Accelerating Dependency Graph Learning from Heterogeneous Categorical Event Streams via Knowledge Transfer

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ABSTRACT
Dependency graph, as a heterogeneous graph representing the intrinsic relationships between different pairs of system entities, is essential to many data analysis applications, such as root cause diagnosis, intrusion detection, etc. Given a well-trained dependency graph from a source domain and an immature dependency graph from a target domain, how can we extract the entity and dependency knowledge from the source to enhance the target? One way is to directly apply a mature dependency graph learned from a source domain to the target domain. But due to the domain variety problem, directly using the source dependency graph often cannot achieve good performance. Traditional transfer learning methods mainly focus on numerical data and are not applicable.

In this paper, we propose ACRET, a knowledge transfer based model for accelerating dependency graph learning from heterogeneous categorical event streams. In particular, we first propose an entity estimation model to filter out irrelevant entities from the source domain based on entity embedding and manifold learning. Only the entities with statistically high correlations are transferred to the target domain. On the surviving entities, we propose a dependency construction model for constructing the unbiased dependency relationships by solving a two-constraint optimization problem. The experimental results on synthetic and real-world datasets demonstrate the effectiveness and efficiency of ACRET. We also apply ACRET to a real enterprise security system for intrusion detection. Our method is able to achieve superior detection performance at least 20 days lead lag time in advance with more than 70% accuracy.

1 INTRODUCTION
The heterogeneous categorical event data are ubiquitous. Consider system surveillance data in enterprise networks, where each data point is a system event that involves heterogeneous types of entities: time, user, source process, destination process, and so on. Mining such event data is a challenging task due to the unique characteristics of the data: (1) the exponentially large event space. For example, in a typical enterprise network, hundreds (or thousands) of hosts incessantly generate operational data. A single host normally generates more than 10,000 events per second; And (2) the data varieties and dynamics. The variety of system entity types may necessitate high-dimensional features in subsequent processing, and the event data may change dramatically over time, especially considering the heterogeneous categorical event streams [1, 2, 25].

To address the above challenges, the recent studies of dependency graphs [13, 19, 33] have witnessed a growing interest. Such dependency graphs can be applied to model a variety of systems including enterprise networks [33], societies [26], ecosystems [17], etc. For instance, we can present an enterprise network as a dependency graph, with nodes representing system entities of processes, files, or network sockets, and edges representing the system events between entities (e.g., a process reads a file). This enterprise system dependency graph can be applied to many forensic analysis tasks such as intrusion detection, risk analysis, and root cause diagnosis [33]. A social network can also be modeled as a dependency graph representing the social interactions between different users. Then, this social dependency graph can be used for user behavior analysis or abnormal user detection [18].

However, due to the aforementioned data characteristics, learning a mature dependency graph from heterogeneous categorical event streams often requires a long period of time. For instance, the dependency graph of an enterprise network needs to be trained for several weeks before it can be applied for intrusion detection or risk analysis as illustrated in Fig. 1. Furthermore, every time, when the system is deployed in a new environment, we need to rebuild the entire dependency graph. This process is both time and resource consuming.

Enlightened by the cloud services [20], one way to avoid the time-consuming rebuilding process is by reusing a unified dependency graph model in different domains/environments. However, due to the domain variety, directly apply the dependency graph learned from an old domain to a new domain often cannot achieve good performance. For example, the enterprise network from an IT company (active environment) is very different from the enterprise network from an electric company (stable environment). Thus, the enterprise dependency graph of the IT company contains many unique system entities that cannot be found in the dependency graph of the electric company. Nevertheless, there are still a lot of room for transfer learning.

Transfer learning has shed light on how to tackle the domain differences [27]. It has been successfully applied in various data mining and machine learning tasks, such as clustering and classification [6]. However, most of the transfer learning algorithms
focus on numerical data [5, 8, 30]. When it comes to graph structure data, there is less existing work [10, 12], not to mention the dependency graph. This motivates us to propose a novel knowledge transfer-based method for dependency graph learning.

In this paper, we propose ACRET, a knowledge transfer based method for accelerating dependency graph learning from heterogeneous categorical event streams. ACRET consists of two sub-models: EEM (Entity Estimation Model) and DCM (Dependency Construction Model). Specifically, first, EEM filters out irrelevant entities from source domain based on entity embedding and manifold learning. Only the entities with statistically high correlations can be transferred to the target domain. Then, based on the reduced entities, DCM model effectively constructs unbiased dependency relationships between different entities for the target dependency graph by solving a two-constraint optimization problem. We launch an extensive set of experiments on both synthetic and real-world data to evaluate the performance of ACRET. The results demonstrate the effectiveness and efficiency of our proposed algorithm. We also apply ACRET to a real enterprise security system for intrusion detection. Our method is able to achieve superior detection performance at least 20 days lead lag time in advance with more than 70% accuracy.

By continuous monitoring/auditing the heterogeneous categorical event data (streams) generated by the physical system, one can generate the corresponding dependency graph of the system, as in [13, 19, 33]. This dependency graph is a heterogeneous graph representing the dependencies/interactions between different pairs of entities. Formally, we define the dependency graph as follows: **Dependency Graph.** A dependency graph is a heterogeneous undirected weighted graph \( G = (V, E) \), where \( V = \{v_0, v_1, \ldots, v_n\} \) is the set of heterogeneous system entities, and \( n \) is the total number of entities in the dependency graph; \( E = \{e_0, e_1, \ldots, e_m\} \) is the set of dependency relationships/edges between different entities. For ease of discussion, we use the terms edge and dependency interchangeably in this paper. A undirected edge \( e_i(v_k, v_j) \) between a pair of entities \( v_k \) and \( v_j \) exists depending on whether they have a dependency relation or not. The weight of the edge denotes the intensity of the dependency relation.

In an enterprise system, a dependency graph can be a weighted graph between different system entities, such as processes, files, users, Internet sockets. The edges in the dependency graph are the causality relations between different entities.

As shown in **Fig. 2**, the enterprise security system utilizes the accumulated historical heterogeneous system data from event streams to construct the system dependency graph and update the graph periodically. The learned dependency graph is applied to forensic analysis applications such as intrusion detection, risk analysis, and incident backtrace etc.

The problems of cold-start and time-consuming training reflect a great demand for an automated tool for effectively transferring dependency graphs between different domains. Motivated by this, this paper focuses on accelerating the dependency graph learning via knowledge transfer. Based on the definitions described above, we formally define our problem as follows:

**Knowledge Transfer for Dependency Graph Learning.** Given two domains: a source domain \( D_S \) and a target domain \( D_T \). In the source domain \( D_S \), we have a well-trained dependency graph \( G_S \) generated from the heterogeneous categorical event streams. In
target domain $D_T$, we have a small incomplete dependency graph $\tilde{G}_T$ trained by a short period of time. The task of knowledge transfer for dependency graph learning is to use $G_S$ to help construct a mature dependency graph $G_T$ in the domain $D_T$.

There are two major assumptions for this problem: (1) The event streams in the source domain and target domain are generated by the same physical system; (2) The entity size of source dependency graph $G_S$ should be larger than the size of the intersection graph $G_S \cap \tilde{G}_T$. Because transferring knowledge from a less informative dependency graph to an informative graph is unreasonable.

### 3.1 EEM: Entity Estimation Model

For the first sub-model, Entity Estimation Model, our goal is to filter out the entities in the source dependency graph $G_S$ that are irrelevant to the target domain. To achieve this, we need to deal with two main challenges: (1) the lack of intrinsic correlation measures among categorical entities, and (2) heterogeneous relations among different entities in the dependency graph.

To overcome the lack of intrinsic correlation measures among categorical entities, we embed entities into a common latent space where their semantics can be preserved. More specifically, each entity, such as a user, or a process in computer systems, is represented as a $d$-dimensional vector and will be automatically learned from the data. In the embedding space, the correlation of entities can be naturally computed by distance/similarity measures in the space, such as Euclidean distances, vector dot product, and so on. Compared with other distance/similarity metrics defined on sets, such as Jaccard similarity, the embedding method is more flexible and it has nice properties such as transitivity [35].

To address the challenge of heterogeneous relations among different entities, we use the meta-path proposed in [31] to model the heterogeneous relations. For example, in a computer system, a meta-path can be a “Process-File-Process”, or a ”File-Process-Internet Socket”. “Process-File-Process” denotes the relationship of two processes load the same file, and ”File-Process-Internet Socket” denotes the relationship of a file loaded by a process who opened an Internet Socket.

The potential meta-paths induced from the heterogeneous network $G_S$ can be infinite, but not every one is relevant and useful for the specific task of interest. There are some works [7] for automatically selecting the meta-paths for specific tasks.

Given a set of meta-paths $P = \{p_1, p_2, ..., p_P\}$, where $p_i$ denotes the $i$-th meta-path and let $|P|$ denotes the number of meta-paths.
We can construct \(|P|\) graphs \(G_{p_i}\) by each time only extracting the corresponding meta-path \(p_i\) from the dependency graph [31]. Let \(u_S\) denotes the vector representation of the entities in \(G_S\). Then, we model the relationship between two entities \(u_S(i)\) and \(u_S(j)\) as:

\[
\|u_S(i) - u_S(j)\|_F^2 \approx S_G(i,j),
\]

In the above, \(S_G\) is a weighted average of all the similarity matrices \(S_{p_i}\):

\[
S_G = \sum_{i=1}^{\mid P \mid} w_i S_{p_i},
\]

where \(w_i\)'s are non-negative coefficients, and \(S_{p_i}\) is the similarity matrix constructed by calculating the pairwise shortest path between each entities in \(A_{p_i}\). Here, \(A_{p_i}\) is the adjacent matrix of the dependency graph \(G_{p_i}\). By using the shortest path in the graph, one can capture the long term relationship between different entities [3].

Putting Eq. 2 into Eq. 1, we have:

\[
\|u_S(i) - u_S(j)\|_F^2 \approx \sum_{i=1}^{\mid P \mid} w_i S_{p_i},
\]

where \(\| \cdot \|_F^2\) is the Frobenius norm [11].

Then, the objective function of EEM model is:

\[
L^W_{\theta}(u_S, W) = \sum_{i,j} (\|u_S(i) - u_S(j)\|_F^2 - S_G(i,j))^2 + \Omega(u_S, W),
\]

where \(W = \{w_1, w_2, ..., w_p\}\), and \(\Omega(u_S, W) = \lambda \|u_S\| + \lambda \|W\|\) is the generalization term [11], which prevents the model from over-fitting. \(\lambda\) is the trade-off factor of the generalization term. In practice, we can choose \(\theta\) as 1 or 2, which bears the resemblance to Hamming distance and Euclidean distance, respectively.

Putting everything together, we get:

\[
L^W_{\theta}(u_S, W) = \sum_{i,j} (\|u_S(i) - u_S(j)\|_F^2 - S_G(i,j))^2 + \Omega(u_S, W)
\]

\[
= \sum_{i,j} \left[\|u_S(i) - u_S(j)\|_F^2 - \sum_{i=1}^{\mid P \mid} w_i S_{p_i}\right]^2 + \lambda \|u_S\| + \lambda \|W\|
\]

Then, the optimized value \([u_S, W]^{opt}\) can be obtained by:

\[
(u_S, W)^{opt} = \arg \min_{u_S, W} L^W_{\theta}(u_S, W).
\]

3.1.1 Inference Method. The objective function in Eq. 5 contains two sets of parameters: (1) \(u_S\), and (2) \(W\). Then, we propose a two-step iterative method for optimizing \(L^W_{\theta}(u_S, W)\), where the entity vector matrices \(u_S\) and the weight for each meta-path \(W\) mutually enhance each other. In the first step, we fix the weight vectors \(W\) and learn the best entity vector matrix \(u_S\). In the second step, we fix the entity vector matrix \(u_S\) and learn the best weight vectors \(W\).

Fix \(W\) and learn \(u_S\): when we fix \(W\), then the problem is reduced to \(\|u_S(i) - u_S(j)\|_F^2 \approx S_G(i,j)\), where \(S_G\) is a constant similarity matrix. Then, the optimization process becomes a traditional manifold learning problem. Fortunately, we can have a closed form to solve this problem, via so called multi-dimensional scaling [11]. To obtain such an embedding, we compute the eigenvalue decomposition of the following matrix:

\[
\frac{1}{2} H S_G H = U \Lambda U^T,
\]

where \(H\) is the double centering matrix, \(U\) has columns as the eigenvectors and \(\Lambda\) is a diagonal matrix with eigenvalues. Then, the embedding \(u_S\) can be chosen as:

\[
u_S = U_k \sqrt{\Lambda_k}.
\]

3.2 DCM: Dependency Construction Model

To construct the missing dependencies/edges in \(\widehat{G}_T\), there are two constraints need to be considered:

- **Smoothness Constraint**: The predicted dependency structure in \(\widehat{G}_T\) needs to be close to the dependency structure of the original graph \(\widehat{G}_T\). The intuition behind this constraint is that the learned dependencies should more or less intact in \(\widehat{G}_T\) as much as possible.

- **Consistency Constraint**: Inconsistency between \(\widehat{G}_T\) and \(\widehat{G}_S\) should be similar to the inconsistency between \(\widehat{G}_T\) and \(\widehat{G}_S\). Here, \(\widehat{G}_S\) and \(\widehat{G}_S\) are the sub-graphs of \(G_S\) which have
the same entity set with \( \bar{G}_T \) and \( \tilde{G}_T \), respectively. This constraint guarantees that the target graph learned by our model can keep the original domain difference with the source graph.

Before we model the above two constraints, we first need a measure to evaluate the inconsistency between different domains. In this work, we propose a novel metric named dynamic factor \( P(\bar{G}_S, \tilde{G}_T) \) between two dependency graphs \( \bar{G}_S \) and \( \tilde{G}_T \) from two different domains as:

\[
F(\bar{G}_S, \tilde{G}_T) = \frac{\| \bar{A}_S - \bar{A}_T \|_F}{|\bar{G}_S| + (|\bar{G}_S| - 1)/2} = \frac{2 \| \bar{A}_S - \bar{A}_T \|_F}{n_S(n_S - 1)} ,
\]

(9)

where \( n_S = |\bar{G}_S| \) is the number of entities in \( \bar{G}_S \), \( \bar{A}_S \) and \( \bar{A}_T \) denote the adjacent matrix of \( \bar{G}_S \) and \( \tilde{G}_T \), respectively, and \( n_S(n_S - 1)/2 \) denotes the number of edges of a fully connected graph with \( n_S \) entities [3].

Next, we introduce the Dependency Construction Model in details.

3.2.1 Modeling Smoothness Constraint. We first model the smoothness constraint as follows:

\[
L_{2,1}^{ur} = \sum_{i=1}^{n_S} \sum_{j=0}^{n_S-1} \left( u_T(i) u_T(j) - \bar{A}_T(i,j) \right)^2_F + \lambda \| u_T \|_F^2 ,
\]

(10)

where \( u_T \) is the vector representation of the entities in \( G_T \), and \( \Omega(u_T) = \lambda \| u_T \|_F^2 \) is the regularization term.

3.2.2 Modeling Consistency Constraint. We then model the consistency constraint as follows:

\[
L_{2,2}^{ur} = \left\| F(u_T u_T^T, \bar{A}_S) - F(\tilde{A}_S, \tilde{A}_T) \right\|_F^2 + \Omega(u_T),
\]

(11)

where \( F(\ast, \ast) \) is the dynamic factor as we defined before. Then, putting Eq. 9 and \( \Omega(u_T) \) into Eq. 11, we get:

\[
L_{2,2}^{ET} = \left\| F(u_T u_T^T, \bar{G}_S) - F(\bar{G}_S, \tilde{G}_T) \right\|_F^2 + \Omega(u_T)
\]

\[
= \frac{2 \| u_T u_T^T - \bar{AS} \|_F^2}{n_S(n_S - 1)} + \frac{2 \| u_T u_T^T - \tilde{A}_S \|_F^2}{n_S(n_S - 1)} + \Omega(u_T),
\]

(12)

where \( C_3 = F(\bar{G}_S, \tilde{G}_T) \).

3.2.3 Unified Model. Having proposed the modeling approaches in Section 3.2.1 and 3.2.2, we intend to put all the two constraints together. The unified model for dependency construction is proposed as follows:

\[
L_{2}^{ur} = \mu L_{2,1}^{ur} + (1 - \mu) L_{2,2}^{ur}
\]

\[
= \mu \left\| u_T u_T^T - \tilde{A}_T \right\|_F^2 + (1 - \mu) \left\| \frac{2 u_T u_T^T - \bar{A}_S}{n_S(n_S - 1)} + \Omega(u_T) \right\|_F^2,
\]

(13)

The first term of the model incorporates the Smoothness Constraint component, which keeps the \( u_T \) closer to target domain knowledge existed in the \( \bar{G}_S \). The second term considers the Consistency Constraint, that is the inconsistency between \( \bar{G}_T \) and \( \tilde{G}_S \) should be similar to the inconsistency between \( \bar{G}_T \) and \( \bar{G}_S \). \( \mu \) and \( \lambda \) are important parameters which capture the importance of each term, and we will discuss these parameters in Section 3.3. To optimize the model as in Eq. 13, we use stochastic gradient descent [11] method. The derivative on \( u_T \) is given as:

\[
\frac{\partial L_{2}^{ur}}{\partial u_T} = \mu u_T (u_T u_T^T - \tilde{A}_T) + (1 - \mu) u_T \left( \frac{2 u_T u_T^T - \bar{A}_S}{n_S(n_S - 1)} + \Omega(u_T) \right)
\]

(14)

3.3 Overall Algorithm

The overall algorithm is then summarized as Algorithm 1. In the algorithm, line 5 to line 11 implements the Entity Estimation Model, and line 13 to 16 implements the Dependency Construction Model.

3.3.1 Setting Parameters. There are two parameters, \( \lambda \) and \( \mu \), in our model. For \( \lambda \), as in [11, 31], it is always assigned manually based on the experiments and experience. For \( \mu \), when a large number of entities are transferred to the target domain, a large \( \mu \) can improve the transferring result, because we need more information to be added from the source domain. On the other hand, when only a
small number of target entities are transferred to target domain, then a larger \( \mu \) will bias the result. Therefore, the value of \( \mu \) depends on how many entities are transferred from the source domain to the target domain. In this sense, we can use the proportion of the transferred entities in \( \hat{G}_T \) to calculate \( \mu \). Given the entity size of \( \hat{G}_T \) as \(|\hat{G}_T|\), the entity size of \( G_T \) as \(|G_T|\), then \( \mu \) can be calculated as:

\[
\mu = (|G_T| - |\hat{G}_T|)/|G_T|.
\]

(15)

The experimental results in Section 4.6 demonstrate the effectiveness of the proposed parameter selection method.

3.3.2 Complexity Analysis. As shown in Algorithm 1, the time for learning our model is dominated by computing the objective functions and their corresponding gradients against feature vectors.

For the Entity Estimation Model, the time complexity of computing the \( \eta_s \) in Eq. 6 is bounded by \( O(d_1 n) \), where \( n \) is the number of entities in \( G_S \), and \( d_1 \) is the dimension of the vector space of \( \eta_s \). The time complexity for computing \( W \) is also bounded by \( O(d_1 n) \). So, suppose the number of training iterations for \( EEM \) is \( t_1 \), then the overall complexity of \( EEM \) model is \( O(t_1 d_1 n) \).

For the Dependency Construction Model, the time complexity of computing the gradients of \( \mathcal{L}_2 \) against \( \eta_T \) is \( O(t_2 d_2 n) \), where \( t_2 \) is the number of iterations, \( d_2 \) is the dimension of feature vector. As shown in our experiment (see Section 4.5), \( t_1, t_2, d_1, \) and \( d_2 \) are all small numbers. So that we can regard them as a constant, say \( C \), so the overall complexity of our method is \( O(Cm) \), which is linear with the size of the entity set. This makes our algorithm practicable for large scale datasets.

4 EXPERIMENTS

In this section, we evaluate ACRET using synthetic data and real system surveillance data collected in enterprise networks.

4.1 Comparing Methods

We compare ACRET with the following methods:

- **NT**: This method directly uses the original small target dependency graph without knowledge transfer. In other words, the estimated target dependency graph \( \hat{G}_T = \hat{G}_T \).

- **DT**: This method directly combines the source dependency graph and the original target dependency graph. In other words, the estimated target dependency graph \( \hat{G}_T = \hat{G}_S + \hat{G}_T \).

- **RW-DCM**: This is a modified version of the ACRET method. Instead of using the proposed EEM model to perform entity estimation, this method uses the random walk to evaluate the correlations between entities and perform entity estimation. Random walk is a widely-used method for relevance search in a graph [16].

- **EEM-CMF**: This is another modified version of the ACRET method. In this method, we replace DCM model with collective matrix factorization [28] method. Collective matrix factorization has been applied for link prediction in multiple domains [28].

4.2 Evaluation Metrics

Since in ACRET algorithm, we use hypothesis-test for thresholding the selection of entities and dependencies, similar to [11, 23], we use the F1-score to evaluate the hypothesis-test accuracy of all the methods.

F1-score is the harmonic mean of precision and recall. In our experiment, the final F1-score is calculated by averaging the entity F1-score and dependency/edge F1-score.

To calculate the precision (recall) of both entity and link, we compare the estimated entity (edge) set with the ground-truth entity/link set. Then, precision and recall can be calculated as follows:

\[
\text{Precision} = \frac{N_C}{N_E}, \quad \text{Recall} = \frac{N_C}{N_T},
\]

where \( N_C \) is the number of correctly estimated entities (edges), \( N_E \) is the number of total estimated entities (edges), and \( N_T \) is the number of ground truth entities (edges).

4.3 Synthetic Experiments

We first evaluate the ACRET on synthetic graph data-sets to have a more controlled setting for assessing algorithmic performance. We control three aspects of the synthetic data to stress test the performance of our ACRET method:

- **Graph size** is defined as the number of entities for a dependency graph. Here, we use \(|G_S|\) to denote the source domain graph size and \(|\hat{G}_T|\) to denote the target one.

- **Dynamic factor**, denoted as \( F \), has the same definition as in Section 3.2.

- **Graph maturity score**, denoted as \( M \), is defined as the percentage of entities/edges of the ground-truth graph \( \hat{G}_T \), that are used for constructing the original small graph \( G_T \). Here, graph maturity score is used for simulating the period of learning time of \( G_T \) to reach the maturity in the real system.

Then, given \(|G_S|\), \(|\hat{G}_T|\), \( F \), and \( M \), we generate the synthetic data as follows: We first randomly generate an undirected graph as the source dependency graph \( G_S \) based on the value of \(|G_S|\) [32]; Then, we randomly assign three different labels to each entity. Due to space limitations, we will only show the results with three labels, but similar results have been achieved in graphs with more than three labels. We further construct the target dependency graph \( G_T \) by randomly adding/deleting \( F = \alpha \% \) of the edges and deleting \(|G_S| - |\hat{G}_T|\) entities from \( G_S \). Finally, we randomly select \( M = \beta \% \) of entities/edges from \( \hat{G}_T \) to form \( G_T \).

4.3.1 How Does ACRET's Performance Scale with Graph Size? We first explore how the ACRET's performance changes with graph size \(|G_S|\) and \(|\hat{G}_T|\). Here, we fix the maturity score to \( M = 50 \% \), the dynamic factor to \( F = 10 \% \), and target domain dependency graph size to \(|\hat{G}_T| = 0.9 \). Then, we increase the source graph size \(|G_S|\) from 0.9K to 1.4K. From Fig. 4a, we observe that with the increase of the size difference \(|G_S| - |\hat{G}_T|\), the performances of DT and RW-DCM are getting worse. This is due to the poor ability of DT and RW-DCM for extracting useful knowledge from the source domain. In contrast, the performance of ACRET and EEM-CMF increases with the size differences. This demonstrates the great capability of EEM model for entity knowledge extraction.

4.3.2 How Does ACRET’s Performance Scale with Domain Dynamic Factor? We now vary the dynamic factor \( F \) to understand its impact on the ACRET’s performance. Here, the graph maturity score is set to \( M=50 \% \), and two domain sizes are set to \(|G_S| = 1.2K\)
and $|\hat{G}_T| = 0.6K$, respectively. Fig. 4b shows that the performances of all the methods go down with the increase of the dynamic factor. This is expected, because transferring the dependency graph from a very different domain will not work well. On the other hand, the performances of ACRET, RW-DCM, and EEM-CMF only decrease slightly with the increase of the dynamic factor. Since RW-DCM and EEM-CMF are variants of the ACRET method, this demonstrates that the two sub-models of the ACRET method are both robust to large dynamic factors.

4.3.3 How Does ACRET’s Performance Scale with Graph Maturity? Third, we explore how the graph maturity score $M$ impacts the performance of ACRET. Here, the dynamic factor is fixed to $F = 0.2$. The graph sizes are set to $|G_S| = 1.2K$ and $|\hat{G}_T| = 0.6$. Fig. 4c shows that with the increase of the $M$, the performances of all the methods are getting better. The reason is straightforward: with the maturity score increases, the challenge of domain difference for all the methods is becoming smaller. In addition, our ACRET and its variants RW-DCM, and EEM-CMF perform much better than DT and NT. This demonstrates the great ability of the sub-models of ACRET for knowledge transfer. Furthermore, ACRET still achieves the best performance.

4.4 Real-World Experiments
Two real-world system monitoring datasets are used in this experiment. The data is collected from an enterprise network system composed of 47 Linux machines and 123 Windows machines from two departments, in a time span of 14 consecutive days. In both datasets, we collect two types of system events: (1) communications between processes, and (2) system activity of processes sending or receiving Internet connections to/from other machines at destination ports. Three different types of system entities are considered: (1) processes, (2) Unix domain sockets, and (3) Internet sockets. The sheer size of the Windows dataset is around 7.4 Gigabytes, and the Linux dataset is around 73.5 Gigabytes. Both Windows and Linux datasets are split into a source domain and a target domain according to the department name. The detailed statistics of the two datasets are shown in Table 1.

In this experiment, we construct one target domain dependency graph $\hat{G}_T$ per day by increasing the learning time daily. The final graph is the one learned for 14 days. From Fig. 5, we observe that for both Windows and Linux datasets, with the increase of the training time, the performances of all the algorithms are getting better. On the other hand, compared with all the other methods, ACRET achieves the best performance on both Windows and Linux datasets. In addition, our proposed ACRET algorithm can make the dependency graph deplorable in less than four days, instead of two weeks or longer by directly learning on the target domain.

4.5 Convergence Analysis
As described in Section 3.3.2, the performance bottleneck of ACRET model is the learning process of the two sub-models: EEM (Entity Estimation Model) and DCM (Dependency Construction Model). In this section, we report the convergence speed of our approach.

We use both synthetic and real-world data to validate the model convergence speed. For the synthetic data, we choose the one with dynamic factor to be $F = 0.2$, the dependency graph size to be $|G_S| = 1.2K$ and $|\hat{G}_T| = 0.6K$, and the graph maturity to be 50%. For the two real-world datasets, we fix the target dependency graph learning time as 4 days.

From Fig. 6, we can see that in all three datasets, ACRET converges very fast (i.e., with less than 10 iterations). This makes our model applicable for the real-world large-scale systems.

4.6 Parameter Study
In this section, we study the impact of parameter $\mu$ in Eq. 13. We use the same datasets as in Section 4.5. As shown in Fig. 7, when the value of $\mu$ is too small or too large, the results are not good, because
Figure 5: Performance on real-world data.

Figure 6: Performance on convergence.

\( \mu \) controls the leverage between the source domain information and target domain information. The extreme value of \( \mu \) (too large or too small) will bias the result. On the other hand, the \( \mu \) value calculated by Eq. 15 is 0.23 for the synthetic dataset, 0.36 for the Windows dataset, and 0.46 for the Linux dataset. And Fig. 7 shows the best results just appear around these three values. This demonstrates that our proposed method for setting the \( \mu \) value is very effective, which successfully addresses the parameter pre-assignment issue.

4.7 Case Study on Intrusion Detection

As aforementioned, dependency graph is essential to many forensic analysis applications like root cause diagnosis and risk analysis. In this section, we evaluate the ACRET’s performance in a real commercial enterprise security system (see Fig. 2) for intrusion detection.

In this case, the dependency graph, which represents the normal profile of the enterprise system, is the core analysis model for the offshore intrusion detection engine. It is built from the normal system process event streams (see Section 4.4 for data description) during the training period. The same security system has been deployed in two companies: one Japanese electric company and one US IT company. We obtain one dependency graph from the IT company after 30 days’ training, and two dependency graphs from the electric company after 3 and 30 days’ training, respectively. ACRET is applied for leveraging the well-trained dependency graph from the IT company to complete the 3 days’ immature graph from the electric company.

In the one-day testing period, we try 10 different types of attacks [15], including Snowden attack, ATP attack, botnet attack, Sniffer Attack and etc., which resulted in 30 ground-truth alerts. All other alerts reported during the testing period are considered as false positives.

Table 2 shows the intrusion detection results in the electric company using the dependency graphs generated by different transfer learning methods and the 30 days’ training from the electric company. From the results, we can clearly see that ACRET outperforms all the other transfer learning methods by at least 18% in precision and 13% in recall. On the other hand, the performance of the dependency graph (3 days’ model) accelerated by ACRET is very close to the ground truth model (30 days’ model). This means, by using ACRET, we can achieve similar performance in one-tenth training time, which is of great significant to some mission critical environments.
Table 2: Intrusion detection performance.

| Method  | Precision | Recall |
|---------|-----------|--------|
| NT      | 0.01      | 0.10   |
| DT      | 0.15      | 0.30   |
| RW-DCM  | 0.38      | 0.57   |
| EEM-CMF | 0.42      | 0.60   |
| ACRET   | 0.60      | 0.73   |
| Real 30 days' model | 0.58 | 0.76 |

5 RELATED WORK

5.1 Transfer Learning

Transfer learning has been widely studied in recent years [4, 27]. Most of the traditional transfer learning methods focus on numerical data [5, 8, 30]. When it comes to graph (network) structured data, there is less existing work. In [10], the authors presented TrGraph, a novel transfer learning framework for network node classification. TrGraph leverages information from the auxiliary source domain to help the classification process of the target domain. In one of their earlier work, a similar approach was proposed [9] to discover common latent structure features as useful knowledge to facilitate collective classification in the target network. In [12], the authors proposed a framework to propagates the label information from the source domain to the target domain via the example-feature-example tripartite graph. Transfer learning has also been applied to the deep neural network structure. In [6], the authors introduced Net2Net, a technique for rapidly transferring the information stored in one neural net into another. Net2Net utilizes function preserving transformations to transfer knowledge from neural networks. Different from existing methods, we aim to expedite the dependency graph learning process through knowledge transfer.

5.2 Link Prediction and Relevance Search

Graph link prediction is a well-studied research topic [14, 21]. In [34], Ye et al. presented a transfer learning algorithm to address the edge sign prediction problem in signed social networks. Because edge instances are not associated with a pre-defined feature vector, this work was proposed to learn the common latent topological features shared by the target and source networks, and then adopt an AdaBoost-like transfer learning algorithm with instance weighting to train a classifier. Collective matrix factorization [28] is another popular technique that can be applied to detect mission links by combining the source domain and target domain graphs. However, all the existing link prediction methods can not deal with dynamics between the source domain and target domain as introduced in our problem.

Finding relevant nodes or similarity search in graphs is also related to our work. Many different similarity metrics have been proposed such as Jaccard coefficient, cosine similarity, and Pearson correlation coefficient [3], and Random Walks [16, 29]. However, none of these similarity measures consider the multiple relations exist in the data. Recent advances in heterogeneous information networks [31] have offered several similarity measures for heterogeneous relations, such as meta-path and relation path [22, 24]. However, these methods can not deal with the multiple domain knowledge.

6 CONCLUSION

In this paper, we investigate the problem of transfer learning on dependency graph. Different from traditional methods that mainly focus on numerical data, we propose ACRET, a two-step approach for accelerating dependency graph learning from heterogeneous categorical event streams. By leveraging entity embedding and constrained optimization techniques, ACRET can effectively extract useful knowledge (e.g., entity and dependency relations) from the source domain, and transfer it to the target dependency graph. ACRET can also adaptively learn the differences between two domains, and construct the target dependency graph accordingly. We evaluate the proposed algorithm using extensive experiments. The experiment results convince us of the effectiveness and efficiency of our approach. We also apply ACRET to a real enterprise security system for intrusion detection. Our method is able to achieve superior detection performance at least 20 days lead lag time in advance with more than 70% accuracy.

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