Essentials of Deep Learning: Introduction to Unsupervised Deep Learning (with Python codes)

ADVANCED ALGORITHM AUTOENCODER COMPUTER VISION DEEP LEARNING IMAGE PYTHON TECHNIQUE UNSTRUCTURED DATA UNSUPERVISED

Introduction

In one of the early projects, I was working with the Marketing Department of a bank. The Marketing Director called me for a meeting. The subject said – “Data Science Project”. I was excited, completely charged and raring to go. I was hoping to get a specific problem, where I could apply my data science wizardry and benefit my customer.

The meeting started on time. The Director said “Please use all the data we have about our customers and tell us the insights about our customers, which we don’t know. We really want to use data science to improve our business.”

I was left thinking “What insights do I present to the business?”

Data scientists use a variety of machine learning algorithms to extract actionable insights from the data they’re provided. The majority of them are supervised learning problems, because you already know what you are required to predict. The data you are given comes with a lot of details to help you reach your end goal.

Source: danielmiessler

On the other hand, unsupervised learning is a complex challenge. But it’s advantages are numerous. It has the potential to unlock previously unsolvable problems and has gained a lot of traction in the machine learning and deep learning community.

I am planning to write a series of articles focused on Unsupervised Deep Learning applications. This article specifically aims to give you an intuitive introduction to what the topic entails, along with an application of a real life problem. In the next few articles, I will focus more on the internal workings of the techniques involved in deep learning.

Note – *This article assumes a basic knowledge of Deep Learning and Machine learning concepts. If you want to brush up on them, you can go through these resources:*

- [Experiments With Data Course]
- [Introduction to Data Science Course]
- [Fundamentals of Deep Learning – Starting with Artificial Neural Network]

So let's get started!

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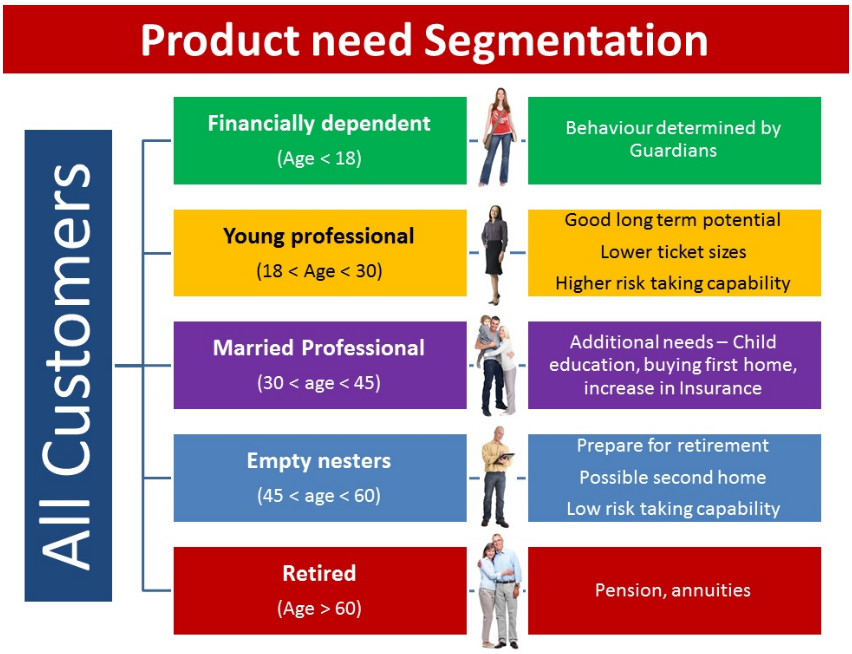
Why Unsupervised Learning?

A typical workflow in a machine learning project is designed in a supervised manner. We tell the algorithm what to do and what not to do. This generally gives a structure for solving a problem, but it limits the potential of that algorithm in two ways:

- **It is bound by the biases in which it is being supervised in.** Of course it learns how to perform that task on its own. But it is prohibited to think of other corner cases that could occur when solving the problem.
- As the learning is supervised – **there is a huge manual effort involved in creating the labels for our algorithm.** So fewer the manual labels you create, less is the training that you can perform for your algorithm.

To solve this issue in an intelligent way, we can use unsupervised learning algorithms. These algorithms derive insights directly from the data itself, and work as summarizing the data or grouping it, so that we can use these insights to make data driven decisions.

Let's take an example to better understand this concept. Let's say a bank wants to divide its customers so that they can recommend the right products to them. They can do this in a data-driven way – by segmenting the customers on the basis of their ages and then deriving insights from these segments. This would help the bank give better product recommendations to their customers, thus increasing customer satisfaction.



Case Study of Unsupervised Deep Learning

In this article, we will take a look at a case study of unsupervised learning on unstructured data. As you might be aware, Deep Learning techniques are usually most impactful where a lot of unstructured data is present. So we will take an example of Deep Learning being applied to the Image Processing domain to understand this concept.

Defining our Problem – How to Organize a Photo Gallery?

I have 2000+ photos in my smartphone right now. If I had been a selfie freak, the photo count would easily be 10 times more. Sifting through these photos is a nightmare, because every third photo turns out to be unnecessary and useless for me. I'm sure most of you will be able to relate to my plight!

Ideally, what I would want is an app which organizes the photos in such a manner that I can go through most of the photos and have a peek at it if I want. This would actually give me context as such of the different kinds of photos I have right now.

To get a clearer perspective of the problem, I went through my mobile and tried to identify the categories of the images by myself. Here are the insights I gathered:

- First and foremost, I found that one-third of my photo gallery is filled with **memes** (Thanks to my lovely friends on WhatsApp).

- I personally collect **interesting quotes / shares** I come across on Reddit. These are mostly motivational or funny, depending on which subreddit I downloaded them from.

- There are at least 200 images I captured, or my colleagues shared, of the famous **DataHack Summit** and the subsequent AV outing we had in Kerala

- There are a few photos of **whiteboard discussions** that happen frequently during meetings.

- Then there are a few **images/screenshots of code tracebacks/bugs** that require internal team discussions. They are a necessary evil that has to be purged after use.

- I also found dispersed **“private & personal” images**, such as selfies, group photos and a few objects/sceneries. They are few, but they are my prized possessions.

- Last but not the least – there were numerous **“good morning”, “happy birthday” and “happy diwali” posts** that I desperately want to delete from my gallery. No matter how much I exterminate them, they just keep coming back!

Now that you know the scenerio, can you think of the different ways to better organize my photos through an automated algorithm? You can discuss your thoughts on [this discussion thread](#).

In the below sections, we will discuss a few approaches I have come up with to solve this problem.

Approach 1 – Arrange on the basis of time

The simplest way is to arrange the photos on the basis of time. Each day could have a different folder for itself. Typically, most of the photo viewing apps use this approach (eg. Google Photos app).

The upside of this will be that all the events that happened on that day will be stored together. The downside of this approach is that it is too generic. Each day, I could have photos that are from an outing, or a motivational quote, etc. Both of them will be mixed together – which defeats the purpose altogether.

Approach 2 – Arrange on the basis of location

A comparatively better approach would be to arrange the photos based on where they were taken. So, for example, with each camera click we would capture where the image was taken. Then we can make folders on the basis of these locations – either country/city wise or locality wise, depending on the granularity we want. This approach is also being used by most photo apps.

The downside of this approach is the simplistic idea on which it was created. How can we define the location of a meme, or a cartoon – which takes a fair share of my image gallery? So this approach lacks ingenuity as well.

Approach 3 – Extract Semantic meaning from the image and use it to define my collection

The approaches we have seen so far were mostly dependent on the metadata that is captured along with the image. A better way to organize the photos would be to extract semantic information from the image itself and use that information intelligently.

Let's break this idea down into parts. Suppose we have a similar variety of photos (as mentioned above). What trends should our algorithm capture?

1. Is the captured image of a **natural scene** or is it an **artificially generated** image?
2. Is there **textual material** in the photograph? If there is – can we identify what it is?
3. What are the **different kinds of objects present** in the photograph? Do they combine to define the aesthetics of the image?
4. Are there **people present** in the photograph? Can we recognize them?
5. Are there **similar images on the web** which can help us identify the context of the image?

So our algorithm should ideally capture this information without explicitly tagging what is present and what is not, and use it to organize and segment our photos. Ideally, our final organized app could look like this:

This approach is what we call an "unsupervised way" to solve problems. We did not directly define the outcome that we want. Instead, we trained an algorithm to find those outcomes for us! Our algorithm summarizes the data in an intelligent manner, and then tries to solve the problem on the basis of these inferences. Pretty cool, right?

Now you may be wondering – how can we leverage Deep Learning for unsupervised learning problems?

As we saw in the case study above, by extracting semantic information from the image, we can get a better view of the similarity of images. Thus, our problem can be formulated as – *how can we reduce the dimensions of an image so that we can reconstruct the image back from these encoded representations?*

Here, we can use a deep learning architecture called **Auto Encoders.**

Let me give you a high level overview of Auto Encoders. The idea behind using this algorithm is that you are training it to recreate what it just learnt. But the catch is that it has to use a much smaller representation phase to recreate it.

For example, an Auto Encoder with encoding set to 10 is trained on images of cats, each of size 100×100. So the input dimension is 10,000, and the Auto Encoder has to represent all this information in a vector of size 10 (as seen in the image below).

An auto encoder can be logically divided into two parts: an encoder and a decoder. The task of the encoder is to convert the input to a lower dimensional representation, while the task of the decoder is to recreate the input from this lower dimensional representation.

This was a very high level overview of auto encoders. In the next article – we will look at them in more detail.

Note – This is more of a forewarning; but the current state-of-the-art methods still aren't mature enough to handle industry level problems with ease. Although research in this field is booming, it would take a few more years for our algorithms to become "industrially accepted".

Code Walkthrough of Unsupervised Deep Learning on MNIST data

Now that you have an intuition of solving unsupervised learning problems using deep learning – we will apply our knowledge on a real life problem. Here, we will take an example of the MNIST dataset – which is considered as the go-to dataset when trying our hand on deep learning problems. Let us understand the problem statement before jumping into the code.

The original problem statement is to identify individual digits from an image. You are given the labels of the digit that the image contains. But for our case study, we will try to ***figure out which of the images are similar to each other and cluster them into groups***. As a proxy, we will check the purity of these groups by inspecting their labels. You can find the data on AV's DataHack platform – the Identify the Digits practice problem.

We will perform three Unsupervised Learning techniques and check their performance, namely:

1. KMeans directly on image
2. KMeans + Autoencoder (a simple deep learning architecture)
3. Deep Embedded Clustering algorithm (advanced deep learning)

We will look into the details of these algorithms in another article. For the purposes of this post, let's see how we can attempt to solve this problem.

Before starting this experiment, make sure you have *Keras* installed in your system. Refer to the official installation guide. We will use *TensorFlow* for the backend, so make sure you have this in your config file. If not, follow the steps given here.

We will then use an open source implementation of DEC algorithm by Xifeng Guo. To set it up on your system, type the below commands in the command prompt:

```
git clone https://github.com/XifengGuo/DEC-keras cd DEC-keras
```

You can then fire up a Jupyter notebook and follow along with the code below.

First we will import all the necessary modules for our code walkthrough.

```
%pylab inline import os import keras import metrics import numpy as np import pandas as pd import keras.backend as K from time import time from keras import callbacks from keras.models import Model from keras.optimizers import SGD from keras.layers import Dense, Input from keras.initializers import VarianceScaling from keras.engine.topology import Layer, InputSpec from scipy.misc import imread from sklearn.cluster import KMeans from sklearn.metrics import accuracy_score, normalized_mutual_info_score
```

```
Populating the interactive namespace from numpy and matplotlib
```

We will then set a seed value to restrict randomness.

```
# To stop potential randomness seed = 128 rng = np.random.RandomState(seed)
```

Now set the working path of your data, so that you can access it later on.

```
root_dir = os.path.abspath('.') data_dir = os.path.join(root_dir, 'data', 'mnist')
```

Read the train and test files.

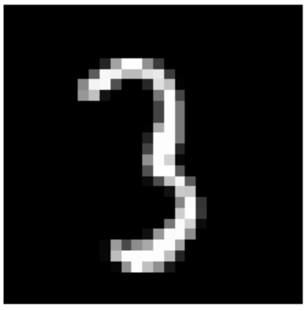
```
train = pd.read_csv(os.path.join(data_dir, 'train.csv')) test = pd.read_csv(os.path.join(data_dir, 'test.csv')) train.head()
```

	filename	label
0	0.png	4
1	1.png	9
2	2.png	1
3	3.png	7
4	4.png	3

Note that in this dataset, you have also been given the labels for each image. This is generally not seen in an unsupervised learning scenario. Here, we will use these labels to evaluate how our unsupervised learning models perform.

Now let us plot an image to view what our data looks like.

```
img_name = rng.choice(train.filename) filepath = os.path.join(data_dir, 'train', img_name) img = imread(filepath, flatten=True) pylab.imshow(img, cmap='gray') pylab.axis('off') pylab.show()
```



We will then read all the images and store them in a *numpy* array to create a train and test file.

```
temp = [] for img_name in train.filename: image_path = os.path.join(data_dir, 'train', img_name) img = imread(image_path, flatten=True) img = img.astype('float32') temp.append(img) train_x = np.stack(temp) train_x /= 255.0 train_x = train_x.reshape(-1, 784).astype('float32') temp = [] for img_name in test.filename: image_path = os.path.join(data_dir, 'test', img_name) img = imread(image_path, flatten=True) img = img.astype('float32') temp.append(img) test_x = np.stack(temp) test_x /= 255.0 test_x = test_x.reshape(-1, 784).astype('float32')
```

```
train_y = train.label.values
```

We will then divide our training data into train and validation set.

```
split_size = int(train_x.shape[0]*0.7) train_x, val_x = train_x[:split_size], train_x[split_size:] train_y, val_y = train_y[:split_size], train_y[split_size:]
```

We will first apply K-Means directly to our image and divide it into 10 clusters.

```
km = KMeans(n_jobs=-1, n_clusters=10, n_init=20)
```

```
km.fit(train_x)
```

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300, n_clusters=10, n_init=20, n_jobs=-1, precompute_distances='auto', random_state=None, tol=0.0001, verbose=0)
```

Now that we have trained our model, let's see how it performs on the validation set.

```
pred = km.predict(val_x)
```

We will use Normalized Mutual Information (NMI) score to evaluate our model.

Mutual information is a symmetric measure for the degree of dependency between the clustering and the manual classification. It is based on the notion of cluster purity pi, which measures the quality of a single cluster Ci, the largest number of objects in cluster Ci which Ci has in common with a manual class Mj, having compared Ci to all manual classes in M. Because NMI is normalized, we can use it to compare clusterings with different numbers of clusters.

The formula for NMI is:

Source: Slideshare

```
normalized_mutual_info_score(val_y, pred)
```

```
0.4978202013979692
```

Now instead of directly applying K-Means on the problem, we will first use an autoencoder to decrease the dimensionality of the data and extract useful information. This will then pass on the information to the K-Means algorithm.

```
# this is our input placeholder input_img = Input(shape=(784,)) # "encoded" is the encoded representation of the input encoded = Dense(500, activation='relu')(input_img) encoded = Dense(500, activation='relu')(encoded) encoded = Dense(2000, activation='relu')(encoded) encoded = Dense(10, activation='sigmoid')(encoded) # "decoded" is the lossy reconstruction of the input decoded = Dense(2000, activation='relu')(encoded) decoded = Dense(500, activation='relu')(decoded) decoded = Dense(500, activation='relu')(decoded) decoded = Dense(784)(decoded) # this model maps an input to its reconstruction autoencoder = Model(input_img, decoded)
```

```
autoencoder.summary()
```

```
_________________________________________________________________ Layer (type) Output Shape Param # ================================================================= input_1 (InputLayer) (None, 784) 0 _________________________________________________________________ dense_2 (Dense) (None, 500) 392500 _________________________________________________________________ dense_3 (Dense) (None, 500) 250500 _________________________________________________________________ dense_4 (Dense) (None, 2000) 1002000 _________________________________________________________________ dense_5 (Dense) (None, 10) 20010 _________________________________________________________________ dense_6 (Dense) (None, 2000) 22000 _________________________________________________________________ dense_7 (Dense) (None, 500) 1000500 _________________________________________________________________ dense_8 (Dense) (None, 500) 250500 _________________________________________________________________ dense_9 (Dense) (None, 784) 392784 ================================================================= Total params: 3,330,794 Trainable params: 3,330,794 Non-trainable params: 0 _________________________________________________________________
```

```
# this model maps an input to its encoded representation encoder = Model(input_img, encoded)
```

```
autoencoder.compile(optimizer='adam', loss='mse')
```

Now let us train our autoencoder model.

```
train_history = autoencoder.fit(train_x, train_x, epochs=500, batch_size=2048, validation_data=(val_x, val_x))
```

```
Train on 34300 samples, validate on 14700 samples Epoch 1/500 34300/34300 [==============================] - 2s 60us/step - loss: 0.0805 - val_loss: 0.0666 ... Epoch 494/500 34300/34300 [==============================] - 0s 11us/step - loss: 0.0103 - val_loss: 0.0138 Epoch 495/500 34300/34300 [==============================] - 0s 10us/step - loss: 0.0103 - val_loss: 0.0138 Epoch 496/500 34300/34300 [==============================] - 0s 11us/step - loss: 0.0103 - val_loss: 0.0138 Epoch 497/500 34300/34300 [==============================] - 0s 11us/step - loss: 0.0103 - val_loss: 0.0139 Epoch 498/500 34300/34300 [==============================] - 0s 11us/step - loss: 0.0103 - val_loss: 0.0137 Epoch 499/500 34300/34300 [==============================] - 0s 11us/step - loss: 0.0103 - val_loss: 0.0139 Epoch 500/500 34300/34300 [==============================] - 0s 11us/step - loss: 0.0104 - val_loss: 0.0138
```

```
pred_auto_train = encoder.predict(train_x) pred_auto = encoder.predict(val_x)
```

```
km.fit(pred_auto_train) pred = km.predict(pred_auto)
```

```
normalized_mutual_info_score(val_y, pred)
```

```
0.7435578557037037
```

We see that our combined Autoencoder and K-Means model performs better than an individual K-Means model.
Finally, we will see the implementation of a state-of-the-art model – known as DEC algorithm. This algorithm trains both clustering and autoencoder models to get better performance. You can go through this paper to get a better perspective – [Junyuan Xie, Ross Girshick, and Ali Farhadi. Unsupervised deep embedding for clustering analysis. ICML 2016.]

```
""" Keras implementation for Deep Embedded Clustering (DEC) algorithm: Original Author: Xifeng Guo. 2017.1.30 """ def autoencoder(dims, act='relu', init='glorot_uniform'): """ Fully connected auto-encoder model, symmetric. Arguments: dims: list of number of units in each layer of encoder. dims[0] is input dim, dims[-1] is units in hidden layer. The decoder is symmetric with encoder. So number of layers of the auto-encoder is 2*len(dims)-1 act: activation, not applied to Input, Hidden and Output layers return: (ae_model, encoder_model), Model of autoencoder and model of encoder """ n_stacks = len(dims) - 1 # input x = Input(shape=(dims[0],), name='input') h = x # internal layers in encoder for i in range(n_stacks-1): h = Dense(dims[i + 1], activation=act, kernel_initializer=init, name='encoder_%d' % i)(h) # hidden layer h = Dense(dims[-1], kernel_initializer=init, name='encoder_%d' % (n_stacks - 1))(h) # hidden layer, features are extracted from here y = h # internal layers in decoder for i in range(n_stacks-1, 0, -1): y = Dense(dims[i], activation=act, kernel_initializer=init, name='decoder_%d' % i)(y) # output y = Dense(dims[0], kernel_initializer=init, name='decoder_0')(y) return Model(inputs=x, outputs=y, name='AE'), Model(inputs=x, outputs=h, name='encoder') class ClusteringLayer(Layer): """ Clustering layer converts input sample (feature) to soft label, i.e. a vector that represents the probability of the sample belonging to each cluster. The probability is calculated with student's t-distribution. # Example ``` model.add(ClusteringLayer(n_clusters=10)) ``` # Arguments n_clusters: number of clusters. weights: list of Numpy array with shape `(n_clusters, n_features)` witch represents the initial cluster centers. alpha: parameter in Student's t-distribution. Default to 1.0. # Input shape 2D tensor with shape: `(n_samples, n_features)`. # Output shape 2D tensor with shape: `(n_samples, n_clusters)`. """ def __init__(self,
```

n_clusters, weights=None, alpha=1.0, **kwargs): if 'input_shape' not in kwargs and 'input_dim' in kwargs: kwargs['input_shape'] = (kwargs.pop('input_dim'),) super(ClusteringLayer, self).__init__(**kwargs) self.n_clusters = n_clusters self.alpha = alpha self.initial_weights = weights self.input_spec = InputSpec(ndim=2) def build(self, input_shape): assert len(input_shape) == 2 input_dim = input_shape[1] self.input_spec = InputSpec(dtype=K.floatx(), shape=(None, input_dim)) self.clusters = self.add_weight((self.n_clusters, input_dim), initializer='glorot_uniform', name='clusters') if self.initial_weights is not None: self.set_weights(self.initial_weights) del self.initial_weights self.built = True def call(self, inputs, **kwargs): """ student t-distribution, as same as used in t-SNE algorithm. q_ij = 1/(1+dist(x_i, u_j)^2), then normalize it. Arguments: inputs: the variable containing data, shape=(n_samples, n_features) Return: q: student's t-distribution, or soft labels for each sample. shape=(n_samples, n_clusters) """ q = 1.0 / (1.0 + (K.sum(K.square(K.expand_dims(inputs, axis=1) - self.clusters), axis=2) / self.alpha)) q **= (self.alpha + 1.0) / 2.0 q = K.transpose(K.transpose(q) / K.sum(q, axis=1)) return q def compute_output_shape(self, input_shape): assert input_shape and len(input_shape) == 2 return input_shape[0], self.n_clusters def get_config(self): config = {'n_clusters': self.n_clusters} base_config = super(ClusteringLayer, self).get_config() return dict(list(base_config.items()) + list(config.items())) class DEC(object): def __init__(self, dims, n_clusters=10, alpha=1.0, init='glorot_uniform'): super(DEC, self).__init__() self.dims = dims self.input_dim = dims[0] self.n_stacks = len(self.dims) - 1 self.n_clusters = n_clusters self.alpha = alpha self.autoencoder, self.encoder = autoencoder(self.dims, init=init) # prepare DEC model clustering_layer = ClusteringLayer(self.n_clusters, name='clustering')(self.encoder.output) self.model = Model(inputs=self.encoder.input, outputs=clustering_layer) def pretrain(self, x, y=None, optimizer='adam', epochs=200, batch_size=256, save_dir='results/temp'): print('...Pretraining...') self.autoencoder.compile(optimizer=optimizer, loss='mse') csv_logger = callbacks.CSVLogger(save_dir + '/pretrain_log.csv') cb = [csv_logger] if y is not None: class PrintACC(callbacks.Callback): def __init__(self, x, y): self.x = x self.y = y super(PrintACC, self).__init__() def on_epoch_end(self, epoch, logs=None): if epoch % int(epochs/10) != 0: return feature_model = Model(self.model.input, self.model.get_layer('encoder_%d' % (int(len(self.model.layers) / 2) - 1)).output) features = feature_model.predict(self.x) km = KMeans(n_clusters=len(np.unique(self.y)), n_init=20, n_jobs=4) y_pred = km.fit_predict(features) # print() print(' '*8 + '|==> acc: %.4f, nmi: %.4f <==|' % (metrics.acc(self.y, y_pred), metrics.nmi(self.y, y_pred))) cb.append(PrintACC(x, y)) # begin pretraining t0 = time() self.autoencoder.fit(x, x, batch_size=batch_size, epochs=epochs, callbacks=cb) print('Pretraining time: ', time() - t0) self.autoencoder.save_weights(save_dir + '/ae_weights.h5') print('Pretrained weights are saved to %s/ae_weights.h5' % save_dir) self.pretrained = True def load_weights(self, weights): # load weights of DEC model self.model.load_weights(weights) def extract_features(self, x): return self.encoder.predict(x) def predict(self, x): # predict cluster labels using the output of clustering layer q = self.model.predict(x, verbose=0) return q.argmax(1) @staticmethod def target_distribution(q): weight = q ** 2 / q.sum(0) return (weight.T / weight.sum(1)).T def compile(self, optimizer='sgd', loss='kld'): self.model.compile(optimizer=optimizer, loss=loss) def fit(self, x, y=None, maxiter=2e4, batch_size=256, tol=1e-3, update_interval=140, save_dir='./results/temp'): print('Update interval', update_interval) save_interval = x.shape[0] / batch_size * 5 # 5 epochs print('Save interval', save_interval) # Step 1: initialize cluster centers using k-means t1 = time() print('Initializing cluster centers with k-means.') kmeans = KMeans(n_clusters=self.n_clusters, n_init=20) y_pred = kmeans.fit_predict(self.encoder.predict(x)) y_pred_last = np.copy(y_pred) self.model.get_layer(name='clustering').set_weights([kmeans.cluster_centers_]) # Step 2: deep clustering # logging file import csv logfile = open(save_dir + '/dec_log.csv', 'w') logwriter = csv.DictWriter(logfile, fieldnames=['iter', 'acc', 'nmi', 'ari', 'loss']) logwriter.writeheader() loss = 0 index = 0 index_array = np.arange(x.shape[0]) for ite in range(int(maxiter)): if ite % update_interval == 0: q = self.model.predict(x, verbose=0) p = self.target_distribution(q) # update the auxiliary target distribution p # evaluate the clustering performance y_pred = q.argmax(1) if y is not None: acc = np.round(metrics.acc(y, y_pred), 5) nmi = np.round(metrics.nmi(y, y_pred), 5) ari = np.round(metrics.ari(y, y_pred), 5) loss = np.round(loss, 5) logdict = dict(iter=ite, acc=acc, nmi=nmi, ari=ari, loss=loss) logwriter.writerow(logdict) print('Iter %d: acc = %.5f, nmi = %.5f, ari = %.5f' % (ite, acc, nmi, ari), ' ; loss=', loss) # check stop criterion delta_label = np.sum(y_pred != y_pred_last).astype(np.float32) / y_pred.shape[0] y_pred_last = np.copy(y_pred) if ite > 0 and delta_label < tol: print('delta_label ', delta_label, '< tol ', tol) print('Reached tolerance threshold. Stopping training.') logfile.close() break # train on batch # if index == 0: # np.random.shuffle(index_array) idx = index_array[index * batch_size:

min((index+1) * batch_size, x.shape[0])] self.model.train_on_batch(x=x[idx], y=p[idx]) index = index + 1 if (index + 1) * batch_size <= x.shape[0] else 0 # save intermediate model if ite % save_interval == 0: print('saving model to:', save_dir + '/DEC_model_' + str(ite) + '.h5') self.model.save_weights(save_dir + '/DEC_model_' + str(ite) + '.h5') ite += 1 # save the trained model logfile.close() print('saving model to:', save_dir + '/DEC_model_final.h5') self.model.save_weights(save_dir + '/DEC_model_final.h5') return y_pred # setting the hyper parameters init = 'glorot_uniform' pretrain_optimizer = 'adam' dataset = 'mnist' batch_size = 2048 maxiter = 2e4 tol = 0.001 save_dir = 'results' import os if not os.path.exists(save_dir): os.makedirs(save_dir) update_interval = 200 pretrain_epochs = 500 init = VarianceScaling(scale=1. / 3., mode='fan_in', distribution='uniform') # [-limit, limit], limit=sqrt(1./fan_in) #pretrain_optimizer = SGD(lr=1, momentum=0.9) # prepare the DEC model dec = DEC(dims=[train_x.shape[-1], 500, 500, 2000, 10], n_clusters=10, init=init) dec.pretrain(x=train_x, y=train_y, optimizer=pretrain_optimizer, epochs=pretrain_epochs, batch_size=batch_size, save_dir=save_dir)

...Pretraining... Epoch 1/500 ... Epoch 494/500 34300/34300 [==============================] - 0s 8us/step - loss: 0.0086 Epoch 495/500 34300/34300 [==============================] - 0s 8us/step - loss: 0.0086 Epoch 496/500 34300/34300 [==============================] - 0s 9us/step - loss: 0.0085 Epoch 497/500 34300/34300 [==============================] - 0s 9us/step - loss: 0.0085 Epoch 498/500 34300/34300 [==============================] - 0s 9us/step - loss: 0.0086 Epoch 499/500 34300/34300 [==============================] - 0s 8us/step - loss: 0.0085 Epoch 500/500 34300/34300 [==============================] - 0s 8us/step - loss: 0.0085 Pretraining time: 183.56538462638855 Pretrained weights are saved to results/ae_weights.h5

dec.model.summary()

____ Layer (type) Output Shape Param # === input (InputLayer) (None, 784) 0 ____ encoder_0 (Dense) (None, 500) 392500 ____ encoder_1 (Dense) (None, 500) 250500 ____ encoder_2 (Dense) (None, 2000) 1002000 ____ encoder_3 (Dense) (None, 10) 20010 ____ clustering (ClusteringLayer) (None, 10) 100 === Total params: 1,665,110 Trainable params: 1,665,110 Non-trainable params: 0 ____

dec.compile(optimizer=SGD(0.01, 0.9), loss='kld')

y_pred = dec.fit(train_x, y=train_y, tol=tol, maxiter=maxiter, batch_size=batch_size, update_interval=update_interval, save_dir=save_dir)

... Iter 3400: acc = 0.79621, nmi = 0.77514, ari = 0.71296 ; loss= 0 delta_label 0.0007288629737609329 < tol 0.001 Reached tolerance threshold. Stopping training. saving model to: results/DEC_model_final.h5

pred_val = dec.predict(val_x)

normalized_mutual_info_score(val_y, pred_val)

0.7651617433541817

As you can see, this gives us the best performance as compared to the methods we have covered above. Researchers have seen that further training of a DEC model can give us even higher performances (NMI as high as 87 to be exact!).

End Notes

In this article, we saw an overview of the concept of unsupervised deep learning with an intuitive case study. In the next series of articles, we will get into the details of how we can use these techniques to solve more real life problems.

If you have any comments / suggestions, feel free to reach out to me below!

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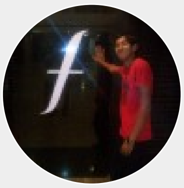
Article Url - https://www.analyticsvidhya.com/blog/2018/05/essentials-of-deep-learning-trudging-into-unsupervised-deep-learning/



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