Integrating Dropout Regularization Technique at Different Layers to Improve the Performance of Neural Networks

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***Abstract*—In many facial expression recognition models it is necessary to prevent overfitting to check no units (neurons) depend on each other. Therefore, dropout regularization can be applied to ignore few nodes randomly while processing the remaining neurons. Hence, dropout helps dealing with overfitting and predicts the desired results with more accuracy at different layers of the neural network like 'visible', 'hidden' and 'convolutional' layers. In neural networks there are layers like dense, fully connected, convolutional and recurrent (LSTM- long short term memory). It is possible to embed the dropout layer with any of these layers. Model drops the units randomly from the neural network, meaning model removes its connection from other units. Many researchers found dropout regularization a most powerful technique in machine learning and deep learning. Dropping few units (neurons) randomly and processing the remaining units can be considered in two phases like forward and backward pass (stages). Once the model drops few units randomly and select 'n' from the remaining units it is obvious that weight of the units could change during processing. It must be noted that updated weight doesn't reflect on the dropped units. Dropping and stepping-in few units seem to be very good process as those units which step-in will represent the network. It is assumed to have maximum chance for the stepped-in units to have less dependency and model gives better results with higher accuracy.**

***Keywords*—Convolutional layer; visible layer; hidden layer; dropout regularization; long short term memory (LSTM); deep learning; facial expression recognition**

I. Introduction

Idea behind introducing the dropout layer (technique) helps classifying accuracies with minimized error rate than without having the same. Many applications process the large data and it is expected to have better accuracy with minimized loss and error rate. Applications will process data from different source e.g., speech, images, videos etc.

This adaptive nature helps developing a robust model. It is also possible to introduce the dropout layer with fully connected layers, recurrent layer such as long short-term memory layer (LSTM) and convolutional layer. There are visible layers, hidden layers and dropout layer can be added later to get better classification of the objects. Actually, dropout is a regularization technique which trains 'n' neural networks in parallel. Neural networks are complex due to various hidden layers. It is necessary to find the relationship between those neurons. If model fails to regularize the network properly then relationship results into noise. There are many techniques that exist to avoid noise, and overfitting and are 'early stopping', 'dropout regularization', 'weight penalties', and 'short weight sharing'. It's a type of generalization and in some cases if the network is larger and complex may consume more memory and time. Dropping and selecting the neurons may consist of 'n' iterations and after each iteration network may get changed. Few researchers termed 'dropout mechanism' as an 'ensemble mechanism' because after each iteration network changes and can be termed as sub-network (new). Actually these are the structures and bunch of these sub-networks can be used for training purpose. Objective is to prevent the overfitting in the model and train the given dataset. To achieve an error rate with minimized losses dropout layer can be added in the proposed model. In some cases, adding dropout have effect of making training process noisy and one can say the model becomes 'adaptive' which learns from every phase. In dropout regularization method few neurons are randomly dropped and select other neurons.

Section II gives introduction to existing methods with advantages and gaps to implement the proposed system. Section III focused on proposed model with algorithmic details and methodologies. Section IV elaborates the results obtained in proposed approach with different dropout rates, epochs, and batch sizes. In the end conclusion remarks the implemented approach with future research directions.

II. Literature Review

Authors [1, 24] have developed a model which extracts features from given images and trained the model to process the upcoming features automatically. Authors have focused on important aspect of the emotion recognition i.e. working on static and dynamic images i.e. real-time images or images extracted (frames) from the video. Model processes the video as sequences of different frames and each frame consists of images. Model processes the features extracted from given images automatically by introducing 03 steps as follows –

- Image acquisition
- Feature extraction
- Expression recognition

Authors [2] also suggested, one can use support vector machine (SVM), naïve bayes, lexicon methods to recognize emotions from different conversations. Hence model generates different vectors according to the different statements/conversations. Model helps identifying sentiments of people and knowing the depth of conversation. Model could help analyzing different styles of conversations, time required for certain conversation etc.

Authors [3, 22] have introduced robots and embed a proposed model to process real-life images. In this model robot extracts images from camera, video etc. and analyzes these frames. FERW model – facial expression recognition in the wild processes the features and gives corresponding feedback.

Authors [4, 11, 18] have used CNN and auto-encoders to extract different features from images for classification purpose. Authors have proposed 06 architectures out of which 02 are trained on Japanese female facial expressions and 04 with Berlin database. 02 architectures dealt with image-based emotions and 04 with speech recognition. CNN architecture consists of 03 convolution layers, 03 pooling layers, 03 dense layers with output layer. These convolution and pooling layers helps in extracting different features from emotions. Auto-encoder helps in reducing the dimensions. Authors [5, 6, 25] suggested that, ML machine learning and methods especially from the deep learning techniques can handle complex feature extraction from images and also helps in classifying them accordingly. “Gabor Filter” is applied to analyze the textures, edge detection, and extracting different features from the images. Authors pointed good response in edge detection can be obtained after application of the Gabor filter. Authors [7] have focused on 06 elementary emotions like happy, sad, fear, anger, surprise and disgust. Using MATLAB deep learning methods are implemented to extract and process the features from images. Model processes the JAFEE dataset which consists of 06 elementary emotions. System processes large volume of data. However, data could be labeled or unlabeled. Authors [8] have proposed a model to process unlabeled data. A hybrid label-less learning is proposed to automatically process the unlabeled data. Main advantage of this approach is human intervention is almost reduced and model automatically labels the data. Authors have proposed “LLEC” label less learning for emotion cognition. Authors suggested when labeling the unlabeled data prediction probability plays an important role. Entropy is used as a measure to assess the prediction uncertainty. Authors [9] have proposed a model using IoT devices which captures the images of the human and passes to the system. Model uses motion sensor to detect the motion of human. Camera attached with the module gets activated once the motion sensor detects the motion of human and captures the image using HAAR - feature based cascade classifier. Authors [10, 13, 26] have proposed a comparative approach for different deep learning architectures available in “Keras” for emotion recognition. Pre-trained models like VGC-16, ResNet152V2, Inception V3 and Xception etc. Authors have used 02 datasets Cohn-Kanade dataset and JAFFE Japanese female facial emotion. All the pre-trained models are evaluated on these datasets and their accuracies are measured.

A three-class annotation approach [12, 19, 23] is proposed to get the stimuli behind emotions. Authors have developed emotion classification framework using LSTM. Framework also consists of threshold scheme and categorizes emotions in different segments like anxiety, anger, disgust, sadness and joy etc. and ratings are assigned in the range from 1 to 9. Authors have also used EEG signals and facial videos to extract the features from images. Authors have also concluded EEG feature-based classifier can give better accuracy when used with thresholding scheme. Authors [14, 27] have considered 05 emotions and developed a model based on deep convolutional neural network. Model is based on few layers like convolutional layer, dropout, fully connected layer and features are extracted from images. Using convolution filter represents the features of interests. Back-propagation algorithm can be embedded in the framework to reduce the errors. Activation function is introduced – ReLu (rectified linear unit) to make negative values zero. If any overfitting of the data is observed then dropout layer can be used to reduce the same.

An interesting topic “micro expression” in the emotion recognition is presented by the authors [15] using deep learning architecture. Authors have used FERC-2013 database to extract the different features to identify the micro expressions. Model is based on cross-entropy loss function and uses “*Adam optimizer*”. This optimizer helps training and providing best results and also reduces the losses. To handle the overfitting of data, dropout layer can be introduced which reduces the overfitting of the model. With the confusion matrix authors have shown different emotions and their scores obtained. Authors [16] have proposed an LDL- label-distribution learning model with conditional probability function to reduce the entropy. A framework EDL-LBCNN is implemented using CNN on the s-JAFFE dataset. Basic emotions like happiness, sadness, fear, anger, surprise and disgust are accurately evaluated. Framework consists of 04 convolutional layers and single LBC (local binary convolutional layer. Initially framework extracts the features from grayscale images. Once the features are extracted next phase is to concatenate them and pass to the next phase. LBC (local binary convolutional layer) consists of few trainable parameters and fixed size of filters. Output of this layer is generation of feature map and in the next layer i.e. FC layer (fully connected layer) concatenates the feature maps generated by CNN and LBC layer. Authors [17, 18, 21] have used LSTM and CNN to learn speech emotion features. Interesting approach proposed by the authors is *combining facial and speech expression*. Advantage of this ***fusion approach*** is, it gives information of audiovisual features. High levels of features are extracted using deep neural networks. Audio features are extracted using *pyAudioAnalysis* an open-source library. Local features of data and global training features can be extracted using *CNN – convolutional neural network*. A multi-modal fusion is carried out on different features, also known as early-fusion or feature-level fusion. Model also consists of decision level fusion known as late-fusion. There is score level fusion implemented in the model to calculate the classification scores. Authors have combined happy and excite category into excite and works on remaining basic emotion like excite, sad and neutral. Authors [20] have implemented a pose-guide estimation model where features are extracted using few methods like pyramid histogram orientation gradient method (PHOG), edge histogram descriptor (EHD) and local binary pattern (LBP). Canny detector is introduced to extract the edge of the image. LBP helps in converting image into integer array. Authors have evaluated their proposed model on the 04 datasets – CK+, JAFFE, CASIA and AR dataset. Model works on 03 steps - target pose estimation, template generation, and target matched.

III. Pproposed Methodology

'Regularization' is a technique that can be used in neural network to reduce the complexity of the proposed model. Once regularization is successfully implemented it helps generalizing the *new* data in efficient manner. The reason behind this approach is model randomly ignores the 'n' neurons and focus on the remaining neurons only. It is obvious that, there would be a significant difference in considering all the neurons and considering few one. With the selected neurons, model can run effectively and produce the results with better accuracy. Therefore, one can say with the help of regularization technique such as 'dropout' it is possible to obtain the useful and effective networks.

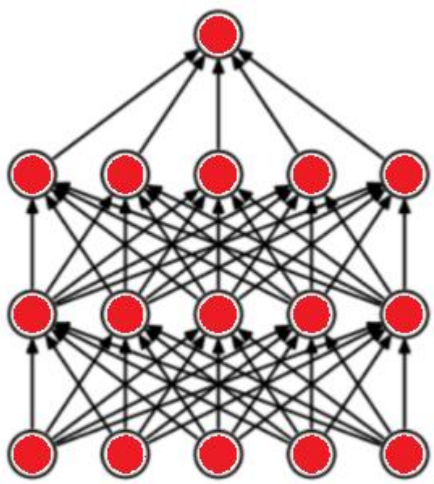

Fig. 1. Dropout regularization.

Drops hidden and visible units from the network, selects few from the remaining neurons as shown in the Fig. 1 and Fig. 2. Model temporarily removes the units as shown in the Fig. 2. One important point in this scenario is even if the weights of the neurons get changed it will not affect the skipped neurons. As its name indicates '***dropout***' randomly drops few units from the given datasets. E.g. if the defined dropout rate is 0.2 then it randomly drops 20% units from the given collection. As discussed earlier, dropout layer can be added with the visible layer, hidden layer and other network layers. During processing the units/objects it creates combinations from all the defined layers. Model trains the dataset in iterations and randomly drops new units based on probability hyper parameter '*P*'. Many authors have termed this concept as formation of thinned network. Model further integrates these thinned networks to identify the *key properties*. However, this phase requires intensive processing the large datasets as there are many thinned networks. Objective behind adding the dropout layer in training the given data is to minimize the overfitting and achieve greater accuracy. Application of dropout method helps reducing the error rate significantly.

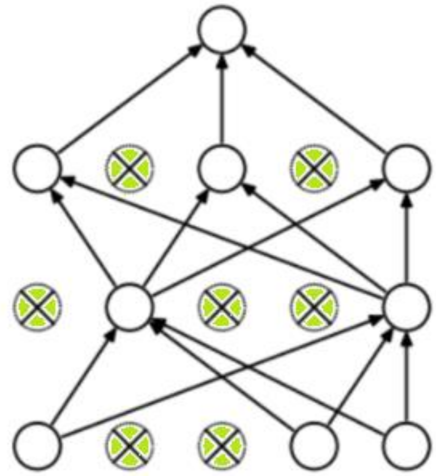

Fig. 2. Successful execution of dropout regularization.

A. Algorithmic Details

Idea behind application of dropout regularization is as follows-

- Consider there are 'i' inputs in the given network.
- If each of these 'i' units produces the output 'o' e.g. O_1, O_2, O_3,….O_n
- Sum of these outputs S_1… S_n
- Model should consider probabilities for these sums using individual scores like P_1, P_2...P_n
- When model drops few neurons randomly and selects others from the remaining neurons, forms different sub-networks.
- Using the outputs and different sums calculated model can find possible probabilities of future sub-networks.

To implement the dropout function with a single layer, one must draw as many samples from a Bernoulli (binary) random variable as our layer has dimensions, where the random variable takes value 1 (keep) with probability 1−p and 0 (drop) with probability p. One easy way to implement this is to first draw samples from the uniform distribution U [0, 1]. Then, model can keep those nodes whose corresponding sample is greater than '*p'* and drop the rest.

Table I explains the results obtained by applying the dropout layer with different dropout rates to the visible layer. Table I elaborates the different dropout rates i.e. 20%, 30%, 40% etc. applied to the visible layer and results obtained using the same. Model also rechecks the results obtained with a specific dropout rate i.e. 20% in the example as shown in the Table I. Similarly dropout rate can be applied to the hidden layer in the network. Table II elaborates the same with different dropout rates to measure the accuracy of the model. If the proposed model consists of 'n' iterations then each time new neurons (elements) will be dropped randomly with the dropout regularization technique. This technique is applied during training phase only.

IV. Results and Discussion

In a network one can add '*dropout layer*' to the hidden and visible layer etc. As shown in the Table I and II dropout regularization applied with different dropout rates, epochs at visible and hidden layer. Accuracy of the proposed model can be checked by using small as well as high dropout rates. It is obvious that, larger network will consist of 'n' neurons and with the dropout regularization technique one can get better performance. Table I and II shows the effective results obtained at different layers. It is also true that if the network is larger with 'n' neurons then training the neurons could be bit expensive.

Table I elaborates application of different dropout rates and epochs at the visible layer of the neural network. Overall the proposed model gives baseline efficiency with approx.85.55% (6.54%). One can observe as shown in Table I that batch size is very important along with epochs and dropout rates. Dropout rate 0.20 indicates 20% data can be randomly removed and remaining will be considered.

The first parameter dropout rate is the probability '*p'* that a given unit (s) will drop out. In Table I, the different probabilities are used 0.2, 0.3, 0.4 and 0.5 which means roughly 20%, 30%, 40% and 50% units will drop out. The value 0.5 has been experimentally determined to be close to the optimal probability for a wide range of models, but feel free to experiment with other probabilities. To check the effectiveness, it is suggested to use variety of dropout rate in different cycles.

TABLE I. REGULARIZATION WITH DIFFERENT EPOCHS AND DROPOUT RATIOS

Dropout	Epochs	Batch size	Results mean and standard
0.20	300	16	Visible: 85.57% (6.18%)
0.30	400	18	Visible: 87.93% (7.57%)
0.40	500	20	Visible: 83.21% (8.26%)
0.20	300	16	Visible: 86% (7.98%)
0.20	300	16	Visible: 85.45% (7.81%)

It is a good approach to average the observations obtained by evaluating the sample data with different dropout rates, epochs and batch size. To improve the performance of neural networks especially in overfitting and regularizing the sample data one can integrate the dropout technique at different layers like hidden and visible layer. Fig. 5 and Fig. 7 give Bayes analysis for the sample data by weighting the settings for prior and posterior probabilities.

It is presumed that every neuron in the neural network has p% of dropout. Many researchers treat dropout technique as an ensemble method. Application of dropout technique at hidden and visible layers helps approximate the sample data and proved that it is computationally very cheap than other approaches.

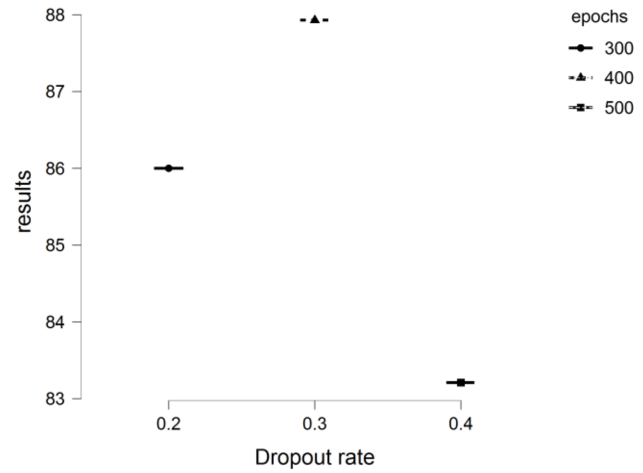

Fig. 3. Flexplot for the visible layer.

Fig. 3 Flexplot gives visual representation for the results obtained with different dropout rates.

A. *Bayesian Coorrelation Pairwise Plots*

Dropout rate - epochs

Scatterplot

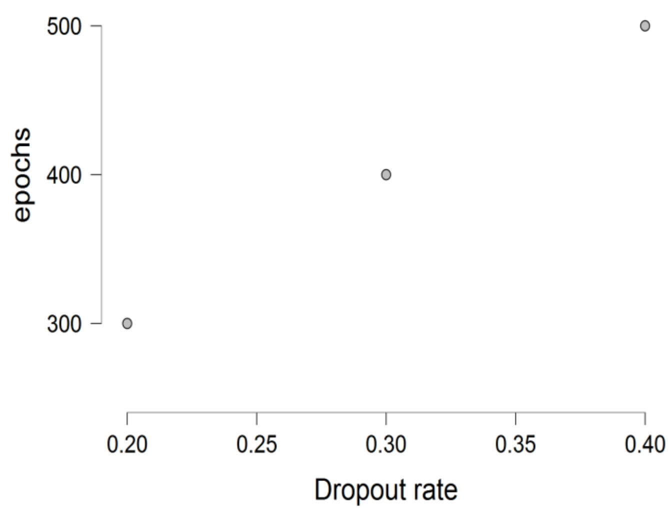

Fig. 4. Dropout rate v/s epochs.

Above Fig. 4 gives visual analysis for different dropout rates with 'n' epochs. Both the factors are very important if there are large distributions.

TABLE II. BAYESIAN PEARSON CORRELATIONS

	n	Pearson's r	BF_{10}
Dropout rate-epochs	3	1.000	1.505
Dropout rate- batch size	3	1.000	1.505
Epochs- batch size	3	1.000	1.505

BF_{10} indicates bayes factor in favor of H1 over H0. Bayesian Pearson correlation helps measuring strength of linear relationship between different variables. Table II gives sample observation for different approaches i.e. dropout rate vs epochs, dropout rate vs batch size, and epochs vs batch size as shown in Table III. The important factor in this observation is BF_{10} which may give different values for ‘n’ samples. Based on this factor one can categorize observed samples into *anecdotal evidence, moderate and strong evidences*.

TABLE III. REGULARIZATION WITH DIFFERENT EPOCHS AND DROPOUT RATIO (HIDDEN LAYER)

Dropout	**Epochs**	**Batch size**	**Results mean and standard**
0.20	300	16	83.62% (10.73%) performance degraded on hidden layers
0.30	400	18	Hidden: 83.71% (7.98%)
0.40	500	20	Hidden: 85.17% (5.81%)
0.20	300	16	Hidden: 84.12% (6.79%)
0.20	300	16	Hidden: 84.12% (6.79%)

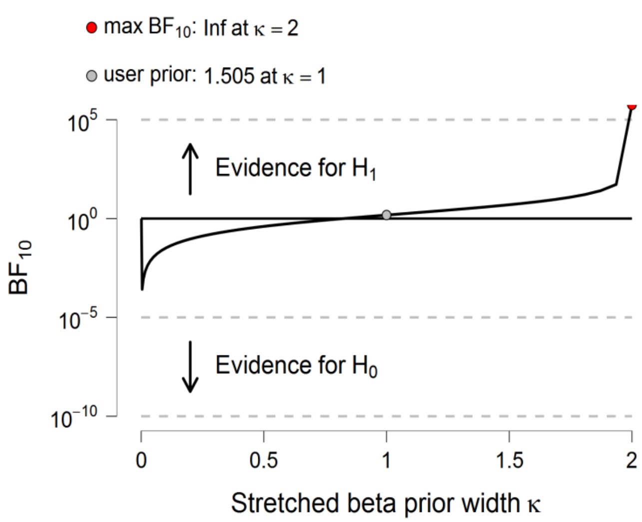

Fig. 5. Bayes factor robustness check.

Bayes factor robustness check is used for the wide range of prior distribution. It helps researchers to distinguish the obtained results in different segments like weak, moderate and strong evidence. Each iteration with different batch size, epochs and dropout rate one can get a new thinned neural network. For the large sample data proposed model with the dropout mechanism can have low classification errors. Even if the network is larger with the help of dropout technique one can reduce overfitting as shown in Fig. 6 to 8.

Dropout rate - batch size

Scatterplot

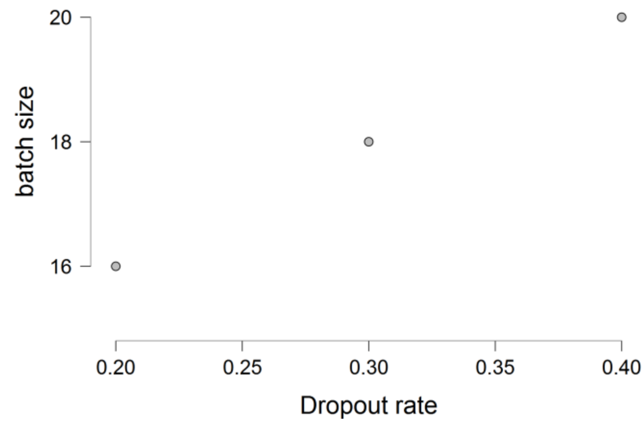

Fig. 6. Dropout rate v/s batch size.

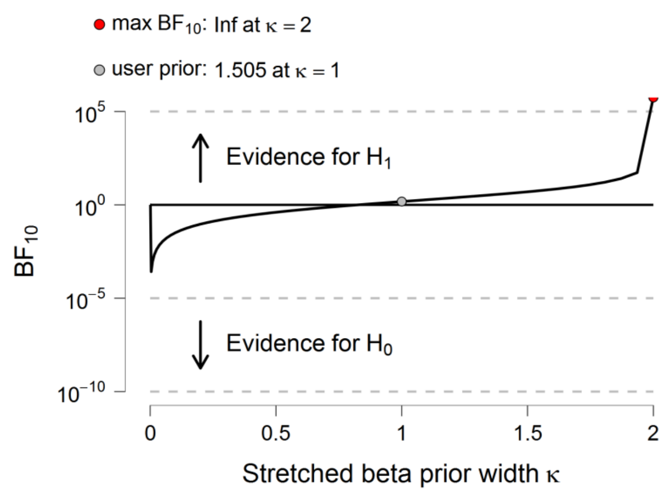

Fig. 7. Bayes factor robustness check for batch sizes.

Linear Modeling

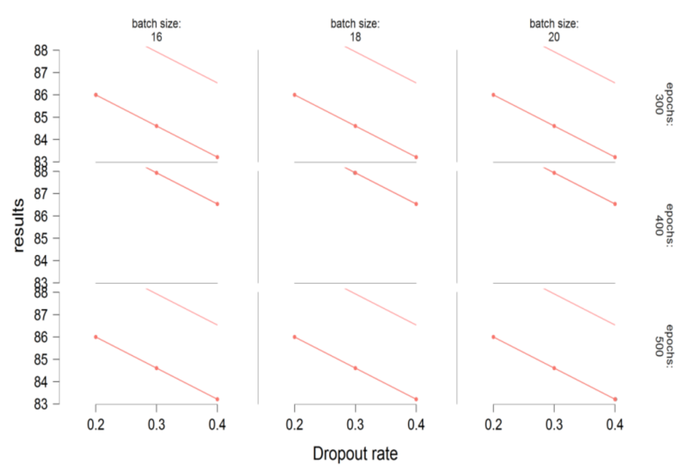

Fig. 8. Plot of the statistical model.

V. Conclusion

Although dropout is a potent tool, it has certain downsides. A dropout network may take 2-3 times longer to train than a normal network. Finding a regularize virtually comparable to a dropout layer is one method to reap the benefits of dropout without slowing down training. This regularize is a modified variant of L2 regularization for linear regression. An analogous regularize for more complex models has yet to be discovered until that time when doubt drops out. One can propose a model with enhanced dropout mechanism i.e., having an effective method for randomly dropping neurons. Future work may include integrating the complex data from image, video etc. and improving the generalization of new data. Results can be improved with the hybrid approach like combining L2 regularization and dropout regularization techniques. If the network is larger and consists of maximum neuron then future research work can be directed to reduce the time complexity required for dropping and selecting the neurons. With the application of dropout technique every unit can act independently and this approach helps breaking co-adaptation in the neural networks.

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