



# Classifying Textual Data with Pre-Trained Vision Models Through Transfer Learning and Data Transformations

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July 20, 2021

# Classifying Textual Data with Pre-trained Vision Models through Transfer Learning and Data Transformations

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**Abstract**—Knowledge is acquired by humans through experience, and no boundary is set between the kinds of knowledge or skill levels we can achieve on different tasks at the same time. When it comes to Neural Networks, that is not the case, the major breakthroughs in the field are extremely task and domain specific. Vision and language are dealt with in separate manners, using separate methods and different datasets. Current text classification methods, mostly rely on obtaining contextual embeddings for input text samples, then training a classifier on the embedded dataset. Transfer learning in Language related tasks in general, is heavily used on obtaining the contextual text embeddings for the input samples. In this work, we propose to use knowledge acquired by benchmark Vision Models which are trained on ImageNet to help a much smaller architecture learn to classify text. A data transformation technique is used to create a new image dataset, where each image represents a sentence embedding from the last six layers of BERT projected on a 2D plane using a t-SNE based method. We trained five models containing layers sliced from vision models pretrained on ImageNet on the created image dataset for the IMDB dataset embedded with the last six layers of BERT. Despite the challenges posed by the very different datasets, experimental results achieved by this approach which links large pretrained models on both language and vision, are very promising, without needing high compute resources. Specifically, Sentiment Analysis is achieved by five different models on the same image dataset obtained after BERT embeddings are transformed into gray scale images.

**Index Terms**—Natural language processing, Text Classification, Image Classification, t-SNE, BERT, Transfer Learning, Convolutional Neural Networks, Domain Adaptation

## I. INTRODUCTION

Attention based architectures and specifically the Transformer [25] sparked a revolution in the world of Natural Language Processing and Deep Learning in General. BERT-representations [5] opened a lot of new goals and challenges for the Machine Learning Community, because of their highly semantic embeddings and the kind of knowledge they encode given textual data. Being pretrained to predicted Masked Language and next sentences, and on a huge Wikipedia Corpus, makes it a powerful benchmark for Natural Language Processing and a current standard for word and sentence representations. Computer Vision made very remarkable achievement [29]. The seminal work introduced in AlexNet [14] and the parallel structure of Convolutional Neural Networks enabled the use of GPU's, then it became a standard for training

Neural Networks for Visual recognition. Different architectures emerged [14] [15] [21] [9] [27] since then using CNN's as a building block and achieving higher accuracies on different datasets. Transfer Learning [1] [2] opened the doors for a very wide range of applications, allowing for the exchange of previously acquired knowledge from a large dataset on a certain task to another task with a much smaller dataset. This philosophy is a current essential practice in both academia and industry as it helps avoid a very long and computationally demanding procedure. In Visual Understanding tasks, transfer learning in the last decade heavily relied on ImageNet [4] as a base or *Source* dataset, ImageNet [4] is a huge dataset containing over 14 million images and their different one-thousand class labels and is considered the de facto for pretraining Vision Models. The work described in this paper aims to use knowledge acquired by vision models to train text-classifiers for Sentiment Analysis, using a t-SNE based transformation method brought about in [19] to transform IMDB Text Embeddings from BERT into Gray Scale Images. The main objective of this paper is to bring *Language* and *Vision* a step closer, and to harness the power of transfer learning from large image datasets in Natural Language Processing and vice-versa. Hoping this would be an opening to further work on the topic using appropriate resources and datasets since none were available during the conception of this paper. Adding yet another approach to the ones mentioned in survey [18] on the integration of language and vision, with a complete *TransferLearning* based fusion between the two, summarized in:

- Using the BERT [5] embeddings for the IMDB-Dataset [16] to create an IMDB-Image Dataset using the method described in [19] with a t-SNE [24] backbone.
- Analysing Domain Shifts between the Source (ImageNet [4]) and Target (IMDB-Image) datasets, and avoiding such problems with feature normalization.
- Using early layers from benchmark Vision Models [14] [15] [21] [9] [27] which are trained on a huge ImageNet [4] dataset as feature extractors in a common architecture between five models.
- Training five models containing pretrained layers on a Vision Dataset(ImageNet [4]) on the IMDB-Image dataset.

In this work, a new approach to classifying textual data is proposed, based on the transformation of text embeddings obtained from the last six layers of BERT [5] into images using t-SNE feature projection. Training five models containing pretrained layers from Vision Models trained on ImageNet [4], on a generated IMDB-Image Dataset. The contributions of this paper are stated as follows:

- Exchanging knowledge between language and vision models through transfer learning and data transformations.
- Generating an image dataset for IMDB textual dataset, analysing data domains between source and target datasets (ImageNet [4] and IMDB-Images), avoiding domain shifts with pixel normalization.
- Harnessing the pretraining of Vision models on large image datasets in text classification, and achieving acceptable and promising results.

## II. RELATED WORK

### A. Transfer Learning

The modern learning paradigm for most Vision models, is mostly based on extracting features from the ImageNet dataset [4], then finetuning certain layers on a new smaller dataset concerned with a new task. The concept of *Transfer Learning* evolved from when it was first introduced by Stevo Bozinovski and Ante Fulgosi [1] [2]. Due to the revolution in hardware allowing training on very large datasets, all training paradigms nowadays are bound to transfer knowledge obtained from a large dataset to solve a target task with a target dataset. Authors in [33] provide a complete survey on *Transfer Learning*, its applications, types, methods, and challenges. Yosinski et al. [28] conducted a detailed study on what kind of features different layers in a Neural Network learn about the source dataset, and how *Transfer Learning* can make the most of the acquired knowledge to solve a target task.

### B. Transfer Learning in Language and Vision

Transfer Learning in Computer Vision and in Natural Language Processing as two separate sub-fields, is the current standard, as it allows large pretrained models to be used in multiple tasks after acquiring a certain understanding of features in a large dataset.

1) *Transfer Learning in Language*: BERT [5] representations and Fine-Tuning, allowed for state-of-the-art results in tasks such as Text Classification, following different approaches mentioned in [22], commonly using the [CLS] representations from certain layers as an input to a classifier, freezing the BERT model or finetuning it depending on the task and size of task dataset. The current approaches mentioned in [22] achieved very low error rates. *Transfer Learning* in this case, is mostly learning contextualized representations for the input text, in a self-supervised manner, where the generated embeddings can be directly used as an input to another model to solve a target task.

2) *Transfer Learning in Vision*: Vision Models, more specifically [14] [15] [21] [9] [27] are pretrained on ImageNet [4]. Considered benchmarks for image classification, they achieved very high accuracies for smaller datasets through *Transfer Learning* and *Domain Adaptation* [3]. Being pretrained on a very large dataset (ImageNet [4]), the features they are able to extract are mostly present in most datasets. Finetuning them on a new dataset for a new task, gives optimal results, since after further training both general and task specific features are visible to the finetuned models as suggested and discussed by Yosinski et al. [28].

### C. Text Classification using Convolutional Neural Networks

The work conducted by Yoon Kim [12] suggested a CNN based architecture with multiple filter widths and feature maps, and a fully connected layer, using padding to fix the input size to a vector with length  $d$ . A similar approach is taken in [31], where sentence classification is achieved, using *Word2Vec* [17] embeddings, 3 filter region sizes, with 2 filters for each region size, which generate 6 variable size feature maps, forming a feature vector after concatenation, then fed into a Softmax layer. The mentioned approach, treats text embeddings as fixed length inputs, with no regard to which order the tokens in a sentence appear, and no consideration of the geometrical abilities and nature of kernels in a Convolutional Neural Network.

## III. PRELIMINARIES

### A. IMDB Dataset

IMDB [16] is a Polarity Dataset for Sentiment Analysis or Text Classification in broader terms, it contains 50000 Sentences and their binary class labels, being either "Positive" or "Negative", IMDB is a relatively small dataset which provides a level of flexibility and a suitable testing for the study this paper is concerned with, due to the computational resources both Data Generation and Training of different models require.

### B. BERT

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding [5], is a language representation model with the Transformer [25] as its building block, pretrained on very large unlabelled textual data for two main tasks: Masked Language Modelling, where the model is required to predict words intentionally masked in a multi-layered context as it was mentioned in the paper, The Second Task is Next Sentence Prediction, also in a self-supervised manner, BERT is trained to classify a sentence as "Next" or "Not Next" for a previous sentence as input. BERT pretraining provides an understanding of the possible relationships, between two sentences especially when being trained on the entire Wikipedia English Corpus and the Books-Corpus [32]. The Attention mechanism heavily used in all layers of BERT produces extremely semantic, and context-sensitive representations, where a token might have many representations depending on the context it is being used in. For the sake of this study, A pretrained BERT model provided by HuggingFace [26] is used, containing twelve layers,

768 hidden-size (Each Layer produces a 768 sized vector for each word), 12 attention heads, and 110M parameters.<sup>1</sup>

### C. DeepInsight

Sharma et al in [19], proposed a methodology to transform non-image data to an image, using t-SNE [24] or K-PCA [6] to project the transpose of a dataset creating a set of features related on a 2D plane with respect to their similarity, re-transposing the set to obtain the original set size with  $[N \times N \times 3]$  images as new samples. The method was heavily used in Cancer Detection and related medical applications.

### D. t-SNE

t-SNE [24] (t-distributed Stochastic Neighbor Embedding), is a similarity measuring and dimensionality reduction technique, developed in 2008 by Geoffrey Hinton and Laurens Van Der Maaten. What separates t-SNE [24] from classical dimensionality reduction techniques, is that it is a non-linear method, meaning that datasets with a very large number of dimensions can be easily viewed or projected on a 2D or 3D dimensional space, even when features are not related linearly. The mapping from the high dimensional space to the lower dimensional space (2D or 3D), happens with respect to the similarity between features and data points, where samples with similar features are clustered together. The similarity between two point is computed as probabilities based on *Euclidean Distances* between pairs of data points.

## IV. METHOD

In this section, the steps taken to generate the dataset used in our experimental part are explained. Going through obtaining BERT-embeddings from the pretrained BERT [5] model for the original IMDB dataset [16], transforming the embeddings into images, and visualization of some obtained IMDB-Image Dataset samples, and normalizing the pixel space. Along with an analysis of *Source* and *Target* domains for the *Transfer Learning* conducted in this paper, and the architectures trained on the generated IMDB-Image dataset, providing sample feature maps produced by the pretrained layers from [9] [15] [21].

### A. Generating the IMDB-Image Dataset

1) *BERT Embeddings Generation*: A very special feature of BERT is the [CLS] token which is added in the beginning of a sentence embedding at each layer output, which indicates the beginning of a sentence and is also a unique Sentence Representation for classification purposes. Since our procedure requires a high Dimensional Space because we attempt to obtain images after a t-SNE [24] projection of different features representing each input from IMDB [16] as it will be further discussed in following sections, and following the study conducted in [11] which demonstrates the semantic nature of the output from the higher layers of BERT, the [CLS] embeddings from the last six layers are concatenated for each input sentence from the

IMDB-Dataset [16], giving a  $[6 \times 768]$  sized vector for each input sample as Fig.1 depicts.

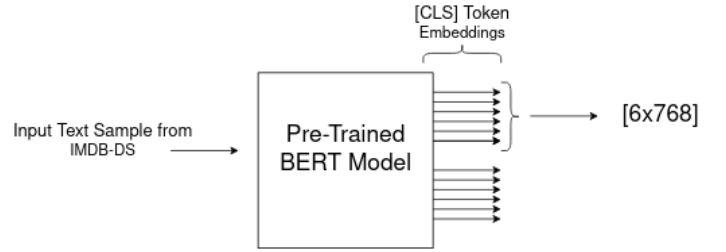


Fig. 1. IMDB [CLS] Embeddings from the Last Six layers of BERT, where the input to the pretrained model is indexes representing each word in a sentence, outputting a fixed [768] sized vector from each layer. The outputs of [CLS] tokens from the last six layers are stacked into a  $[6 \times 768]$  sized embedding for each text sample.

2) *Transforming BERT Embeddings into Images*: After stacking 6 vectors with 768 features for each sample in the original IMDB [16] dataset, our dataset is now of shape  $[50000, 4608]$ . Following the pipeline introduced in [19], We have  $n = 50000$  samples, with  $d = 4608$  features for each sample, thus our dataset can be defined as  $D = \{x_1, x_2, \dots, x_n\}$ , where each feature vector  $x$  is defined as  $x = \{f_1, f_2, \dots, f_d\}$ , our feature set is then defined as  $F = \{f_1, f_2, \dots, f_d\}$ , where each feature  $f$  has  $n$  dimensions. In short terms  $F = D^T$ , and transposing the dataset allows for features to be treated as elements which can be related on a 2D plane according to similarity measuring using t-SNE [24]. The obtained 2D plane demonstrated in Fig.2, represents the location of features, and a Convex Hull algorithm is used to isolate the rectangle containing all the points as depicted in Fig.2, the rectangle is then rotated in order to obtain a horizontal matrix containing Cartesian coordinates which are converted to pixels.

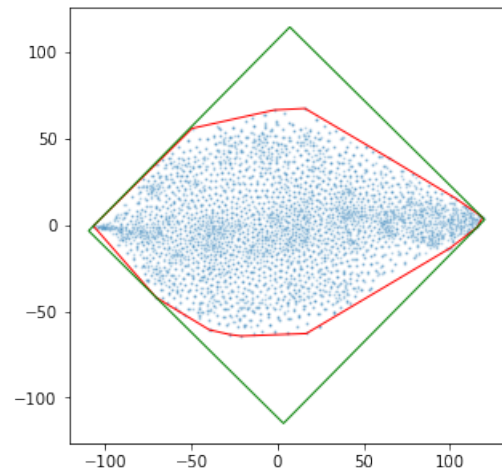


Fig. 2. Feature locations represented by blue points on a 2D plane, as described above. The green rectangle represents the smallest rectangle containing all points and is obtained using a Convex Hull algorithm. We can observe a size of  $[50 \times 50]$  is obtained for the rectangle which is then rotated to obtain a horizontal image, ready for use in a Convolutional Neural Network.

<sup>1</sup>more information on the BERT model used is at: [https://huggingface.co/transformers/pretrained\\_models.html](https://huggingface.co/transformers/pretrained_models.html)

Since the frame is limited by image size, the points representing feature locations can have more than 1 feature per location, therefore, during mapping features to their locations, averaging is required to avoid confusion which may lead to noisy pixels. Each feature is then mapped to its location, averaging features which fall on the same point or location on the 2D plane. Respecting our hardware capacity and to avoid excessive overlapping of features on the same location, a size of [50x50] for our pixel frames is chosen.

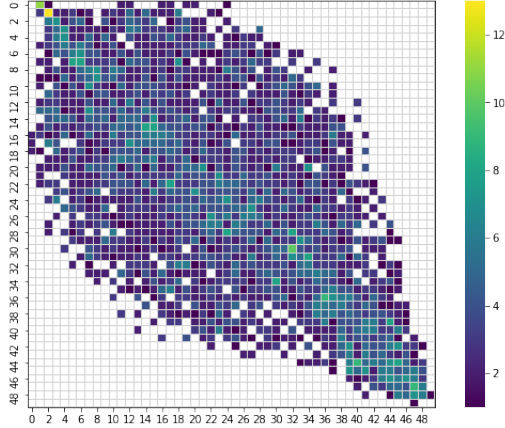


Fig. 3. A Density Matrix, after rotating the Convex containing all the points representing locations projected on a 2D plane with respect to their Cartesian Coordinates obtained from t-SNE [24]. Showing regions that are more dense, due to features being mapped to the same locations causing overlapping. We can observe that our new IMDB-Image Dataset has a certain geometrical distribution of features, with clear edges and blobs.

Fig.3 is an experimental result of applying t-SNE [24] to our [50000,4608] shaped dataset. The Density Matrix reflects the actual distribution of features in the new IMDB-Image Dataset, with obvious concentration of features on the diagonal, this is due to the overlapping of features if more than one feature is projected with the same Cartesian coordinates on the 2D plane. The next step is to map feature values to their Cartesian coordinates, and averaging feature values that share the same coordinates.

3) *Image Data Visualization*: After running the method with a t-SNE [24] backbone on our [50000,6x768] IMDB-bert dataset, we obtain gray-scale images with height=50, width=50 and 3 channels having the same values for each pixel, most probably caused by the unnatural data-source which is the pretrained BERT model which is used to obtain all the values in the [6x768] sized vectors, theoretically forcing the same regularities and irregularities between all samples. Fig.4 demonstrates the Image-Embeddings for the first three IMDB input-samples.

Text Samples for Images in Fig.4:

- "One of the other reviewers has mentioned that after watching just 1 Oz episode you'll be hooked. The..."

- "A wonderful little production. <br /><br />The filming technique is very unassuming- very old-time-B..."
- "I thought this was a wonderful way to spend time on a too hot summer weekend, sitting in the air con..."

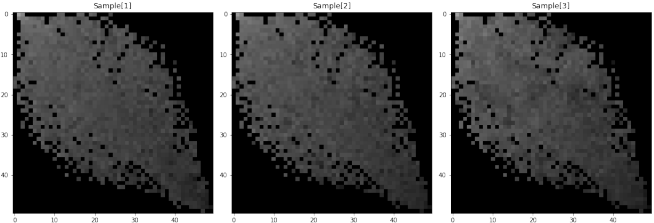


Fig. 4. Image Embeddings for the three first IMDB samples, each image is a projection of a [6x768] sized embedding obtained from BERT for each sample in the IMDB [16] dataset (The text samples above respectively). A new IMDB-Images dataset is generated in the same manner, giving 50000 images, each one representing a text sample in 50000 from the original IMDB [16] dataset.

### B. Data Domains and Transfer Learning

Our generated IMDB-Image dataset and the original dataset (ImageNet [4]) on which the models used in this work are trained, are extremely different as depicted in Fig.5, which according to [3] causes a distribution mismatch and domain shift problems to the classifiers. Generalization across domains is extremely affected by the nature of domains and the style of the data especially in Visual Understanding related tasks.

According to [33] a domain  $D$  is composed of a feature space  $\chi$  and a marginal distribution  $P(X)$  formulated as:

$$D = \chi, P(X) \quad (1)$$

where  $X$  is an instance set which is defined as:

$$X = x | x_i \in \chi, i = 1, \dots, n$$

The Task  $T$  is composed of a label space  $Y$  and a decision function  $f$ , meaning:

$$T = (Y, f) \quad (2)$$

where  $f$  is learned explicitly via training data samples.

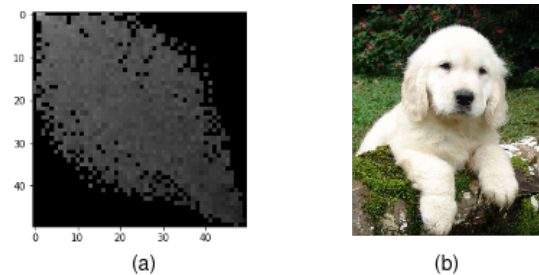


Fig. 5. (a): An image sample from the generated IMDB-Images dataset, showing a gray scale distribution with weak edges and no obvious geometrical features or shapes, (b): An image of a Dog from the Source Dataset (ImageNet [4]), an RGB image with clear geometrical features and shapes. This figure depicts the differences between the Source and Target datasets, and suggests inevitable domain shifts between the two.



1) *Data Domains*: fig.5 shows obvious differences in data style in the source and target datasets, which according to [23] and [20] and further discussed in [30] causes a distribution mismatch and domain shifts, due to the differences between the two domains like channels, colors, background, lighting, etc. This is a major problem in Transfer Learning between image datasets. Survey [3] gives a broad overview of the recent approaches and methods developed for Transfer learning to overcome the mentioned issues through Domain Adaptation.

2) *Transfer Learning*: For successful Transfer Learning to be achieved, an architecture should be able to adapt the Target Domain  $D_T$  to Source Domain  $D_S$ , which are IMDB-images and ImageNet [4] respectively in our case. One special technique for domain adaptation so far proposes specific training for domain prediction [7]. Limited by compute power and extreme domain shifts, in this work, another approach is taken. In [28], Jason Yosinski et al, stress on the different kinds of features different zones of layers learn in a neural network, stressing on the generality observed in lower layers and specificity in higher layers, meaning general features like curves, color blobs, and edges are extracted in the lower layers, and task specific features are handled by higher layers. Threatened by the large model sizes in our pretrained arsenal [14][15][21][9][27], and the relatively small dataset with only 50000 samples, which could lead to extreme overfitting, the approach taken in this work is to focus on features which both datasets share instead of forcing the model to learn the domains themselves as targets. Since the color channels are clearly going to cause a major domain shift, the focus should be on geometrical features like edges, curves and blobs. in order to have more defined edges, normalization of the entire pixel space is applied, a normalization technique named *Z - Normalization* [8], adjusting image contrast after moving our input images to a clearer pixel space:

$$\begin{aligned} \mu &= \mathbb{E}_{\mathcal{X}} \in [X], \\ \sigma^2 &= \mathbb{E}_{\mathcal{X}} \in \mathcal{X}[(x - \mu)^2], \\ \hat{x}_i &= \frac{x_i - \mu}{\sigma + \epsilon} \end{aligned} \quad (3)$$

$\mathcal{X}$  is a set of input vectors,  $\mu$ ,  $\sigma$  are the mean and standard deviation of the entire image pixel space,  $\epsilon$  is a small value to prevent dividing by zero or small denominators.

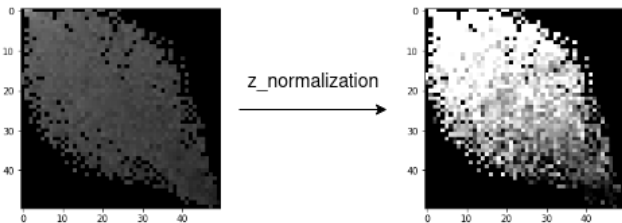


Fig. 6. The image to the left, represents a raw image from the generated IMDB-Images dataset. The image to the right, is the same as the one to its left after *Z - Normalization*, showing stronger edges and more defined geometrical shapes like blobs.

As fig.6 shows, the mentioned normalization technique prevails in creating more distinguishable feature zones in one

image, due to the new mean which is close to 0.0 and standard deviation nearing 1.0, which imposes a standard normal distribution on the features, removing noisy regions and enhancing outlying pixels.

### C. Architectures used

Since our IMDB-Image dataset is very small compared to the source ImageNet dataset [4], the Convolutional Feature Extractors are sliced from their original pretrained models, and stacked to a Convolutional Auto-Encoder with randomly initialized parameters, followed by a Dense (Linear) Classifier. A common approach would be to freeze the pretrained feature extractors, which was followed in this paper to avoid any overfitting problems.

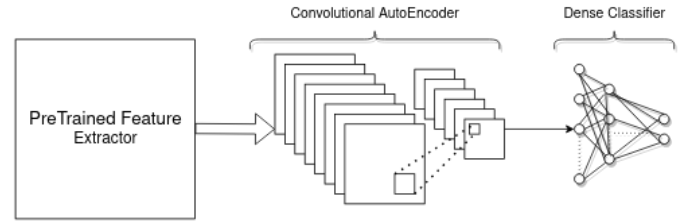


Fig. 7. Main Architecture Used, the PreTrained block represents early layers from five pretrained Vision Models [14][15][21][9][27], outputting the input to a Convolutional Auto-encoder, stacked to a Dense Classifier (3 Linear fully connected layers)

As it is depicted in fig.7, the most important part of the architecture is the pretrained feature extractor. In this paper, for the sake of comparison and confirmation, early layers from five pretrained models were used as feature extractors, followed by the exact same Conv-AE (Convolutional AutoEncoder) and Dense classifier to ensure fairness in results. The detailed architectures of the pretrained models are outside the scope, of this paper.

#### 1) Pretrained Feature Extractors: <sup>2</sup>

Visualization of feature maps produced by frozen early layers from the models to be mentioned, depicted in fig.8 lead to choosing specific layers from each model to construct fixed feature extractors to be appended to our standard Conv-AE and Dense Classifier as discussed earlier.

- AlexNet: introduced in [14], Using the first two pretrained Convolutional Layers, outputs 192 feature map for each input image from the IMDB-image dataset, with fairly distinguishable differences and focus.
- ResNet: A deep residual model from [9], known as wide-resnet50-2, in torchvision terms. Using the first downsampling Convolutional layer and the first residual layer which contains skip connections described in the original paper.
- ResNext: [27], proposes an aggregated version of the previous ResNet, for the feature extractor we need, the first Convolutional layer, and the first Residual layer are used as well.

<sup>2</sup>All pretrained models can be found at: <https://pytorch.org/vision/stable/models.html>

- ShuffleNet V2: From [15] the first Convolutional layer followed by Batch normalization, and stage2 mentioned in the paper.
- VGG16: introduced in [21], We only use the first 12 layers, containing 4 Convolutional layers for the feature extractor.

fig.8 shows sample Feature maps from the feature extractors from: resNet [9], ShuffleNet [15], Vgg16 [21].

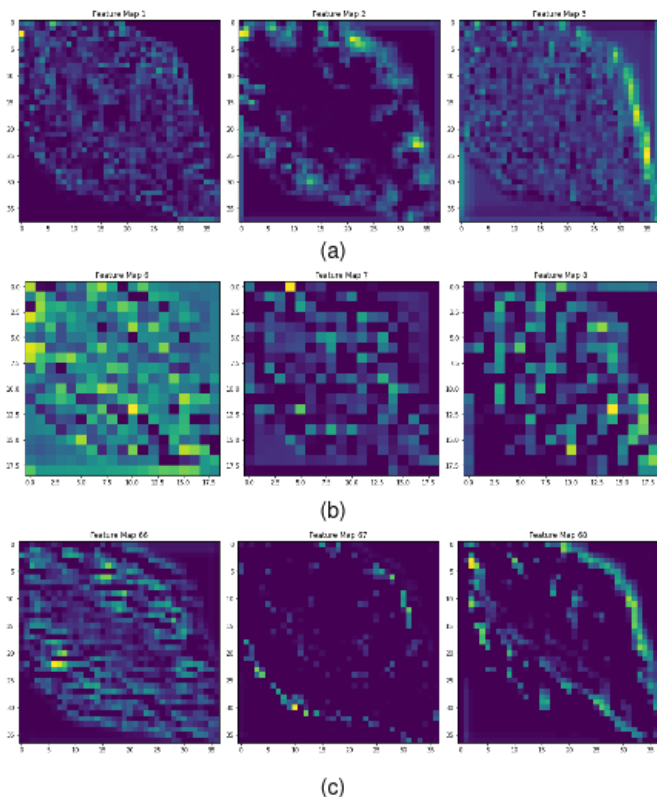


Fig. 8. Feature Maps from early layers of (a) : resNet, (b) : shuffleNet, (c) : VGG16. The pretrained feature extractors used in our common architecture do in fact output feature maps with defined geometrical features extracted due to the pretraining on the ImageNet [4] dataset. We can observe the adjusted edges and blobs using  $Z - Normalization$  being successfully detected by all pretrained feature extractors, clearest in the depicted three.

In fig.8 we can observe that the pretrained models are in fact able to extract global features from new dataset, edges and curves are distinguished by all the pretrained feature extractors, but clearest in the depicted three. Yielding that [28] stated a concrete study of the transfer-ability of pretrained models to other datasets and tasks, requiring a considerate treatment of the nature of the features learned by different layers, and the different natures and domains of the source and target datasets.

## V. EXPERIMENT

This section discusses the training procedure for the mentioned architecture containing five different pretrained feature extractors from the Vision Models [14] [15] [21] [9] [27], pretrained on ImageNet [4], and the experimental results achieved by each one on the generated IMDB-Image dataset.

### A. Training

As shown in Fig.7, our five models share a Convolutional AutoEncoder, and three Linear Layers, and differ in the pre-trained feature extractors obtained from 5 different pretrained vision models [14] [15] [21] [9] [27]. Given the differences in data domains depicted in Fig.5, avoiding any possible dataset and covariate shifts is necessary. Using *ReLU* to keep the same activation patterns within layers of our architecture, given that all 5 pretrained feature extractors contain *ReLU* activations. Batch Normalization [10] is applied after each convolutional layer in our Convolutional AutoEncoder block, since our pre-trained feature extractors are trained with 1000 classes on the label side, and our classification task only has 2 classes, this causes an Internal Covariate Shift, representing the change in the distributions of internal nodes of our network as mentioned in [10]. Adam Optimizer [13], is used for all 5 models, to ensure fairness in comparisons, and a fixed batch size of 32. Our IMDB-Image dataset contains 50000 images samples, we split the dataset into a 40000 train and a 10000 validation samples. Differential learning rates are used for our Adam [13] optimizer, while keeping the pretrained feature extractors frozen during training, since our dataset is very small compared to the *Source* Dataset (imageNet [4])

An NVIDIA GEFORCE GTX 1060 GPU was used for the entire procedure.

### B. Experimental Results

As mentioned in the previous subsection, the different models were trained, with different learning rates, but yet reached very close Validation Accuracies. Higher learning rates caused all models to stagnate and converge very fast to local optimal points, which prevented the models to further learn features necessary to distinguish between different variations contained in each image representing the text samples in the original IMDB-dataset [16].

The following table depicts the number of feature maps outputted by each Feature Extractor along with different Learning Rates used for each one, and the corresponding achieved Validation Accuracies. Fig.9 shows the progress of the validation performance of the five models during training. TABLE 1 and Fig.9 both emphasize on the very close results obtained from training all five models on the same IMDB-Image dataset.

Freezing the pretrained Feature Extractors allows for the complexity of the model as a whole for the five variations to drop, avoiding any chance of overfitting due to the gray scale nature of our IMDB-Image dataset and the *RGB* channel space of the *Source* Dataset (ImageNet [4]). The experimental analysis conducted in this paper, is explicitly dedicated to the results obtained by our method and architectures. No comparison with benchmarks or state-of-the-art results in either Image or Text Classification is necessary, since our method is explicitly probing the *Text to Image Transformation* approach described throughout this work.

Given that the pretrained Feature Extractors, followed by the exact same Convolutional AutoEncoder and Dense Classifier, are trained on the same generated IMDB-Image dataset, and

Feature Ext	Nbr of FM's	CAE LR	LC LR	Val Acc
AlexNet [14]	192	0.00001	0.0005	0.81 ( $\pm 0.01$ )
ResNet [9]	256	0.00005	0.0001	0.82 ( $\pm 0.01$ )
ResNext [27]	256	0.00005	0.001	0.82 ( $\pm 0.01$ )
ShuffleNet [15]	116	0.0005	0.001	0.81 ( $\pm 0.01$ )
VGG16 [21]	256	0.00005	0.001	0.81 ( $\pm 0.01$ )

TABLE I  
NBR OF FM'S (NUMBER OF FEATURE-MAPS), LEARNING RATES FOR CONV-AE (CONVOLUTIONAL AUTOENCODER AND LC (LINEAR CLASSIFIER) AND VAL ACC (VALIDATION ACCURACY) FOR EACH MODEL DEFINED BY ITS FEATURE EXT (EXTRACTOR)

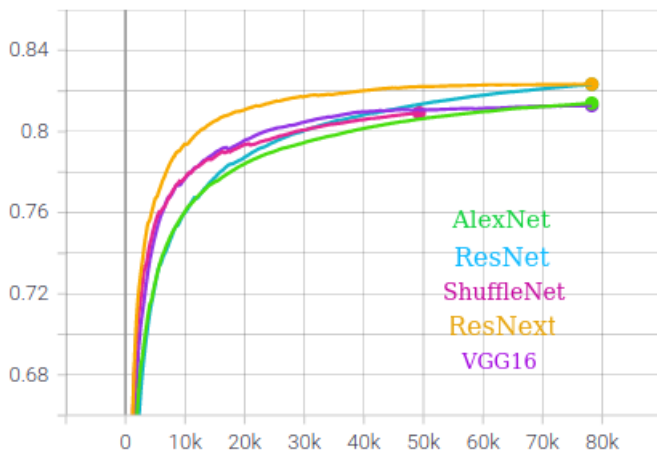


Fig. 9. Validation Accuracy for Five Models during Training process VS. Steps(10 Epochs), where each graph is identified by the model from which its feature extractor is taken. Showing relatively close learning graphs.

observing the experimental results obtained in TABLE 1 and Fig.9, suggests the following:

- The normalized IMDB-Image Dataset, is still not fully avoiding domain shifts due to its raw gray-scale nature.
- The different number of features outputted by each feature extractor, and the almost identical Validation Accuracies, suggests that some feature maps are duplicated, also due to the gray scale nature of the IMDB-Image dataset.
- We can clearly see in Fig.9 that the five models learned at different rates, yet reached close Validation results, this can imply that the models do indeed vary in complexity and generalization abilities, yet limited by dataset size, forcing a maximum validation performance which is almost achieved by all of them.
- The general features learned from the early layers used as feature extractors are extremely similar as suggested in [28], yielding similar results even with different learning rates, since the feature maps play the role of fixed

representations for the same dataset.

- Although the Validation Results accomplished do not rise to the State-Of-The-Art in Text Classification, they are still promising given the circumstances and the complexity of the methodology underwent to obtain them.
- The main goal of the paper is achieved, being the classification of text after transforming it into images, with Vision Models pretrained on ImageNet [4].

As mentioned above, our work is by no means an attempt to reach state-of-the-art results in either *Image Classification* nor *Text Classification*. Hence, the only comparison conducted in our experiment, measures how different pretrained models with different architectures vary in the way they extract feature maps for the new generated IMDB-Image Dataset.

## VI. DATA AND CODE AVAILABILITY

Both the generated IMDB-image dataset, the code for:

- BERT Embedding, Data Transformation and loading.
- Different architectures and training scripts using PyTorch.
- Reproducible paradigm with commented and explained steps.

Are available and ready to be shared.

After initial replies from the conference reviewers, the available dataset and entire code with explained steps for the whole procedure described in this paper will be posted and shared, and links will be added to future versions, with respect to the review period.

## VII. CONCLUSION

In this paper a new approach to Sentiment Analysis via Supervised Learning is suggested, using Transfer Learning of pretrained Vision Models on an Image Dataset (ImageNet [4]), to a textual polarity Dataset (IMDB [16]) embedded using a pretrained BERT [5] model, where text embeddings are transformed into images using t-SNE [24] feature similarity measuring (Inspired from the work done in DeepInsight [19]), and pretrained Vision models, are used as feature extractors for a much smaller Neural Classifier to learn sentiment labels. The contributions of our work, is mainly the generation of a new dataset representing textual data from the IMDB [16], avoiding possible domain shifts with pixel normalization, and the expansion to possible future applications using larger datasets and resources. Our results are not compared to the state-of-the-art results because of the unfairness due to *DomainShifts* and hardware requirements for the generation of an Image Dataset for a larger Textual Dataset. Future work aims to further normalize the discussed approach, as it gives promising results for a small dataset, opening a new challenge for the fusion of Language and Vision via Transfer Learning and Data transformation.



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