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Representation Learning of Tangled Key-Value Sequence Data for Early Classification

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Outline

Background and Problem Formulation

D Motivation

□ Framework Design

D Evaluation

D Conclusion

Background

□ Tangled Key-Value Sequence



Background

□ Tangled Key-Value Sequence



Application:

...

- ✓ Product Recommendation
- ✓ Networking QoS Improvement
- ✓ Malicious Intrusion Detection

Background

□ Tangled Key-Value Sequence



Application:

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- ✓ Product Recommendation
- ✓ Networking QoS Improvement
- ✓ Malicious Intrusion Detection

D Two core performances for sequence data classification:

- Earliness
- Accuracy



Problem Formulation

D Tangled Key-Value Sequence Early Classification Problem:

- Given a tangled key-value sequence: $S \triangleq (\langle k, \mathbf{v} \rangle : k \in \mathcal{K}, \mathbf{v} \in \mathcal{V}_1 \times \cdots \times \mathcal{V}_l)$
- Each key-value sequence sharing a same key: $S_k \triangleq (\langle k, \mathbf{v} \rangle : \langle k, \mathbf{v} \rangle \in S)$



Our Target: classify each S_k within S both **early** and **accurately**.

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Our Target: classify each S_k within S both **early** and **accurately**.

□ Challenges: Earliness and Accuracy are two conflicting goals.





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□ The multi-objective optimization of "earliness-accuracy"

Stop

Decompose it to two targets:

• how to learn an informative representation from partial observations?

When?

• how to adaptively determine the number of observations for each S_k ?

□ The multi-objective optimization of "earliness-accuracy"

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Earliness: 😳 & Accuracy: 😳 Decompose it to two targets:

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When?

✓ exploit rich inner- and inter-sequence correlations in S.

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Earliness: 😳 & Accuracy: 😳

Decompose it to two targets:

- how to learn an informative representation from partial observations?
- how to adaptively determine the number of observations for each S_k ?

 ✓ formulate it as the Partially Observable Markov Decision Process (POMDP), and solve it through a halting policy.



When?



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Overview

Key-Value sequence Early Co-classification (KVEC) framework



□ Key-Value Sequence Representation Learning (KVRL) module



□ Key-Value Sequence Representation Learning (KVRL) module



□ Key-Value Sequence Representation Learning (KVRL) module





Early Co-classification Timing Learning (ECTL) module

sample action from halting policy

halt: <u>enough items have been observed</u> جي wait: more items in need to be observed



D Early Co-classification Timing Learning (ECTL) module sample action from halt: enough items have been observed halting policy wait: more items in need to be observed (1) input embedding (3) embedding fusion (2) attention mechanism $(\mathbf{E}^{(t)})^{\top}$ a session e1 e2 e3 e4 Fusion($\mathbf{s}_{\iota}^{(t-1)}$. $, \mathbf{E}_{e_t}^{(t)}$ value correlation key correlation value embedding E_a e_t \mathcal{S}_k membership value correlation policv embedding a session Si $\pi(\mathbf{s}_k^{(t)})$ relative position halt wait embedding time embedding E'sample invisiblevisible -classifier wait $a_k^{(t)}$ $C(\mathbf{s})$ $\leftarrow t + 1$ dynamic mask matrix 10/19 **ECTL module KVRL** module

Multi-objective Optimization

- <u>minimize the prediction error of the classification network</u> $l_1(\boldsymbol{\theta}_1) \triangleq -\sum_{k=1}^{K} \sum_{c=1}^{C} \mathbf{1}(y_k = c) \log \mathbf{p}_{k,c}(\boldsymbol{\theta}_1)$
- maximize the accumulate reward gained by the policy network

$$l_2(\boldsymbol{\theta}_2) \triangleq -\sum_{k=1}^K \sum_{i=1}^{n_k} \left(R_k^{(i)} - b_k^{(i)}(\boldsymbol{\theta}_b) \right) \log P(a_k^{(i)} | \mathbf{s}_k^{(i)}; \boldsymbol{\theta}_\pi)$$

• <u>encourage early prediction</u> $l_3(\boldsymbol{\theta}_3) \triangleq -\sum_{k=1}^{K} \sum_{i=1}^{n_k} \log P(a_k^{(i)} = \text{Halt}|\mathbf{s}_k^{(i)}; \boldsymbol{\theta}_{\pi})$

Total Training Loss: $l(\theta_1, \theta_2, \theta_3) \triangleq l_1(\theta_1) + \alpha l_2(\theta_2) + \beta l_3(\theta_3)$

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Evaluation

Datasets:

- USTC-TFC2016: malware and intrusion network traffic dataset
- MovieLens-1M: movie rating dataset
- Traffic-FG / Traffic-App: service-level / App-level traffic dataset
- Synthetic-Traffic: synthetic network traffic dataset

dataset	#keys	avg $ \mathcal{S}_k $	avg session length	#classes
USTC-TFC2016	3,200	31.2	8.3	9
MovieLens-1M	6,040	163.5	1.7	2
Traffic-FG	60,000	50.7	2.4	12
Traffic-App	50,000	57.5	2.7	10
Synthetic-Traffic	10,000	100.0	2.1	2

Evaluation

□ Metrics:

- Earliness
- Accuracy, Precision, Recall, F1-score
- HM: harmonic mean of Accuracy and Earliness, measure the multiobjective balancing ability of different methods.

$$HM \triangleq \frac{2 \times (1 - Earliness) \times Accuracy}{1 - Earliness + Accuracy}$$

Evaluation

□ Results: KVEC achieves 4.7–17.5% accuracy improvement, 3.7–14.0% HM improvement.









Figure 11. Distribution of halting positions predicted by different methods.

 <u>The advantages of KVEC primarily comes from the proposed</u> <u>representation learning.</u>

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Conclusion

Formulate the tangled key-value sequence early classification problem.

We propose the KVEC framework to solve this problem which mainly consists of two core modules, i.e., KVRL and ECTL.

Extensive experiments conducted on both real-world and synthetic datasets demonstrate that KVEC outperforms all alternative methods.

Thanks for listening!



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