B.Tech. Project Report

On

A Comparative Analysis of Image Annotation Techniques

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ABSTRACT

Image annotation refers to a process by which the computer assigns labels/captions to an image, which has many applications in today's world and hence is a topic of great interest. In this project, we have studied and implemented four different approaches to image annotation, namely *KNN based Label Transfer* [1], *Multi Label Image Recognition with Graph Convolutional Networks (ML-GCN)* [2], Incorporating Semantic Information in ML-GCN [3], and Training GCN based Binary Classifiers to perform Image Annotation. The techniques provide different approaches towards the problem, and hence have their parameters and values to tune. A comparative analysis is done for all the methods on the basis of 6 metrics, i.e. *Precision (P), Recall (R), F1 score (F1), Semantic Precision (SP), Semantic Recall (SR)* and *Semantic F1 score (SF1)*. In the end, we provide a conclusion to the report in the form of explanation of results, and improvements that can be made in the methods.

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CHAPTER-1

INTRODUCTION

1.1 What is Image Annotation?

Image Annotation is the process by which a computer assigns labels to an image sample, which can be used in image retrieval systems to organize and locate images of interest from a database.

This form of classification is done by analysing the features of a given image and trying to predict its labels on that basis. The methods used for this analysis may vary, and this is what we try to study in this report.

1.2 Image Annotation Methods

Image annotation can be accomplished using several different methods. In this report we explore some of them and try to modify and apply them for our given task. The main methods that we analyse are:

1.2.1 Label Transfer Using KNN

The KNN method forms a baseline for our experiments and uses greedy heuristics for performing label transfer for K nearest neighbours of an image.

1.2.2 Multi Label Classification using GCN

The given method aggregates information for labels using GCN operations performed on its correlation matrix, in order to generate label classifiers, which are then used for annotating image samples.

1.2.3 Binary Classification using GCN

In this method we create a GCN based classifier for each of the given labels, and then assign a label score for each image. By selecting the K labels by highest score for each image, we perform image annotation.

1.3 ESP Game Dataset Description

For the purposes of evaluation of our models, we have used the ESP Game dataset, for which we have considered 18689 train images and 2081 test images.

CHAPTER-2

METHODOLOGY

2.1 KNN Based Label Transfer

2.1.1 Ideology

In this method the image annotation problem is treated as that of an image retrieval problem using the KNN algorithm.

We calculate the k nearest neighbours using standard KNN algorithm and then transfer labels to images from the nearest neighbours.

The different distance metrics mentioned in [1] are

$$L_1 = \sum (x_i - y_i)$$

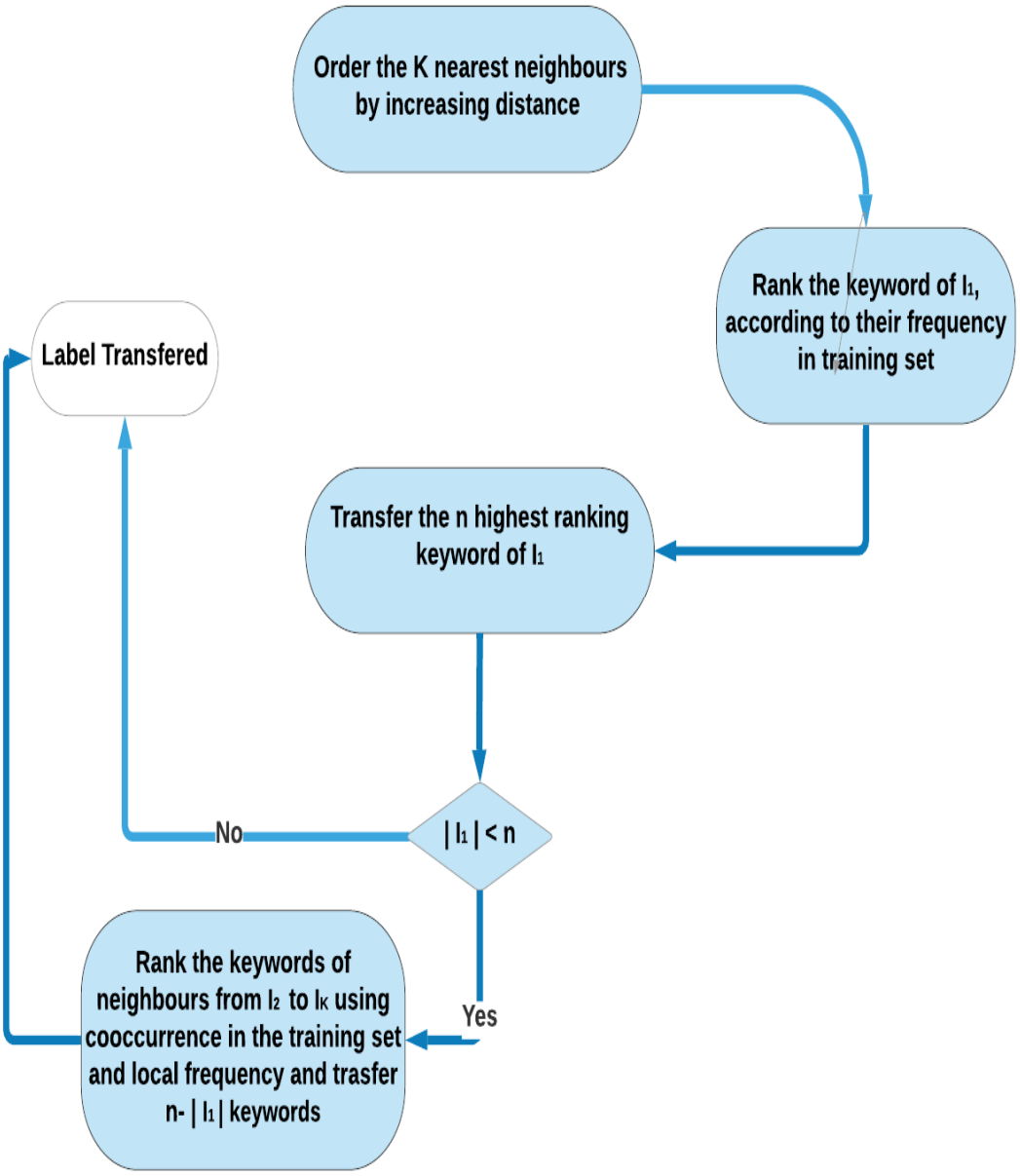
$$L_2 = \sqrt{\sum (x_i - y_i)^2}$$

$$\chi^2 = \frac{1}{2} \sum \frac{(x_i - y_i)^2}{(x_i + y_i)}$$

In this method, we have used VGGF features after applying PCA for ESP Game images, on which we find nearest neighbours by comparing L_2 distances.

2.1.2 Implementation

The given technique uses L_2 normalized features for each image, and finds L_2 distances between the test images and the train images. For each test image it takes the nearest K = 5 neighbours and then performs a label



transfer using a greedy algorithm described below [1].

Figure-1: Image Label Transfer Algorithm

2.2 Multi Label Classification using GCN

2.2.1 Ideology

2.2.1.1 Graph Convolutional Networks (GCN)

The goal of GCN [4] is to learn a function $\boldsymbol{f}$ of features on a graph $\mathcal{G} = (\mathcal{V}, E)$, which takes a feature description matrix $\mathcal{X}^{\ell}$ of dimensions $N \times D$ and the corresponding correlation matrix $\mathcal{A}$ of dimensions $N \times N$, where N denotes the number of nodes, and D the dimensions of the node feature vectors. Every GCN layer can be written as:

$$\mathcal{X}^{\ell+1} = \boldsymbol{f}\,(\mathcal{X}^{\ell}, \boldsymbol{\mathcal{A}})$$

where $\mathcal{X}^{\ell+1}$ is a $N \times D'$ matrix. The layer wise propagation rule is as follows:

$$\mathcal{X}^{\ell+1} = \boldsymbol{\sigma}(\mathcal{A}'\mathcal{X}^{\ell}\mathcal{W}^{\ell}),$$

where $\mathcal{W}$ is a $D \times D'$ *weight* matrix, $\mathcal{A}'$ is the normalized correlation matrix, and $\boldsymbol{\sigma}(.)$ is a nonlinear function, here LeakyReLU.

2.2.1.2 GCN for Multi Label Recognition

The method for ML-GCN consists of two parts, i.e. extracting image feature representations and performing GCN on the label representations. The image features are taken from the ResNet-101[9] which is pre-trained on ImageNet [10], with each image represented as a 2048-dimension vector. For the label representations, we use a stacked GCN consisting of two layers, with output dimensions of 1024 and 2048 respectively. Thus the GCN operation takes in a label representation $\boldsymbol{\mathcal{Z}}$ of dimension $N \times D$ and returns output $\boldsymbol{\mathcal{W}}$ of dimensions $N \times D'$ where N is the number of labels and D and D' are dimensions of feature

representations. The output classifier $\mathcal{W}$ is then applied to image representations $\boldsymbol{x}$ to get predicted scores as

$$\mathcal{y} = \mathcal{W}x$$

The matrix $\boldsymbol{y}$ of dimensions $N \times 1$ gives the predicted scores of each label for an image. The entire network is trained using the multi-label classification loss function.

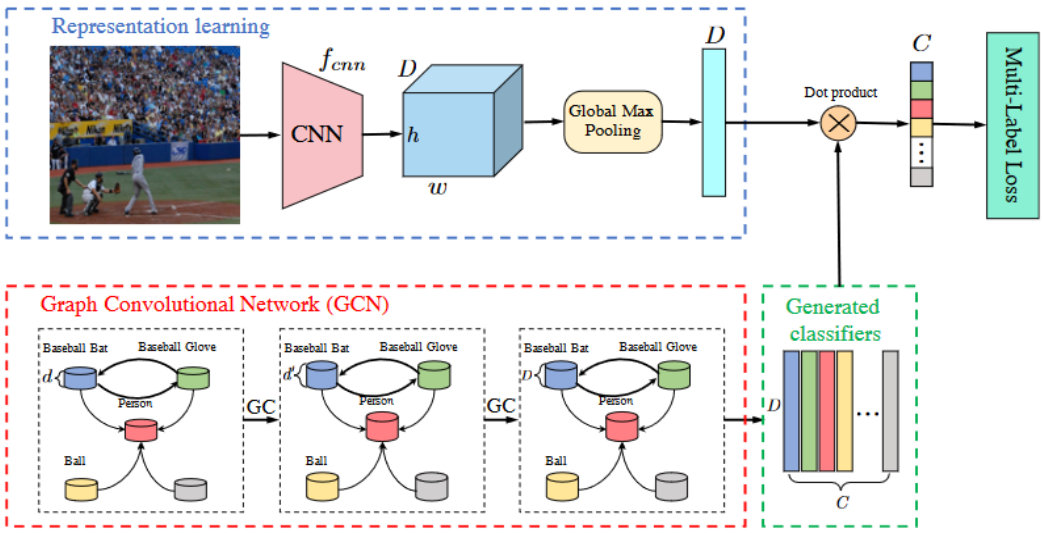


Figure-2: A diagrammatic representation of the framework [2]

2.2.1.3 Correlation Matrix of ML-GCN

The correlation matrix, as defined in [2], relates the nodes i.e. the labels with each other, hence serving as an adjacency matrix for the graph formed by these nodes. The correlation values indicate the probability $P(\boldsymbol{L_j}|\boldsymbol{L_i})$ which denotes the probability of occurrence of label $\boldsymbol{L_j}$ given that label $\boldsymbol{L_i}$ already occurs. Thus to construct the correlation matrix, we first the co-frequency matrix $\boldsymbol{\mathcal{M}}$, where $\boldsymbol{\mathcal{M}}_{ij}$ indicates the number of times label $\boldsymbol{L_i}$ and $\boldsymbol{L_j}$ occur together. Thus we can construct the probability matrix $\boldsymbol{\mathcal{P}}$ as

$$\mathcal{P}_{ij} = \frac{\mathcal{M}_{ij}}{N_i}$$

So that $\mathcal{P}_{ij}$ denotes the probability that label L_j appears given that label L_i is already present, and $\mathcal{N}_i$ is the number of occurrences of label L_i.

Using the matrix $\mathcal{P}$, we can construct the binary correlation matrix $\mathcal{A}$ as

$$\mathcal{A}_{ij} = \begin{cases} 0 \; if \; \mathcal{P}_{ij} < \Gamma \\ 1 \; if \; \mathcal{P}_{ij} \geq \Gamma \end{cases}$$

where a threshold Γ is used to filter noisy edges.

To prevent over-smoothing after GCN, a re-weighted correlation matrix $\mathcal{A}'$ is constructed as:

$$\mathcal{A'}_{ij} = \begin{cases} \dfrac{p}{\sum_{\substack{j=1 \\ i \neq j}}^{C} \mathcal{A}_{ij}} \; if \; i \neq j \\ 1 - p \text{ if i = j} \end{cases}$$

where p is a hyper-parameter which determines the weight assigned to a node itself and other correlated nodes.

2.2.2 Implementation

The implementation for this method in the project is nearly identical to that of [2], the results being measured on the ESPGAME dataset, with images being taken from [5] and train/test splits from [3]. The label representations come from the 300-dim GLoVe [7] trained on the Wikipedia dataset. For the correlation matrix, we have set Γ = 0.4 and p = 0.2. For the activation function, we have chosen LeakyReLU [8] with a negative slope of 0.2. ResNet-101 [9] is used for feature extraction, which is pre-trained on ImageNet [10]. For network optimization, SGD is used as the optimizer, with momentum set to 0.9. The Weight Decay is 10^{-4}. The model is trained for 100 epochs and is implemented in PyTorch.

2.3 ML-GCN with Semantic Information

2.3.1 Ideology

2.3.1.1 Semantic Hierarchy(SH)

Semantic Hierarchy is a way to explore semantic dependencies between tags [11]. The Primary link between semantic types is the "is-a" link. Let's consider two tags: *apple* and *fruit*. Here *apple* "is a" *fruit*. Therefore, in a semantic hierarchy between these two tags, the *fruit* is the ancestor of *apple*, and *apple* conveys more information about image than fruit.

2.3.1.2 Synonyms

Synonyms in the pair of tags that share the same meaning. Consider two tags, *rock* and *stone*, they have the same meaning thus they are synonyms.

2.3.1.3 Weighted Semantic path (SP)

We now combine the idea of Semantic Hierarchy and synonyms. In some cases, two paths may represent a similar meaning as their tags are synonyms, so we merge those paths that are different only at anonymous tags. All semantic paths corresponding to the whole tag set T is denoted as

$$SP_T = \{sp_1, \dots, sp_r\}$$

We take two important observations into consideration

1. The weight of the descendant tag should be higher than the weights of its ancestor tags.

2. The more descendent of a tag implies that the tag is less discriminative and vice versa

Combining both observations

$$\omega_{ij} = \frac{\tau^{l_{ij}}}{|d_i|}$$

where $|d_i|$ indicates the number of descendants of y_i, l_{ij} represents the layer of y_i in sp_j, and $\tau \in (0, 1)$. Here we set $\tau = 0.7$.

The weight of tag y_i in the whole set of semantic paths is defined as the sum of its weights in all semantic paths, i.e.,

$$\omega_i = \sum_j^{|SP|} \omega_{ij}$$

The weights of all tags can be concatenated into one vector

$$\omega = (\omega_1, \dots, \omega_m)$$

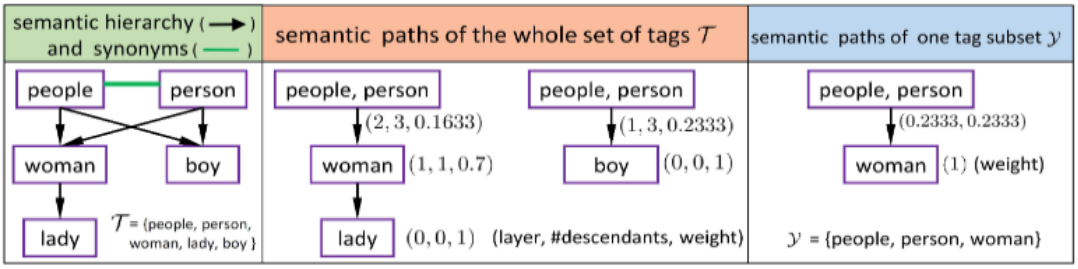


Figure-3: A diagram showing semantic paths and weights [3]

2.3.2 Implementation

We generate a new correlation matrix.

$$\mu_{ij} = \frac{\omega_i}{\omega_j} \mathcal{M}_{ij}$$

where $\mathcal{M}_{ij}$ is the cofrequency matrix for the labels. This matrix is now used to create the correlation matrix in ML-GCN instead of $\mathcal{M}_{ij}$.

2.4 GCN Based Binary Classifiers

2.4.1 Ideology

2.4.1.1 Negative Sample Mining for Training

When considered for a single label, on average the training dataset is quite large when compared to the actual number of images to which the label is assigned. If such values are considered for training the classifier, it can create a bias in favour of negative labelling. Thus a need for sampling the data is created so as to have an equal number of positive and negative samples.

This is accomplished by using the cofrequency matrix between labels, from where we assign negative samples to a label on the basis of its cofrequency with other labels. Suppose $\boldsymbol{\mathcal{N}}_{ij}$ is the number of images that contain label L_j but don't contain label L_i. Then,

$$\mathcal{N}_{ij} = \frac{\mathcal{M}_{ij}}{\sum_k \mathcal{M}_{ik}} \mathcal{C}_i$$

Where $\boldsymbol{\mathcal{M}}_{ij}$ is the cofrequency of labels L_i and L_j and $\boldsymbol{\mathcal{C}}_i$ is the total number of positive samples of label L_i.

2.4.1.2 GCN based Binary Classifier

The binary classifier that we use to classify images for a single label uses a single layer GCN model to operate on the neighbourhood aggregation of train data for each label.

The first part consists of performing a neighbourhood feature aggregation for each image, which consists of the mean of the features of the top 5 nearest images (considered using L2 distance) for each image.

This aggregate image data is then fed to the model to train, and serves as a combination of the correlation matrix and feature matrix in the original GCN. For the forward pass, a sigmoid function is used as the nonlinear activation function, and MSE loss is considered for optimization.

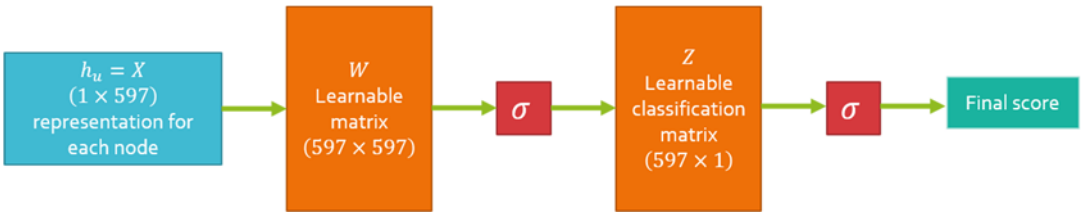


Figure-4: A diagram showing schematics of binary classifier

2.4.2 Implementation

The image feature representations are taken from the VGGF features from [3] for the ESPGAME dataset, where each image is represented as a 597-dimension feature vector. Training is done for 2500 epochs for each label, with 0.1 as the learning rate. The weights and aggregated features returned from the classifier are then multiplied to get test scores, which are stored in a matrix of images and labels. For each image, we pick the top 5 labels with the highest score, and assign them to it.

CHAPTER 3:

RESULTS AND DISCUSSION

3.1 Metrics Considered

3.1.1 Class Precision

Class Precision measures the probability that an assigned label is correct, i.e. the accuracy of the model. We define CP_i for label L_i as:

$$CP_i = \frac{Number\ of\ correctly\ annotated\ samples}{Number\ of\ times\ the\ label\ is\ predicted}$$

3.1.2 Class Recall

Class Recall is defined as the ratio of correctly assigned samples to that of the number of samples in the ground truth, i.e. CR_i for label L_i is:

$$CR_i = \frac{Number\ of\ correctly\ annotated\ samples}{Number\ of\ times\ it\ appears\ in\ the\ ground\ truth}$$

3.1.3 Class F1 Score

Class F1 score is the harmonic mean of mean precision(P) and mean recall(R), i.e.

$$CF_1 = \frac{2 * CP * CR}{(CP + CR)}$$

3.1.4 Example Precision

Example Precision measures the fraction of correctly assigned labels out of the labels predicted, i.e. the accuracy of the model. We define EP_i for example E_i as:

$$EP_i = \frac{Number\ of\ labels\ correctly\ assigned\ to\ an\ example}{Number\ of\ labels\ predicted\ for\ the\ example}$$

3.1.5 Example Recall

Example Recall is defined as the ratio of correctly assigned labels to that of the number of labels in the ground truth, i.e. ER_i for example E_i is:

$$ER_i = \frac{Number\ of\ labels\ correctly\ assigned\ to\ an\ example}{Number\ of\ labels\ appearing\ in\ ground\ truth}$$

3.1.6 Example F1 Score

Example F1 score is the harmonic mean of mean precision (EP) and mean recall (ER), i.e.

$$EF_1 = \frac{2 * EP * ER}{(EP + ER)}$$

3.1.7 Semantic Metrics

Suppose y is the ground truth label subset, and y' is the predicted label subset for label L_i. Then set of semantic paths SP_y and $SP_{y'}$ are constructed, and algorithm-2 from [3] is used to calculate semantic precision, recall and F1 score.

3.2 Sample Output

Figure-5: ESP Game – 15097.jpg

Method	Labels Predicted
Ground Truth	***Blue, Brown, Building, Car, Cloud, Grass, Road, Window***
KNN	***Building, Road, Car, Grass, Sky***
ML-GCN	***Brown, Building, Car, Road***
Semantic ML-GCN	***Building, House, Sky***
GCN based Binary Classifier	***Building, Globe, Mountain, Shoes, Train***

Table-1: Label Prediction for image ESP Game – 15097.jpg

Figure-6: ESP Game – 15138.jpg

Method	Labels Predicted
Ground Truth	***Door, Field, Green, House, Mountain, Sky, Tent, Tree, White***
KNN	***Blue, House, Sky, Tree, Wood***
ML-GCN	***Forest, Green, House, Mountain, Sky***
Semantic ML-GCN	***House, Sky, Tree***
GCN based Binary Classifier	***Building, Home, Mountain, Poster, Ship***

Table-2: Label Prediction for image ESP Game – 15138.jpg

3.3 Results

3.3.1 Class Based Metrics

Method	CP	CR	CF_1
KNN	28.74	23.6	26
ML-GCN	38.2	21.4	27.44
ML-GCN with Semantic Information	14.29	4.8	7.19
GCN based Binary Classifier	10.1	6.9	8.25

Table-3: Class Based Metrics (in %age)

3.3.2 Example Based Metrics

Method	EP	ER	EF_1
KNN	35.21	39.78	37.35
ML-GCN	49.95	34.50	40.81
ML-GCN with Semantic Information	42.75	16.5	23.8
GCN based Binary Classifier	4.06	5.37	4.62

Table-4: Example Based Metrics (in %age)

3.3.3 Semantic Metrics

Method	SP	SR	SF1
KNN	44.15	37.2	39.2
ML-GCN	50.15	34.3	40.73
ML-GCN with Semantic Information	51.4	15.6	22.5
GCN based Binary Classifier	5.77	5.34	5.46

Table-5: Semantic Metrics (in %age)

3.4 Analysis

The results obtained from application of the methods to the ESPGAME dataset are shown in the table-1. The first method KNN, which we

considered as a baseline method performs well enough, since its metrics are similar to those obtained in [1] for the same dataset. ML-GCN outperforms the rest, and is the best performing method in our project. From the table we can theorise that incorporating semantic information into ML-GCN disturbs the graph structure, which could account for the disparity between precision and recall. GCN based Binary Classifiers method performs the worst as can be seen, which can perhaps be improved by normalizing the CNN features beforehand.

CHAPTER 4:

CONCLUSION AND SUGGESTIONS

4.1 Conclusion

We have explored the basic concepts of image annotation and implemented some of the methods to perform the same. We modified the method of ML-GCN to incorporate semantic information, applied KNN baseline algorithm to VGGF CNN features, and created a method to use binary classifiers for multi-label classification. We also created a new train data sampling algorithm for binary classifiers.

4.1.1 Learning Outcomes

The main learning outcome is that we got an insight into the world of machine learning and deep learning, and we learnt several new and important concepts. We got to see models working in action and also got to modify two of them. We also learnt basics of PyTorch framework, and programming in Matlab. We also created a negative sample mining algorithm as part of the GCN-Binary classifiers task.

4.2 Suggestions

After a thorough investigation

1 ML-GCN results can be improved by decreasing the learning rate after a fixed number of epochs, in order to decrease the chances of overshooting of minima.

2 Better constructs can be explored for incorporating semantic information into ML-GCN.

3 The label transfer algorithm can be explored further in hopes of getting better results.

4 Performing appropriate normalization of features beforehand can perhaps get better results in the binary classifier method.

4.3 A Note for The Reader

This project was done in collaboration with Manul Goyal (B18CSE030) and Manan Shah (B18CSE030) whose project serves as a companion to ours. Both of our projects explore 4 methods that we studied above, and we collaborated on understanding and explanation of the techniques we have shown.

The differences in our projects lie in the choice of datasets for evaluation, implementations , and the methods devised for the last task, i.e. GCN based Binary Classifiers. The dataset we used for evaluation is ESPGAME, while they have used the dataset IAPRTC-12. The implementation of the methods on both of these datasets was independent. We also proposed different algorithms for the sampling of negative training samples in the last task, and there exists a difference in our choices of normalization of features in the same model.

It has been a great experience collaborating with them and we learnt a lot about the topic during this journey. We would like to express our heartfelt gratitude towards them for the same.

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