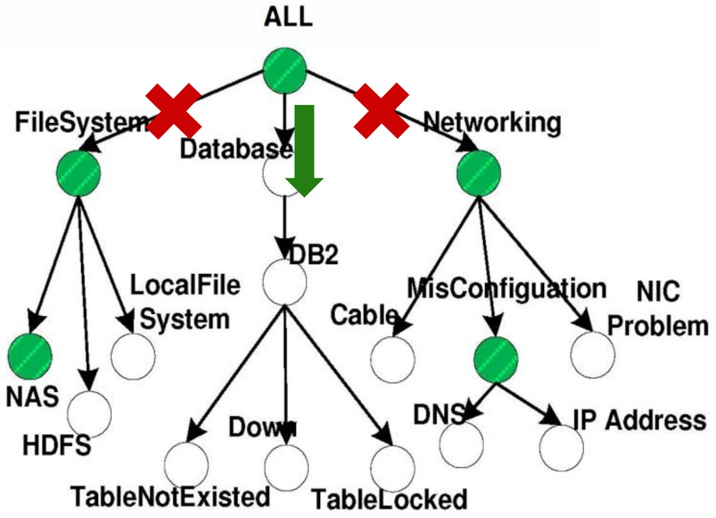


Figure 3: An example of taxonomy in IT tickets.

[3] Zeng, Chunqiu, et al. "Knowledge guided hierarchical multi-label classification over ticket data." *IEEE Transactions on Network and Service Management* 14.2 (2017): 246-260.

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:** $\boldsymbol{A} = \{\boldsymbol{a}^{(1)}, \dots, \boldsymbol{a}^{(N)}\}$ 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 $\boldsymbol{x_t} \in \boldsymbol{X}$, where $\boldsymbol{X}$ denotes the *d-dimensional* feature space.

- **Instant feedback:** Every recommended automation ($\boldsymbol{a}^{(i)} = \pi(\boldsymbol{x_t})) \in \boldsymbol{A}$ 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:

$$R_\pi = \sum_{t=1}^{T} r_{\pi(\boldsymbol{x_t})}.$$

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

$$\pi^* = \operatorname*{argmax}_{\pi} E(R_\pi) = \operatorname*{argmax}_{\pi} \sum_{t=1}^{T} E(r_{\pi(\boldsymbol{x_t})} \,|t)$$

Online IT Automation Recommendation Modeling

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

a d-dimension feature vector

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

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

a d-dimension coefficient vector

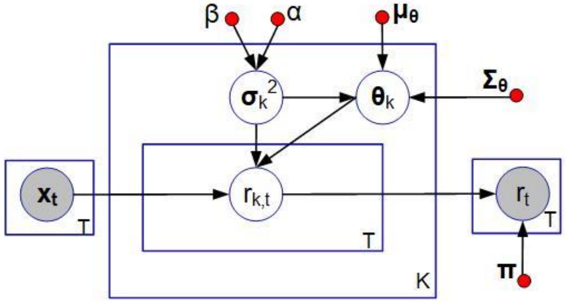
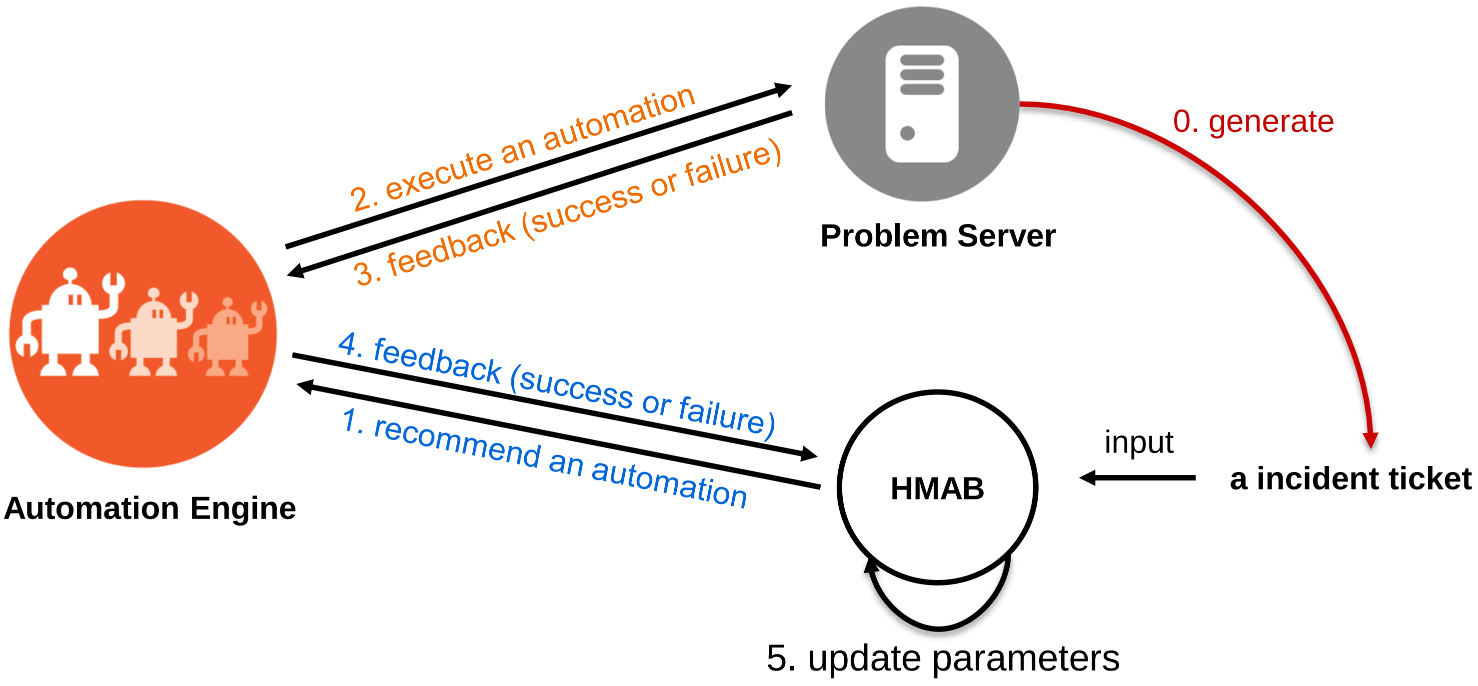


Figure 4: A graphic model of contextual MAB [8]

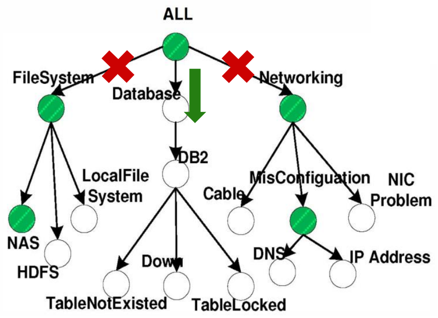
[8] C. Zeng, Q. Wang, S. Mokhtari, and T. Li. Online context-aware recommendation with time varying multi-armed bandit. In SIGKDD, pages 2025-2034. 2016.

Hierarchical IT Automation Recommendation Modeling



Hierarchical IT Automation Recommendation Modeling

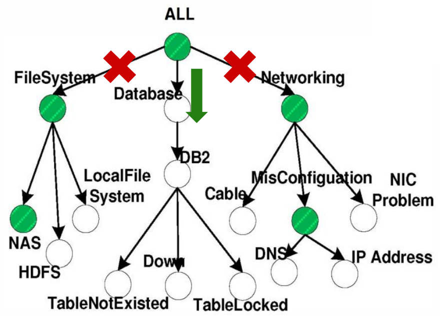
Let $\boldsymbol{H}$ denote the taxonomy. Given a node $\boldsymbol{a}^{(i)} \in \boldsymbol{H}$, $\boldsymbol{pa}(\boldsymbol{a}^{(i)})$ and $\boldsymbol{ch}(\boldsymbol{a}^{(i)})$ are used to represent the parent and children sets, respectively.



- A leaf node of $\boldsymbol{H}$ represents an automation, $\boldsymbol{ch}(\boldsymbol{a}^{(i)})$ 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 $\boldsymbol{H}$ 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 $\boldsymbol{x_t}$ at time t.

Hierarchical IT Automation Recommendation Modeling

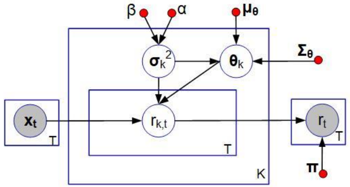
PROPERTY 3.2. *Given the contextual information* $\mathbf{x}_t$ *at time* t*, if a policy* π *selects a node* $a^{(i)}$ *in the hierarchy* $\mathcal{H}$ *and receives positive feedback (i.e., success), the policy* π *receives positive feedback as well by selecting the nodes in* $pth(a^{(i)})$.



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

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

Solution and Algorithm



- The reward $r_{k,t}$ depends on $\boldsymbol{x_t}, \theta_k, \sigma_k^2$.

$$p(r_{k,t}|\boldsymbol{x_t}, \theta_k, \sigma_k^2) \sim N(x_t^T \theta_k, \sigma_k^2)$$

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

$$p(\sigma_k^2|\alpha_k, \beta_k) \sim \mathcal{IG}(\alpha_k, \beta_k)$$
$$p(\theta_k|\mu_{\theta_k}, \boldsymbol{\Sigma}_{\theta_k}, \sigma_k^2) \sim \mathcal{N}(\mu_{\theta_k}, \sigma_k^2 \boldsymbol{\Sigma}_{\theta_k})$$

- 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 $\mathrm{pth}(a^{(p)})$.

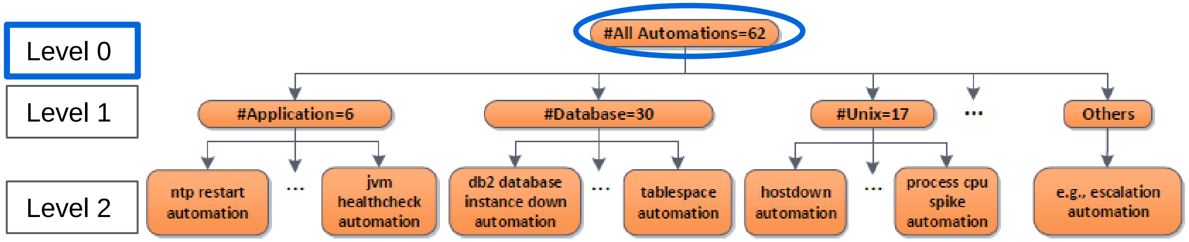
$$\boldsymbol{\Sigma}_{\theta_{k,t}} = (\boldsymbol{\Sigma}_{\theta_{k,t-1}}^{-1} + \mathbf{x}_t \mathbf{x}_t^T)^{-1}$$
$$\mu_{\theta_{k,t}} = \boldsymbol{\Sigma}_{\theta_{k,t}}(\boldsymbol{\Sigma}_{\theta_{k,t-1}}^{-1} \mu_{\theta_{k,t-1}} + \mathbf{x}_t r_{k,t})$$

$$\alpha_{k,t} = \alpha_{k,t-1} + \frac{1}{2}$$
$$\beta_{k,t} = \beta_{k,t-1} + \frac{1}{2}[r_{k,t}^2 + \mu_{\theta_{k,t-1}}^T \boldsymbol{\Sigma}_{\theta_{k,t-1}}^{-1} \mu_{\theta_{k,t-1}} - \mu_{\theta_{k,t}}^T \boldsymbol{\Sigma}_{\theta_{k,t}}^{-1} \mu_{\theta_{k,t}}]$$

- 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,…,T]:



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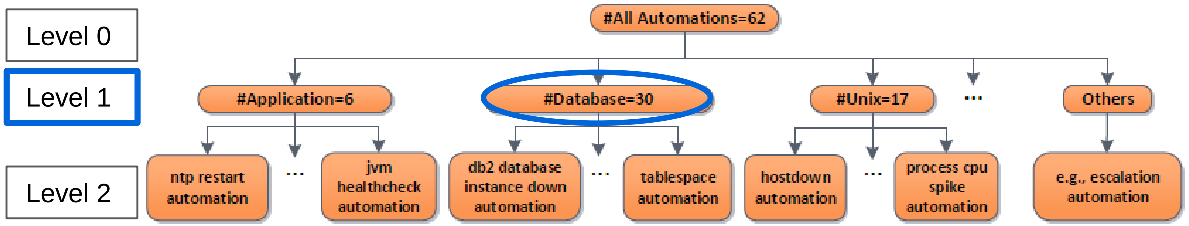

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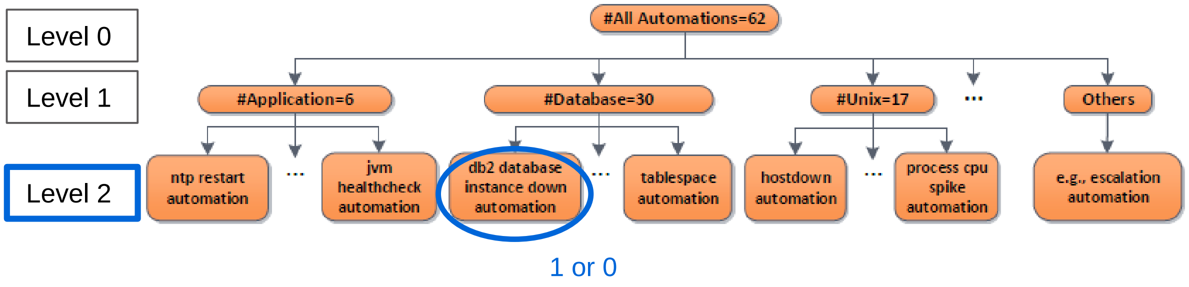
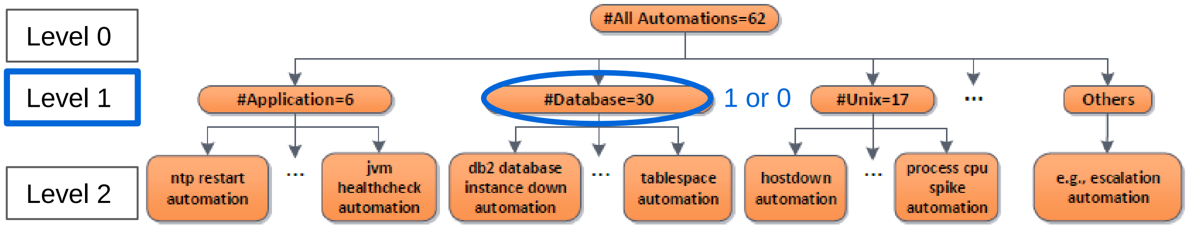


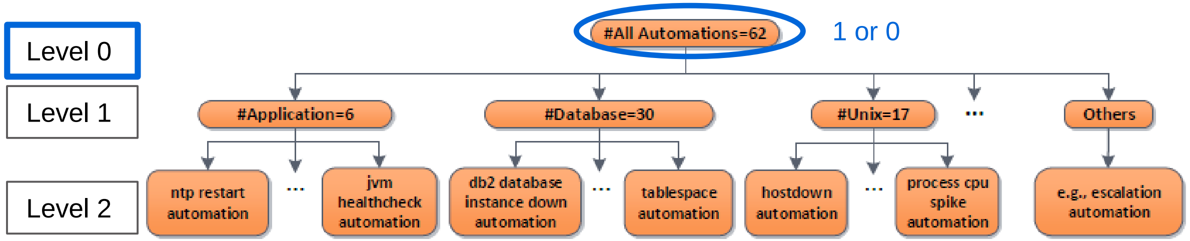
Example: Hierarchical Multi-armed Bandit Algorithm

At time t = [1,…,T]:



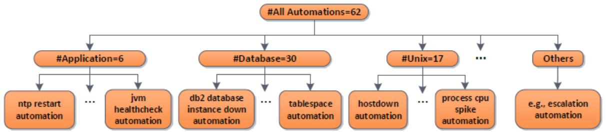
Example: Hierarchical Multi-armed Bandit Algorithm

At time t = [1,…,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 **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



[8] L. Li, W. Chu, J. Langford, T. Moon, and X. Wang. An unbiased offline evaluation of contextual bandit algorithms with generalized linear models. JMLR, 26:19-36, 2012.

Experiment

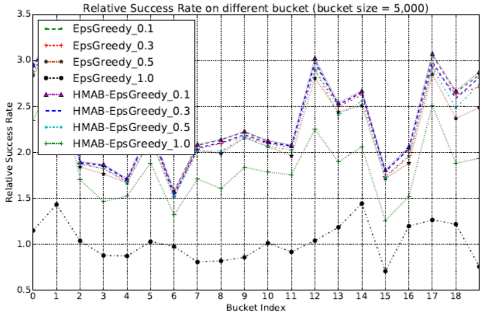


Figure 5: The Relative Success Rate of EpsGreedy and HMAB-EpsGreedy on the dataset is given along each time bucket with diverse parameter settings.

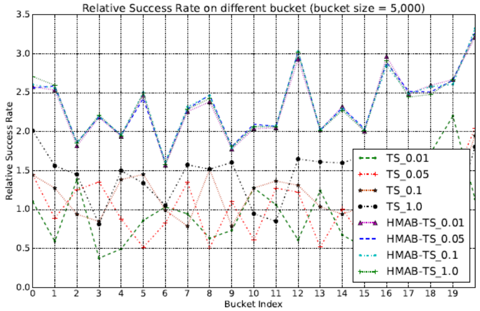


Figure 6: The Relative Success Rate of TS and HMAB-TS on the dataset is given along each time bucket with diverse parameter settings.

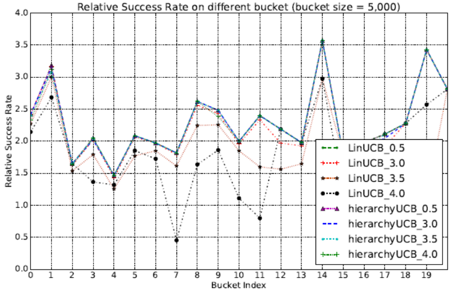


Figure 7: The Relative Success Rate of LinUCB and HMAB-LinUCB on the dataset is given along each time bucket with diverse parameter settings.

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.

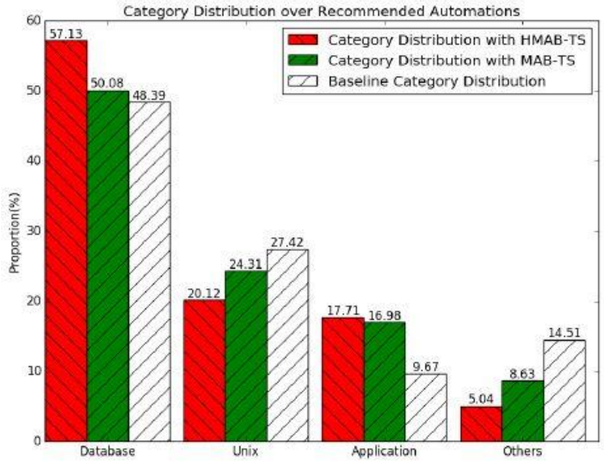


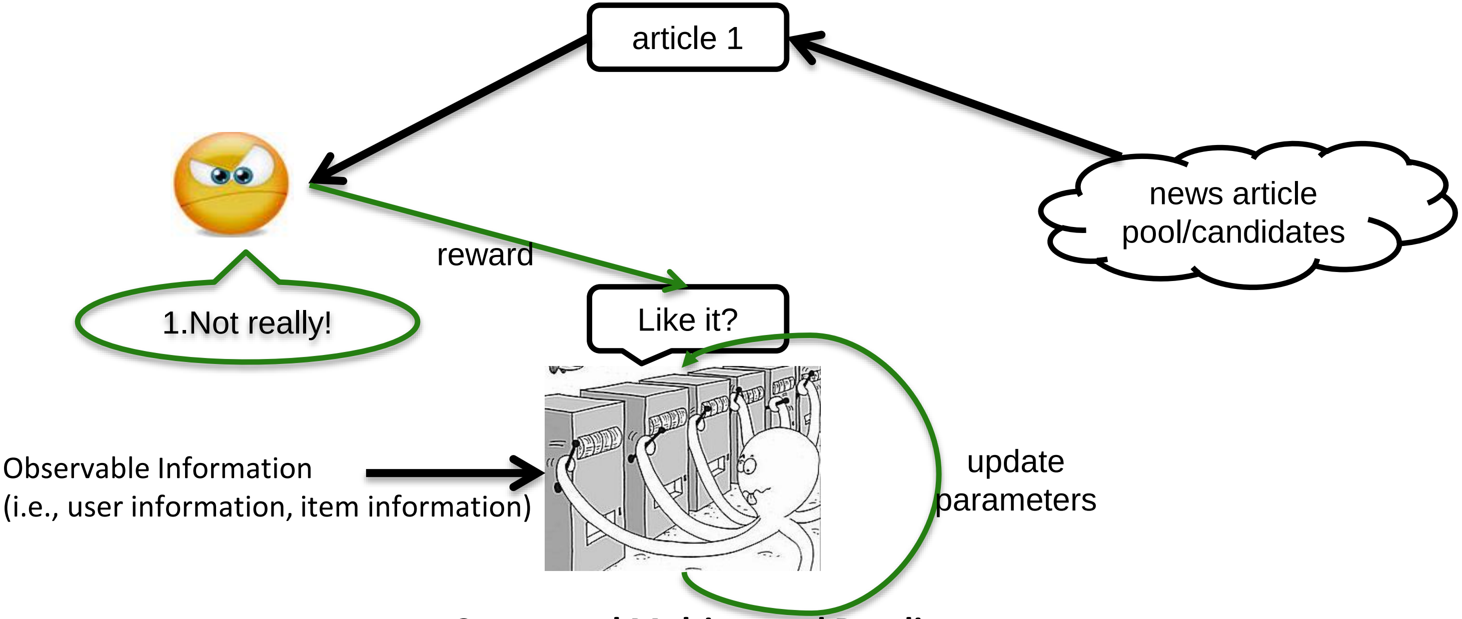
Figure 9: The comparison of category distribution on the recommended automations.

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

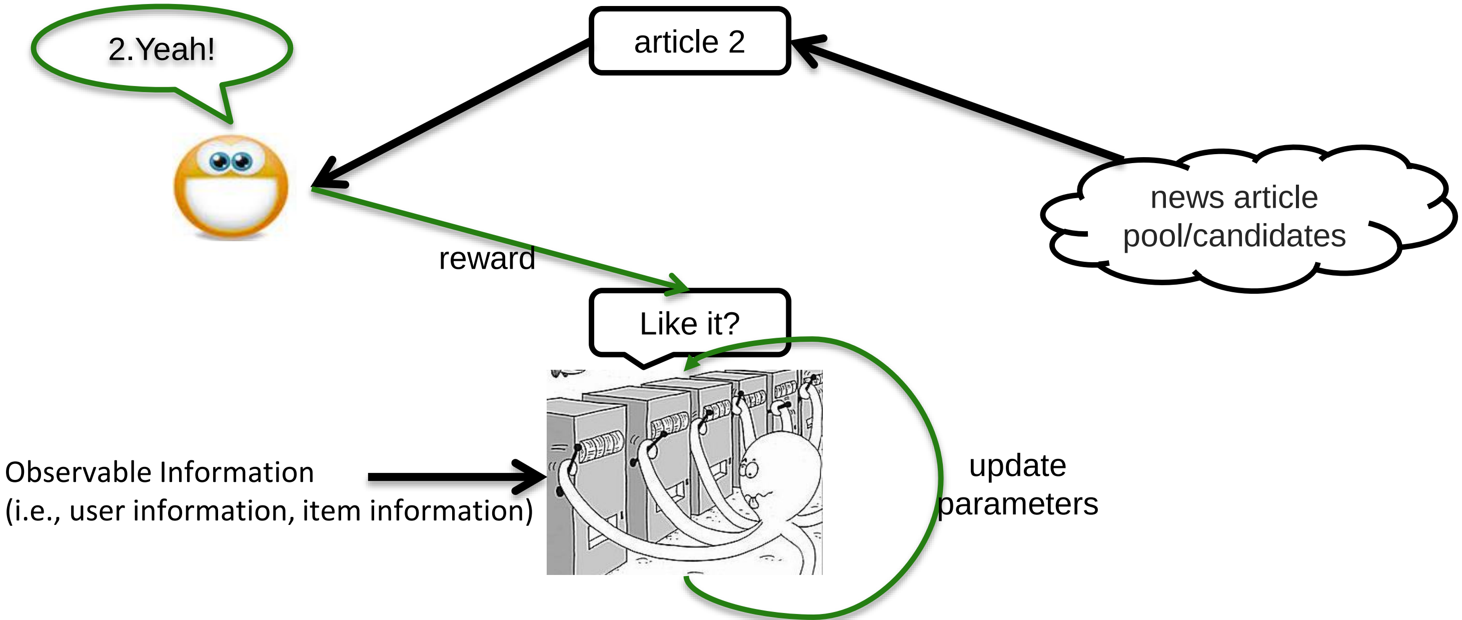
Q & A

Example: News Recommendation



Contextual Multi-armed Bandit

Example: News Recommendation



Contextual Multi-armed Bandit