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A Dynamic Knowledge Graph Embedding Framework Based on Adaptive Relation Spaces and Matrix Factorization Techniques

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Abstract

Knowledge graph is the knowledge of the world which provides strong support to the applications of artificial intelligence. The knowledge graph is composed of a head entity, tail entity and relation that is called as triplets. The entities and relationships of the knowledge graph give the information about the neighborhood. Over the past few years, knowledge graph embedding has proven to be indispensable in enhancing intelligent applications based on data. In this paper, a dynamic knowledge graph embedding framework with adaptive relation spaces and matrix factorization is proposed to enhance link prediction and triplet classification. A knowledge graph has triples (head, relation, tail) and entities and relations are represented in the vectors spaces. The suggested approach proposes dynamic mapping matrices created based on projection vectors, which makes the computational complexity lower because of the absence of multiplication of matrices. Benchmark datasets FB15K-237 (237 relations, 14,541 entities) and WN18RR (11 relations, 40,943 entities) are used to conduct experiments. Findings indicate a better performance, Mean Rank is lower to 199 (filtered) on FB15K-237 than on TransE, 243, and Hits10 is higher to 47.1. In WN18RR, Hits@10 is 71.9 and it is better than baseline models. In the triplet classification, the accuracy is better at 86.4% (FB15K-237) and 88.7% (WN18RR). N-to-N relation prediction is also improved by the model by about 10.1%. Also, the training time is minimized in comparison to the current models and only 24 seconds are needed instead of 70 seconds in TransR. In general, the framework is more accurate with fewer parameters and lower-cost to compute.

Keywords: Knowledge graph, embedding, dynamic matrix, relation mapping, link prediction, triplet classification, vector representation, matrix factorization, and computational efficiency

1. Introduction

The knowledge graph (KG) is a kind of data structure and it is developed by incorporating the structural properties of graph. The semantic network of any relation is denoted by “node-edge-node”, which represent an “entity” or “concept”. The relationship among any entity is represented by the edges in the graph. The real world concepts are described via rich relations in the graph and it is extensivelyused in the fields of semantic search [1], medical [2] and finance [3].The insufficiency of information in the knowledge graph leads to the incompleteness of data that makes the data processing as incomplete. The meagerness of the information makes the data processing incomplete and the process of completing the missing value is a tedious process. The completion of missing values and generating true relation in knowledge graph is a dynamic research area.

The knowledge graph approaches available in the graph mining is established mainly by embedding of entity in graph and it ignores the impact on the diverse relations on the signification of the triple. The existing methods uses the strategy of equal allocation of weights to various relations on the similar path of the graph [4]. Hence, the significance of the relation is treated correspondingly and it results in inaccuracy in prediction of links. The event prediction is significant and it is accomplished through event knowledge graph whereas the accuracy is important in event prediction [5].If the critical path identification results with inaccurate value then the relation reasoning and the prediction process goes wrong, which gives entirely differing information. The process of decision analysis will mislead by the acquired inaccurate data. Therefore, enrichment of accuracy and reduction of computational complexity is necessary [6, 8].

The study by Fu X. et al. (2018) introduces a financial knowledge graph framework combined with stochastic optimization to improve market return prediction. Their method illustrates that structured relational data can increase the predictive power in the financial sectors. Likewise, Rotmensch M. et al. (2017) concentrate on building a health knowledge graph based on electronic medical records, which allows improved clinical understanding and decision-making processes due to the structured relations between medicine.

Xiong C. et al. (2017) present a semantic ranking model, based on knowledge graph embedding, to academic search, enhancing relevance with entity relations in the field of information retrieval. Moving the embedding methods forward, Nathani D. et al. (2019) propose attention-based embeddings, whereby the significance of the various relations is given, boosting the performance of relation prediction.

To overcome reasoning problems, Lv X. et al. (2019) create a multi-hop reasoning approach in few-shots cases based on the information on meta knowledge graphs and enhances inference with small data amounts. The TransE model of Bordes A. et al. (2013) is based on a translation of relations in the vector space, and the model is the foundation of many other models.

To overcome TransE limitations, Wang Z. et al. (2014) propose TransH, introducing relation-specific hyperplanes for better handling complex relations. Likewise, Tan Z. et al. (2016) create dynamic relation spaces in order to reflect various relational patterns in a more efficient way. Lastly, Fan M. et al. (2014) include properties of relational mapping to enhance the quality of embedding with relation-specific transformations.

In general, these works demonstrate how the knowledge graph embedding models have been developed as simple translational models to more sophisticated models with attention mechanisms, dynamical spaces, and domain-specific applications.

In this paper, a novel scheme is introduced, and it incorporate the dynamic matrix with mapping properties. The basic notion of dynamic matrix representation is shown in Figure 1.The relation and entity is expressed by vectors where the denotation of a relation or an entity is by one vector and the embedding scheme in the entity is denoted by the other projection vector.The process of embedding entity into a vector space in the relation will create the mapping matrices and each entity relation in the graph has distinctive mapping matrix. The matrix by vector and multiplication operations are replaced by simple vector operations. The proposed dynamic matrix is evaluated with the relation prediction and triplet classification. The proposed model is compared with previous knowledge graph models.

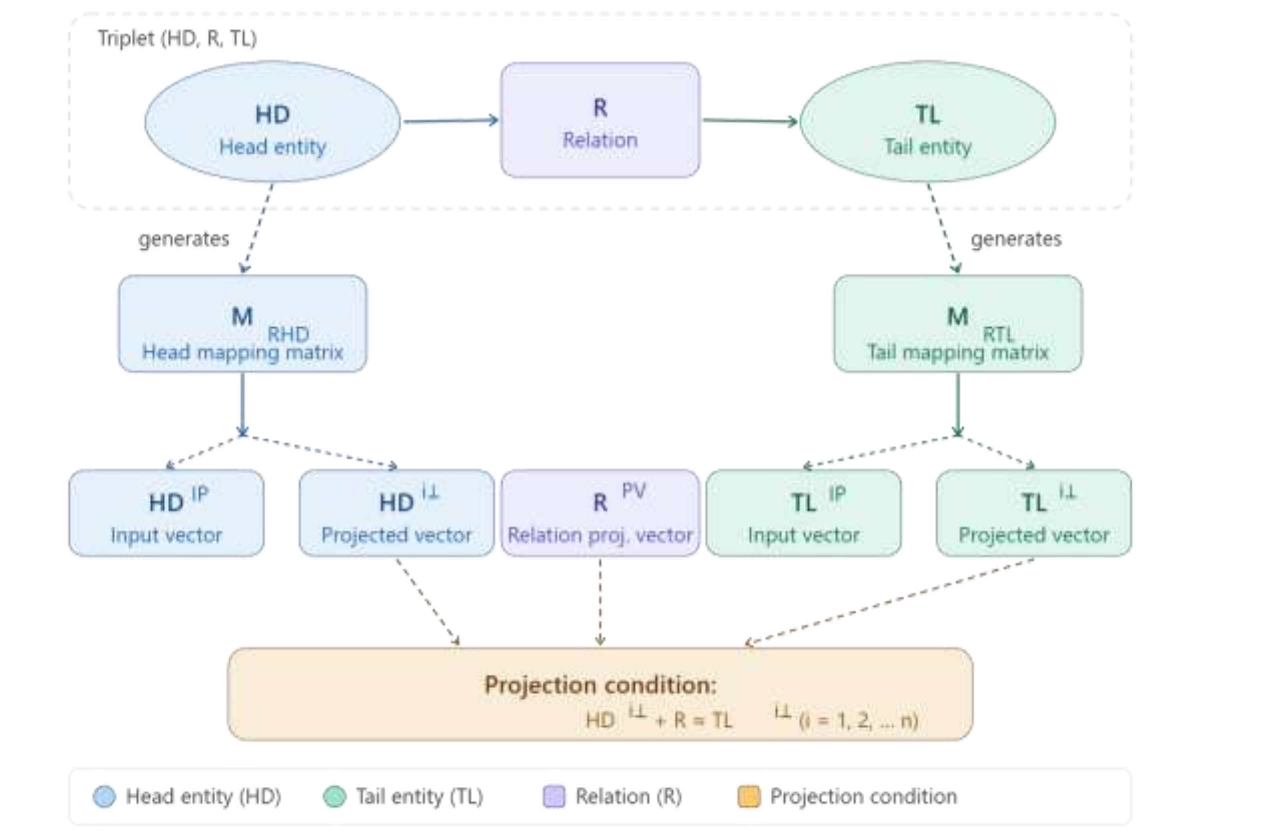

Figure 1: Simple Notion of Dynamic Matrix Representation

In Figure 1, every shape denotes every individual entity pair relies in the triplet that holds relation R. The mapping matrices are signified by M_{RHD} and M_{RTL}, where the head is HD and tail is TL in the matrix. The notion of projection vector and vector entities are R_{PV} and HD_{IP}, TL_{IP}. The vector projection of every entity is represented by $HD_{i\perp}$ and $TL_{i\perp}$(i=1,2,...n). The vector projected in the graph must fulfill the condition $HD_{i\perp}$+R $TL_{i\perp}$.

Contribution

- The proposed novel method dynamic matrix using mapping properties will generates a mapping matrix dynamically for every pair of entity relation with the support of diverse nature of relation and entity. The representation of every vector to the space of relation vector is attained simply.
- The developed approach uses minimum parameters, and the multiplication is not required, which makes the proposed scheme effective in the large-scale graphs. The triple features in the graph will be explored deeper, and the attainment of knowledge is effective.
- In the extensive experiment, dynamic matrix scheme outperforms the available knowledge graph approaches in the task of triplet classification and the relation prediction.

The rest of the paper is emphasised as follows: the reviews and surveys of various schemes are discussed in section 2, detailed the proposed approach in section 3, analysis of result is illustrated in section 4 and proposed work is concluded with future idea in section 5.

2. Related Work

In this section, similar research on knowledge graph mining and two major graph mining category is discussed. The two diverse aspects namely translational and compositional models are briefed.

Translational Model

Translational models interpret relationships in a knowledge graph as vector translations between entities. In these models, a triplet (h, r, t) is considered valid if the vector of the head entity (h) combined with the relation vector (r) closely approximates the tail entity (t). The foundational TransE model follows this principle by ensuring that **h + r ≈ t**, meaning the relation acts as a translation operation in the embedding space. The scoring function measures the distance between (h + r) and t, where a smaller distance indicates a stronger and more valid relationship. This approach is simple, efficient, and effective for one-to-one relations but may struggle with more complex relations such as one-to-many or many-to-many.

$$f_s(HD, TL) = \|HD + R - TL\|^2_{l_1/l_2}$$

The seminal TransE model is incorporated to the simple 1 to 1 relation and it faces the complexity for facing the relations such as N to N, 1 to N and N to 1. To rectify the complicated relation issue, a new TransH is developed that permit every entity with unique representation for every relation [7]. TransH architects the relation as a vector R on a hyperplane and the entity vectors such as HD and TL, where the entities areprojected into a relation-specific hyperplanes ($HD_{i\perp}$ and $TL_{i\perp}$). The score function is equated as,

$$f_s(HD, TL) = \|HD \perp + R - TL \perp\|^2_{l_1/l_2}$$

Recent advancements in translational models, such as TransDR, enhance relation representation by introducing weighted relation-specific spaces, along with concepts like eigenstate and mimesis to better capture relational patterns. Other improved models further refine performance by incorporating adaptive strategies: some assign weights to relations based on the number of associated entities, while others define triplet-specific margins depending on entity and relation distribution. Additionally, certain approaches enforce orthogonality between the combined head-relation vector and the tail entity, improving relational distinction. Another enhancement includes leveraging textual or semantic descriptions of entities to enrich embeddings, leading to more accurate and expressive knowledge graph representations.

Compositional Model

In addition to the translation models, there are numerous knowledge graph approaches are available that are knowledge embedding models and it is reasonable for denoting the graphs as well as retrieving the knowledge.

Structured Embedding

Structure embedding (SE) model considers the correspondence of head entity HD and tail entity TL. During the existence of triplet values (HD,TL,R),overlap in a definite relation space RS^n occur. It utilizes two mapping matrices namely M_RHD and M_RTL, that extracts the needed features from the relevant entities of HD and TL. The scoring function of SE is equated by

$$f_s(HD, TL) = \left\|M_{R\_HD}HD + M_{r\_TL}TL\right\|^2_{l_1/l_2}$$

Unstructured Model

Unstructured Model (UM) deems the head entity HD and tail entity TL in every triplet holds similar semantic and the correlation between them is ignored. The scoring function utilizes the l_2 norm to restrain the embedding's, that is,

$$f_s(HD, TL) = \|HD + TL\|^2_{l_2}$$

The diversification among the relations elucidate the features of minimum effectiveness in the knowledge graph.

Semantic Matching Energy

The main intent of semantic matching energy (SME) is to attain the accurate and correct triplet value where the feature vectors are orthogonal (head and tail). After the process of mapping, every entity will be added with the bias of the relevant relation. The feature extraction process is accomplished by non-linear and linear method. The scoring function is equated by,

$$f_s(HD,TL) = (M_H HD + M_{HD\_R}R + B_{HD})^{TL}.(M_{TL}TL + M_{TL\_R}R + B_{TL})$$

$$f_s(HD,TL) = (M_H HD \otimes M_{HD\_R}R + B_{HD})^{TL}.(M_{TL}TL \otimes M_{TL\_R}R + B_{TL})$$

For the non-linear case of feature extractors, the feature extractors are M_{HD}, M_{HD_R}, M_{TL}, M_{TL_R} and the hadamard product is $\otimes$ and BR and BTL are consider as the biases for the values HD and TL. Various approaches have been developed that enhances the performance of SME.

Single layer Model

In comparison with the model SE, the single layer model (SLM) is effective in translated feature extraction, and it incorporate the non-linear activation function. After the activation process of feature vector, they are orthogonal with the relation with the obtained feature vector. The extracted features consist ofthe entities' features after mapping and adding a bias of itsrelation.

Neural Tensor Network

Neural tensor network (NTN) is a more complex model, in which tensor is harnessed as a better feature extractor.

Complex Embedding

The function of logistics inverse link is predicted using the complex embedding model (CompIEX). The function of logistic inverse link is,

$$P(K_{Rso} = 1) = \sigma(\emptyset(RL, s, o; \delta))$$

where the value of Y_{Rso} belongs to the value {-1,1} and it is the identified fact, RL is the relation, s and o denotes the subject value and object value respectively. The relevant parameters for relevant model is represented by δ. Generally, the scoring function σ is obtained from the factorization of relations observed in the graph.

The DisMult model utilizes bilinear scheme that denote the relations and entities. The logical rules in the knowledge graph is acquired by exploiting the learned embedding scheme.The HOLE model is formulated vector space with compositional model, which is based on the vector relation in the form of circular correlation.

Latent Factor Model

The latent factor model (LFM) adopts the features of head entity is orthogonal to the tail entity, whereas the head is mapped in a definite relation space. The scoring function is determined by

$$f_s(HD,TL) = HD^{TL} M_R TL$$

3. Proposed Model

The triplet values are signified as HD_i, R_i and TL_i, where i =1,2,3….n_{TL}. The HD_i represents the head, R_i represents the relation and TL_i represents the tail. Their relevant embedding's are denoted by HD_i, R_i and TL_i, i =1,2,3….n_{TL}.The golden triplets are signified by Δ and the negative triplets are signified byΔ'. The relation set and entity set is represented by R_S and E_S, respectively. The identity matrix with the size m×n is signified by $IM^{m \times n}$.

3.1 Entities and Relations with multiple type

The consideration of diverse relations, CTransR partitions the triplets to a definite relation R into various groups and representation of vector is learned for every group. Conversely, every entities contains diversified types. In the knowledge graph approaches namely TransR/CTransR and TransH, all the varieties of entities share similar matrices and mapping vectors. Diversified nature of entities have diverse attribute and function. The process of sharing the similar parameters for a relation is insufficient and not applicable. The mapping properties must be similar for similar entities and dissimilar for other varieties. Figure 2 reveals numerous varieties of head and tail entities of relations location that are partially acquired in the FB15k.

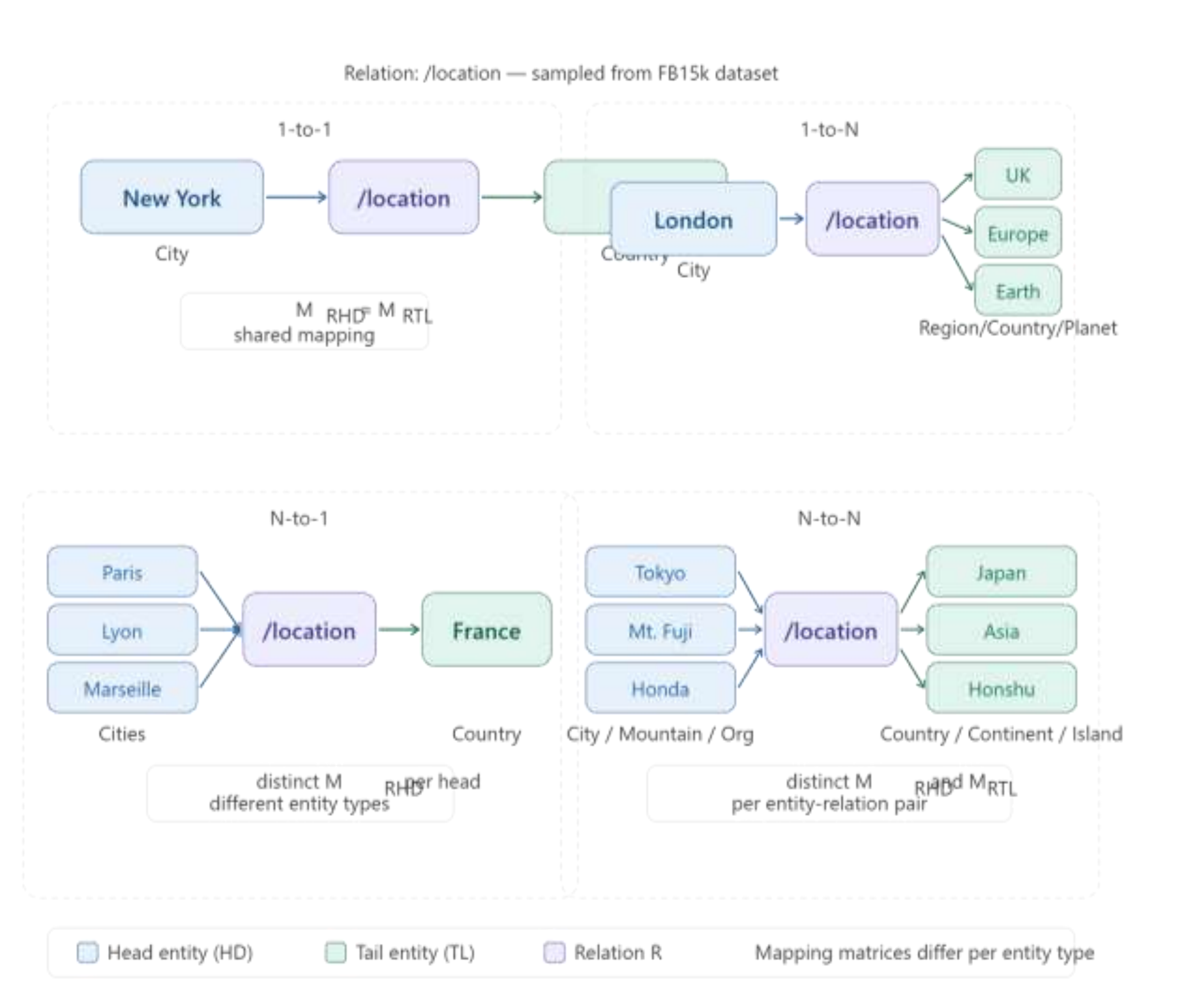

Figure 2: Various types of relation and entities

The process of mapping in a transaction among the relations and entities have numerous varieties. Hence, a well-organized scheme dynamic matrix with mapping properties is developed that considers diverse types of relation and knowledge to code the knowledge graph into the embedding vectors through matrices with dynamic mapping properties, which are generated by the projection vectors.

3.2 Dynamic Matrix and Mapping Property

In the dynamic matrix with mapping matrix, every named symbol objects namely relations and entity are signified by vectors. Initially, the meaning of the entity is captured and subsequent process is carried to build the mapping matrix with relevant properties. For example, for the given triplet (HD, R, TL) and their vectors are HD,HD_p,R,R_p,T,T_P, where the projection vector is represented by the subscript vale p, HD, HDpT, TP $\in R^n$ and R, Rp $\in R^m$. The two matrix with mapping properties is $M_{R\_HD}, M_{R\_TL} \in R^n$ to venture the space of entity from the space of relation. They are equated as,

$$M_{R\_HD} = R_p HD_p^{\perp} + IM^{m\times n}$$

$$M_{R\_TL} = R_p TL_p^{\perp} + IM^{m\times n}$$

The mapping matrices are jointly determined by both entities and relations, enabling strong interaction between their projection vectors, where each element influences all others. By initializing these matrices with an identity matrix, stability and consistency in transformation are maintained. This approach allows entities to be effectively projected into relation-specific spaces, resulting in refined vector representations that capture the underlying structure of the knowledge graph more accurately.

$HD_{\perp} = M_{R\_HD} HD,$

$$TL_{\perp} = M_{R\_TL} TL$$

Then the scoring function is equated as,

$$f_s(HD, TL) = -\|HD_{\perp} + R - TL_{\perp}\|_2^2$$

Training Objective

The training objective of the proposed model is formulated to minimize the difference between valid and invalid triplets using a margin-based ranking loss. It ensures that correct triplets receive better (lower) scores than corrupted ones by a predefined margin. Mathematically, the objective function is expressed as

$$\mathcal{L} = \sum_{(h,r,t)\in\Delta} \sum_{(h',r,t')\in\Delta'} \max\left(0, \gamma + f_s(h,r,t) - f_s(h',r,t')\right)$$

where Δrepresents the set of valid triplets, Δ'denotes the set of negative triplets, and $\gamma$is the margin parameter. The scoring function is defined as

$$f_s(h,r,t) = -\| h_{\perp} + r - t_{\perp} \|_2^2$$

This formulation forces the model to learn embeddings such that the projected head entity combined with the relation is close to the projected tail entity for valid triplets, while pushing apart invalid ones, thereby improving prediction accuracy.

4. Evaluation of Result

To investigate the performance of proposed approach two benchmark data sets has been used, which are FB15k-237 [9] and WN18RR [9]. The identification information in the knowledge graph composed of identification of relation and classification of triplets. The performance of the proposed model is testified by the relation identification and also it can handle the inferences in the relation. The optimal results obtained by general inverse rule model and the effective prediction of link is attained when the proposed model is applied on the datasets FB15k-237 and WN18RR. The reverse relation in the dataset is achieved from the relevant sub-datasets of FB15k-237 and WN18RR [9]. The information about the dataset is explained in the Table 1.

Table 1. Dataset Description

Dataset	#relation	#entity
FB15K237	237	14541
WN18RR	11	40943

4.1 Prediction of Relation

Link prediction aims to identify a missing head or tail entity in a triplet by replacing it with all possible entities and ranking them based on computed scores. The correct entity's rank is used to evaluate performance rather than just selecting the top result. Two key metrics are used: Mean Rank, which measures the average position of correct entities, and Hits@10, which indicates how often the correct entity appears in the top 10 predictions. A good model achieves lower Mean Rank and higher Hits@10. Evaluation is done under two settings: "Raw," which considers all generated triplets, and "Filter," which removes corrupted triplets that already exist in the dataset to ensure fair assessment.

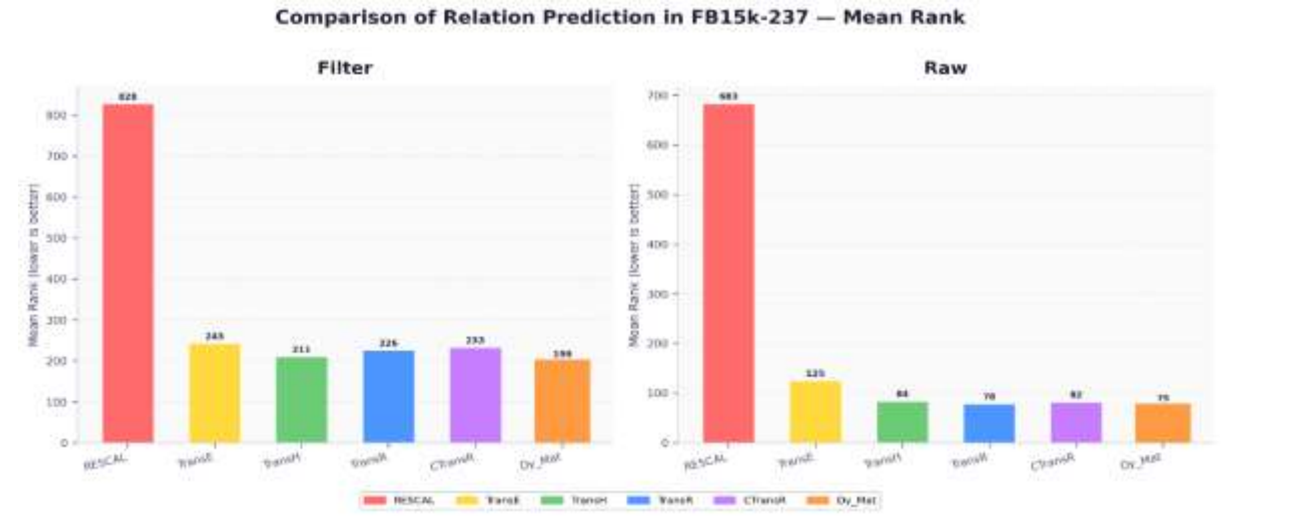

Figure 3: Comparison of Relation Prediction in FB15k-237 for the metric Mean

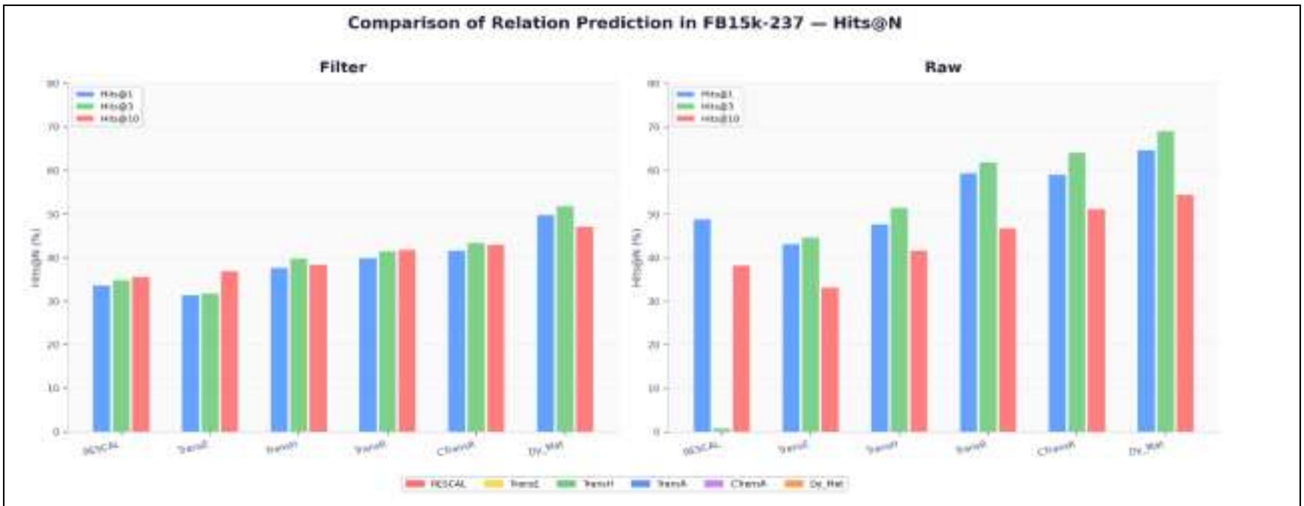

Figure 4: Comparison of Relation Prediction in FB15k-237 for Hit@N

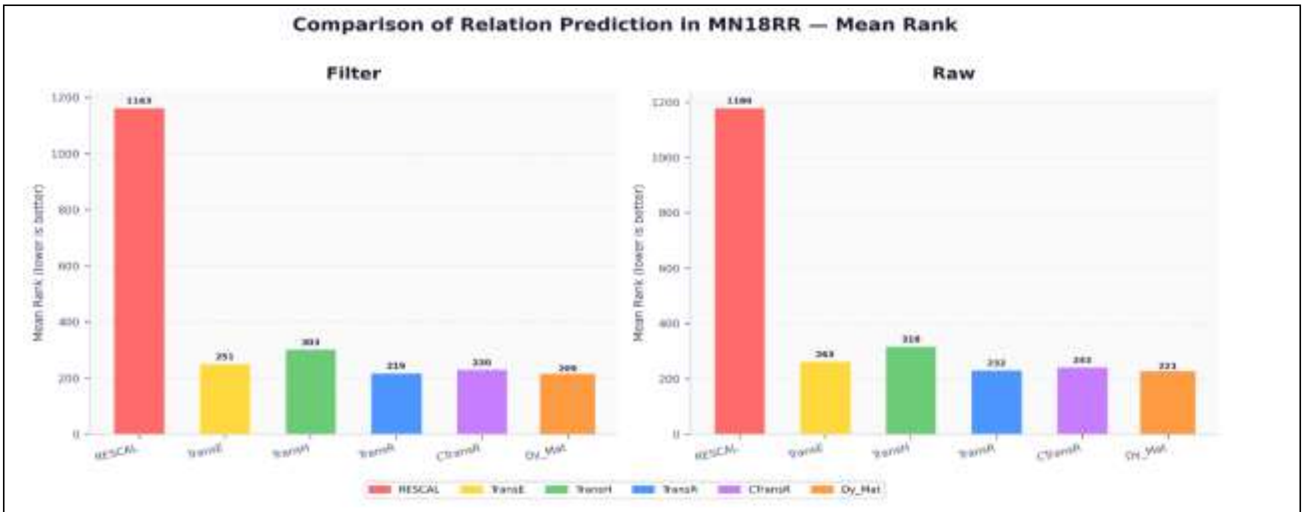

Figure 5: Comparison of Relation Prediction in MN18RR for the metric Mean

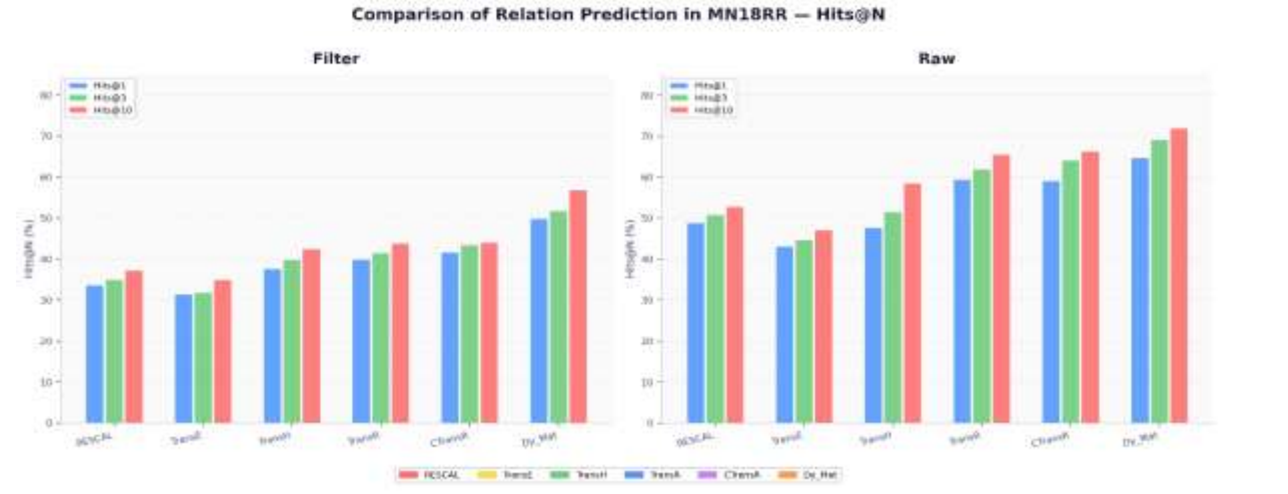

Figure 6: Comparison of Relation Prediction in MN18RR for Hit@N

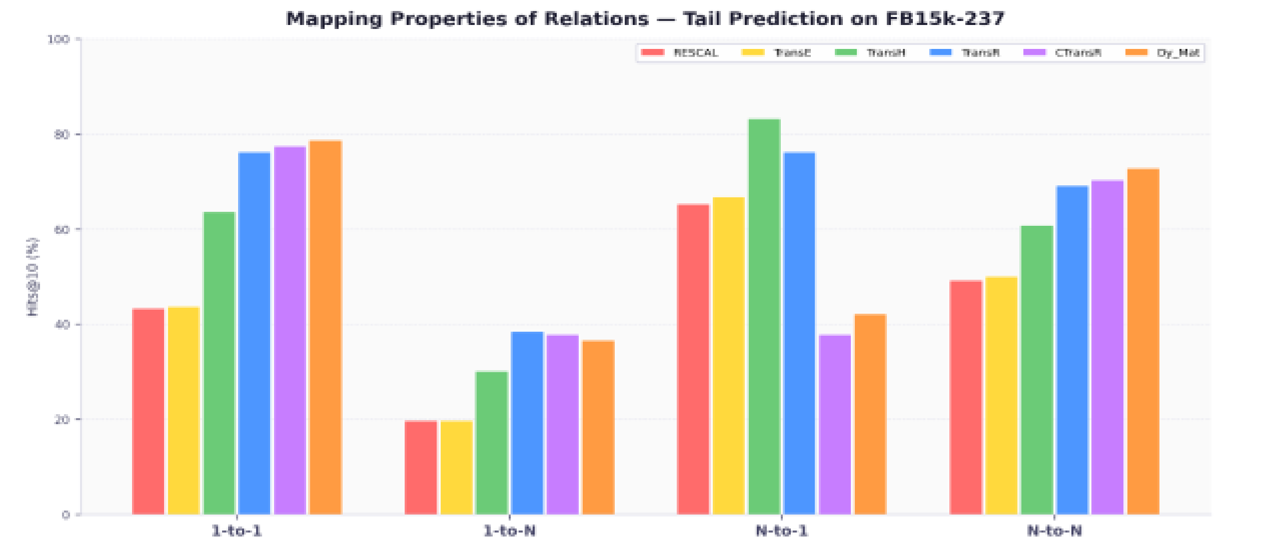

Figure 7: Comparison of mapping properties of relations (Tail) on FB15K.

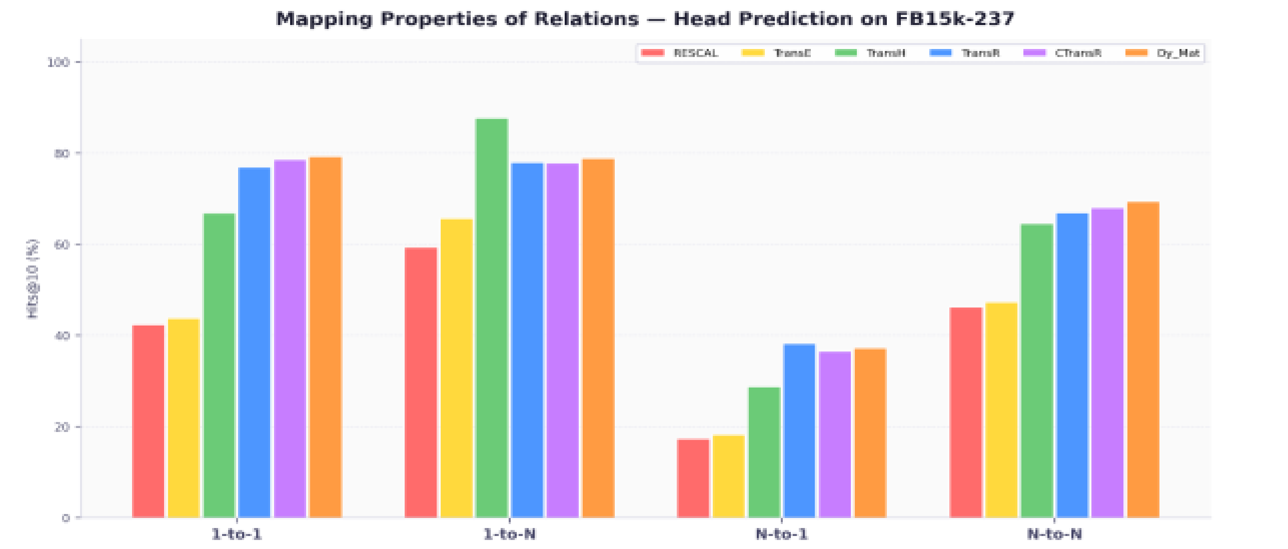

Figure 8: Comparison of mapping properties of relations (Head) on FB15K.

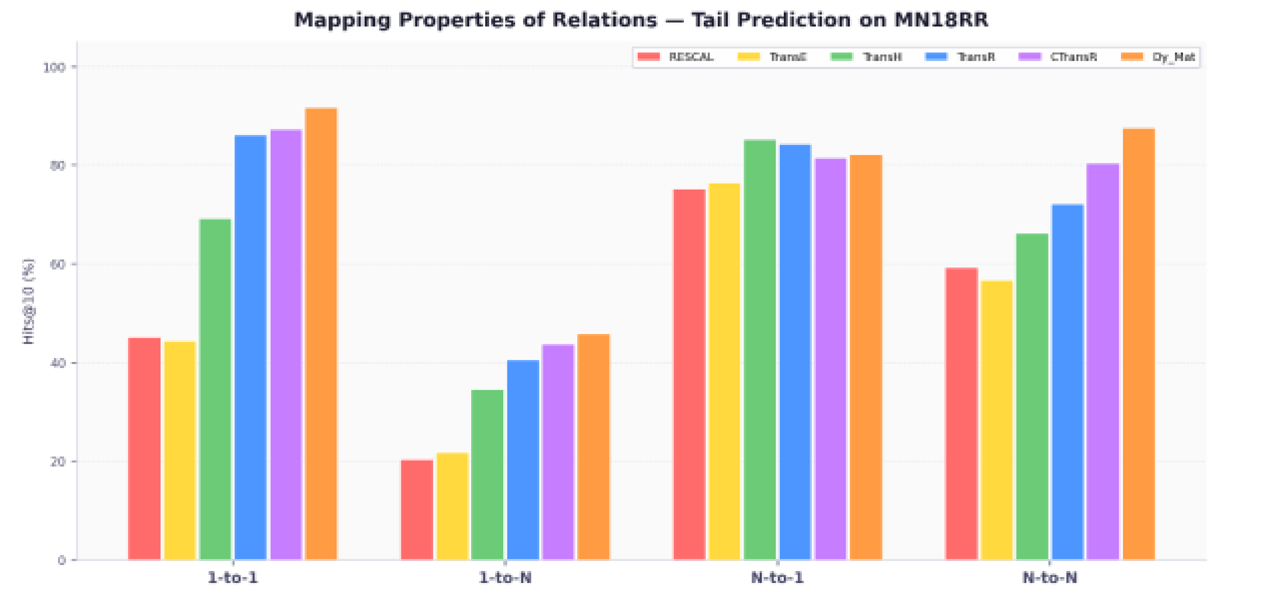

Figure 9: Comparison of mapping properties of relations (Tail) on MN18RR.

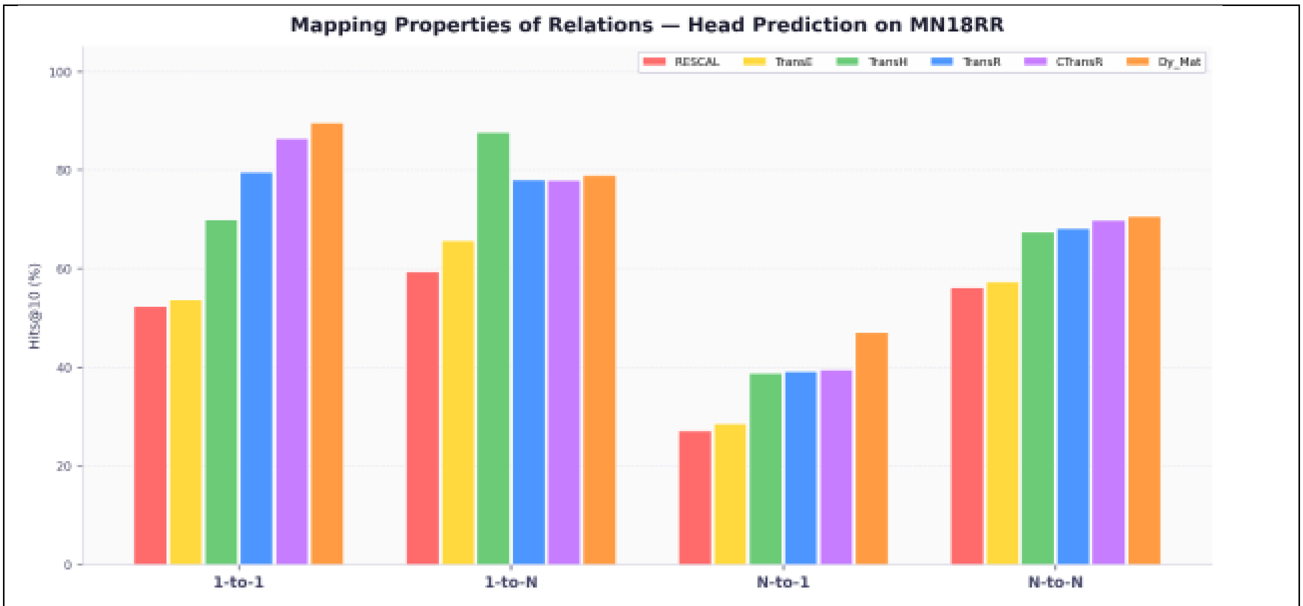

Figure 10: Comparison of mapping properties of relations (Head) on MN18RR

The experimental results on the datasets FB15k-237 andMN18RR is shown in the Table 2 and 3. From the observation of results, it is concluded that the dynamic matrix with mapping properties outperforms the existing knowledge graph model, exclusively on the sparse dataset. For comparison multiple types of relations and entities are used from the available models.The proposed approach achieved better result, and it levers the intricate relation of relation and entity in the knowledge graph. Figure 3-6, depicts the illustration of relations among the graph at various Hit@N values and the Mean rank for Raw and Filtered relations in the knowledge model.

The detailed outcomes of mapping properties and their relation on the datasets FB15k-237 andMN18RR is shown in the Table 4 and 5. The diverse relations used to compare the results that are 1-to-1, 1-to-N, N-to-1 and N-to-N. For the N-to-N relation in knowledge graph, the dynamic mapping matrix is enriched almost by 10.1% and the accuracy is enhanced in every relation. The diverse nature of graph and entities in the knowledge graph is a significant factor and the proposed dynamic matrix with mapping properties is appropriate for formulating the knowledge graphs. Figure 7-10, depicts the illustration of relations among the graph at various levels of relations in the knowledge model.

4.2 Triplet Classification

The process of classifying the triplet is to judge whether the triplets (HD,R,TL) is exact or not that is carried by the classification task. In this paper two benchmark datasets are used namely FB15k-237 andMN18RR to investigate the approach. For every classification of triplets. A threshold value is needed is assigned for every triplets and the threshold value is acquired by maximizing the accuracies of classification that is on the valid set.

The marginal value γ elected among the values {1, 2, 5, 10}, the dimension of the relation vectors Dn and the dimension values of entity vectors Dm among the values {20, 50, 80, 100}. The enhanced configuration values acquired by valid set of values, they are γ = 1, m, n = 100, B = 1000 and taking L2 as dissimilarity on MN18RR; γ = 2, m, n = 100,B = 4800 and taking L1 as dissimilarity on FB15k-237. The proposed approach trains much faster than TransR (The available approach TransRnessitates 70 seconds and TransD merely expends 24 seconds on the dataset FB15k).

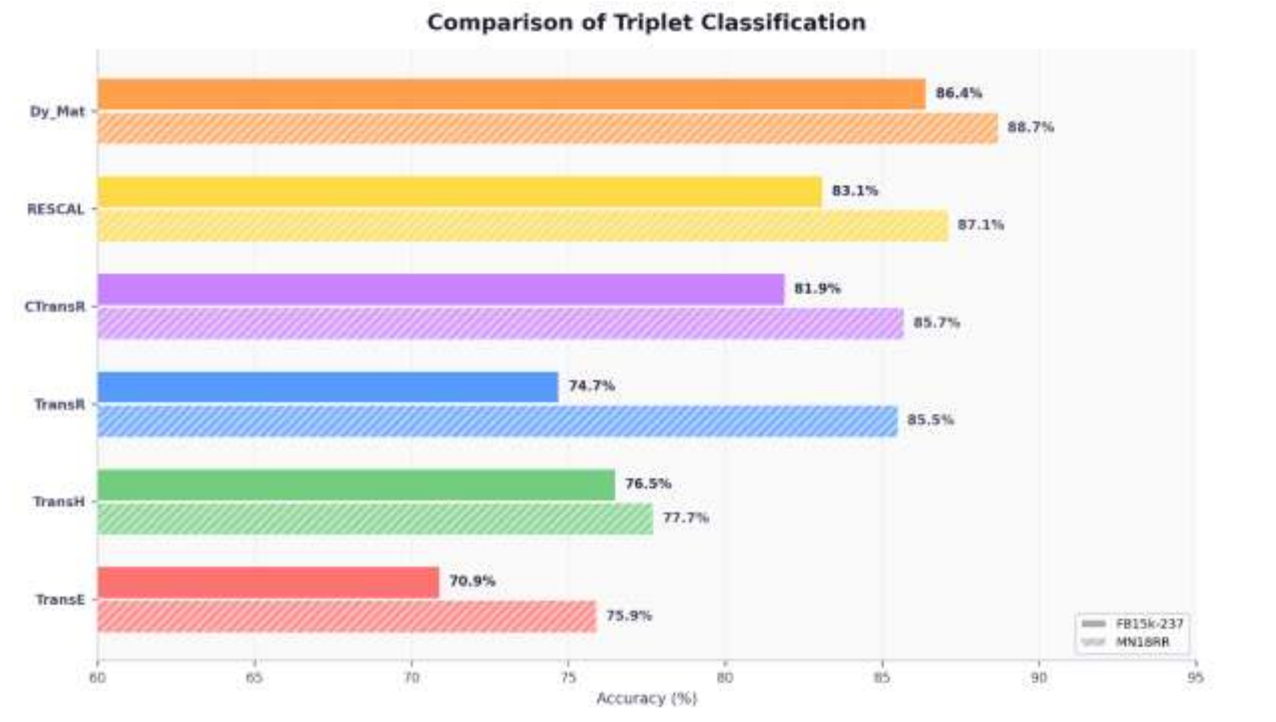

Figure 11: Comparison of Triplet Classification.

The experimental analysis starts with relation prediction on FB15k-237, with the mean rank and Hits at N when using Filter and Raw settings in six models. RESCAL is the lowest in overall performance with a Filter Mean Rank of 828 and Raw Mean Rank of 683. TransE is also improved to 243 (Filter) and 125 (Raw). The TransH and TransR further decrease to 211 and 226 respectively under the Filter setting. CTransR is at rank 233, and the proposed Dy_Mat has the lowest Filter Mean Rank of 199 and Raw Mean Rank of 75, proving it is the best one. In Hits@1 (Filter), Dy_Mat leads at 49.8%, ahead of CTransR at 41.6% and TransR at 39.9%. With Hits@3 (Filter), Dy_Mat is 51.8% as compared to TransR 41.5 a difference of more than 10 points. Hits@10 (Filter) shows Dy_Mat at 47.1%, with CTransR close at 43.0%.

MN18RR is a more challenging and lean dataset. RESCAL has a very high Filter Mean Rank of 1,163 and Raw Mean Rank of 1,180, indicating that it is very poor in scaling to sparse graphs. TransE decreases this to 251 (Filter) and 263 (Raw). TransH has 303 (Filter) and 318 (Raw) which are slightly worse than TransR with 219 and 232. CTransR is placed at 230 (Filter) and 243 (Raw) and Dy_Mat is once again the most successful at 209

(Filter) and 221 (Raw). The Hits/10 (Filter) of Dy_Mat is 56.8, whilst the CTransR 44.0, which is a result of 12.8 points.

Switching to mapping property analysis on FB15k-237, Hits at 10 is now assessed on four relation types: 1-to-1, 1-to-N, N-to-1, N-to-N on Tail and Head prediction. In the case of N-to-N Tail prediction, Dy Mat achieves 72.7% compared to TransE 50.0, which is a 22.7-point difference. Dy_Mat has a 1-to-1 Tail prediction score of 78.6, slightly higher than CTransR with 77.4. For Head prediction, Dy_Mat's 1-to-1 score reaches 79.2%, edging TransR (76.9%) and CTransR (78.6%).

Mapping property outcomes are the most notable in all the evaluations on MN18RR. Dy_Mat has 91.6% 1-to-1 Tail prediction - the highest single value in any condition in all experiments. In N-to-N Tail prediction, it has a score of 87.5, which is 7.2 points above that of CTransR. Head prediction on 1-to-1 is also 89.5% compared to TransR 79.5% and N-to-N Head prediction is 70.5% compared to CTransR 69.8%.

The last analysis is the accuracy of triplet classification on the two datasets. TransE records the lowest scores — 70.9% on FB15k-237 and 75.9% on MN18RR. TransH and TransR is elevated to 76.5 percent and 77.7 percent and 74.7 percent and 85.5 percent respectively. CTransR scores 81.9% and 85.7%, followed closely by RESCAL at 83.1% and 87.1%. Dy_Mat is most accurate both on FB15k-237 (86.4) and on MN18RR (88.7) which is 3.3 and 1.6 points above RESCAL respectively, and validates the idea that it gains consistently across all the baseline models across all the experimental conditions tested in this study.

5. Conclusion

The dynamic matrix is introduced to mine the significant knowledge from the knowledge graph, the dynamic matrix implant the knowledge graphs into the vector space in a continuous form. The proposed dynamic matrix is less complex in processing and highly flexible than the existing knowledge graph approach. When learning the named symbols embeddedin the relations or entity that is diverse from the relation or entity.

The experimental investigation shows that dynamic matrix using mapping properties outperforms the TransH, TransR/CTransR and TransE. Through the prediction of relation and classification of triplets knowledge graph is evaluated.From the classification of triplet section, all the new information's that is inferred from the available knowledge graph in the triplet. The relations are complicated to deduce from all other knowledge.

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