

Machine Learning Engineer Nanodegree

Transfer learning: comparison of VGG16, Resnet and Inception networks performance for image recognition

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I. Definition

Project Overview

Transfer learning is the improvement of learning in a new task through the transfer of knowledge from a task that has already been learned.

We can see the concept of transfer learning in the real world, when a person tries to learn a new task, that person is going to use previously acquired concept to accelerate the process of learning. Learning to play the guitar is going to be an relatively easier task for a person who has an extensive experience playing music.

Most of the time, obtaining training data is an expensive task, this is one of the reasons to use Transfer Learning of a big previously acquired dataset [1] to a new task. Transfer Learning becomes increasingly important if we take into consideration that the “state-of-the-art” models are trained for months using high performance computers. [2] [3]

Image recognition is the task of determining whether or not a image contains a specific object or not. There has been a boom of startups using this technology to solve real life problems. [4] Currently the best algorithms to solve the task are Convolutional Neural Networks [1].

This capstone aims to provide a comparison of the performance of several pre-trained models for the task of image recognition. Can transfer learning be applied to an image recognition task? The findings of this capstone would be invaluable for people who either do not have the monetary resources or the time to train a model from scratch.

As I started to compete on kaggle competitions, I was wondering if it would be better to train my own models from scratch on each competition’s dataset or re-train one of the models trained on a big dataset like ImageNet. This capstone aims to answer this question. It is going to be show that re-training achieves better results.

The dataset to be used contains 25,000 images of dogs and cats and can be obtained in the Kaggle’s Competition site: <https://www.kaggle.com/c/dogs-vs-cats-redux-kernels-edition/data>.

This capstone also use the “weights” (knowledge) of the pretrained models on the ImageNet dataset, these weights files are listed below:

- VGG: <https://goo.gl/go2y7h>
- Resnet50: <https://goo.gl/MuftHu>
- Inverption V3: <https://goo.gl/R0Ig5B>

Problem Statement

The objective of this capstone is to compare the accuracy obtained by state-of-the-art Convolutional Neural Networks using the technique know as transfer of learning. The pretrained convolutional neural networks to be used are VGG16, Reasnet50 and Inception V3. All this models has been trained with the ImageNet dataset[1] . These networks are going to be applied to solve the Kaggle’s Dogs vs. Cats competition. A small CNN trained directly on the Cats and Dogs dataset is going to be used as a becnhmark.

The aim of the capstone is to give a comparison of the performance obtained by the pre trained models on the dataset of Cats and Dogs. As a new kaggle competitor, people ask themselves if it is better to train their own models or to re-train a previously trained model.

Although transfer of learning has been addressed by several papers: [https://arxiv.org/pdf/1411.1792v1.pdf], [https://arxiv.org/pdf/1403.6382.pdf] and [https://arxiv.org/pdf/1310.1531.pdf], this capstone has a more practical approach. Is going to shown experimentally that in general is better to re-train a previously trained model, taking advantage of the features already learned by the model.

Metrics

The evaluation metric is going to be the one used in the kaggle’s competition “Cats and Dogs” (the one used for the input dataset), a logaritmhc loss function. This can be calculated with the following formula:

$$LogLoss = -\frac{1}{n} \sum_{i=1}^n [y_i \log(p_i) + (1 - y_i) \log(1 - p_i)]$$

where

n is the number of images in the test set

pi is the predicted probability of the image being a dog

yi is 1 if the image is a dog, 0 if cat

log() is the natural (base e) logarithm

In order to calculate the logarithmic loss, the classifier implemented has assign a probability to each predicted class, in contrast to just yielding the predicted class.

II. Analysis

Data Exploration

All the code used to obtained the metrics showed in this section can be found in the following link: <https://goo.gl/pXMz8K>.

There are 25000 images in the dataset. The train directory consist of labelled data with the following convention for each image: data/train/CLASS.id.jpg. The class of each image is given in the file name. In this capstone keras.preprocessing.image library is going to be used, to do so, we need the folder structure to be: data/train/CLASS/image-name.jpg. Figure 1 shows some metadata of the five first entries of the dataset, we can see the filename convention and each class.

In [7]: `df.head()`

Out[7]:

	fpath	h	w	category
0	../data/original_train/dog.11385.jpg	372	500	dog
1	../data/original_train/cat.12119.jpg	499	474	cat
2	../data/original_train/dog.2388.jpg	270	359	dog
3	../data/original_train/cat.2564.jpg	143	135	cat
4	../data/original_train/cat.4640.jpg	296	400	cat

Figure 1: Sample table of the dataset showing the first five entries.

Image 2 gives some metrics of the image. We can see that the mean size of the images is (360.478080,404.09904). The smallest height is 32 pixels and the smallest width is 42 pizels.

Figure 3 and Figure 4 show a sample of the images to be used in the capstone, this is useful to know whitth what we are going to be dealing.

The are nomajor anormalities beside the stadistics shown in this section, one thing to mention is that there are some images that contain some other object besides cats and dogs, an example can be shown in Figure 5.

	h	w
count	25000.000000	25000.000000
mean	360.478080	404.09904
std	97.019959	109.03793
min	32.000000	42.000000
25%	301.000000	323.000000
50%	374.000000	447.000000
75%	421.000000	499.000000
max	768.000000	1050.000000

Figure 2: Metrics of the dataset.

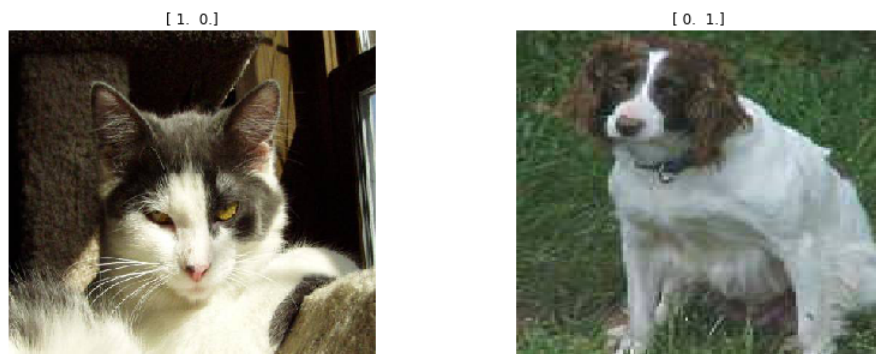


Figure 3: Sample table of the dataset showing the first five entries.



Figure 4: Sample table of the dataset showing the first five entries.

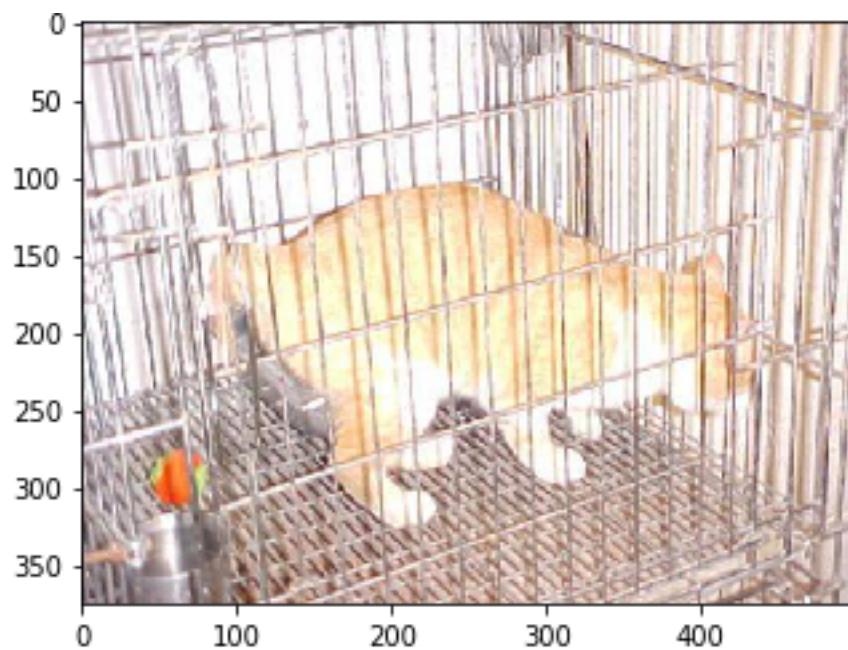


Figure 5: Sample table of the dataset showing the first five entries.

Algorithms and Techniques

To conduct transfer learning, the pre-trained weights of three models were used. These three models are InceptionV3, ResNet50 and Vgg16. Although we are not going to enter in detail, these models have several layers of convolution and pooling (and several other operations) with different network's architecture.

The "weights" (knowledge) of the models used in this capstone, where pretrained on the ImageNet dataset, the weights files used are listed below:

- VGG: <https://goo.gl/go2y7h>
- Resnet50: <https://goo.gl/MuftHu>
- Inception V3: <https://goo.gl/R0Ig5B>

The process used to transfer the learned features of the CNN to the new domain is the same for every pre-trained CNN. The main steps are explained below:

1. Create the model's network architecture and load the weight file. In this step we are not going to create the "classification" head of the original network, only the CNN layers are created. All these layers are set to be NON trainable.
2. On top of the network created in the step one, a small Fully Connected Network was connected with the objective to classify the images.
3. We feed our complete network with the images from the Cats and Dogs data set. The CNN uses its weights to compute pre-learned useful features. The FCN receives these "features" computed by the pre-trained CNN and try to use these features to predict image in the new domain.

We repeat these process by several epochs.

4. Once we have our FCN classifier fully trained, we set the last layers of the CNN to be "trainable". Set the learning rate to a lower value and feed the complete network. This way we slightly modify the weights of the last layers of the CNN to be tuned with the new dataset.

A CNN completely trained on the Dogs and Cats dataset was used. The architecture of the network can be seen in Figure 6.

Benchmark

The benchmark used was the results of the logarithmic loss obtained by the CNN trained from scratch on the data set of Cats and Dogs. The CNN architecture

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 360, 404, 3)	0
conv2d_1 (Conv2D)	(None, 358, 402, 16)	448
max_pooling2d_1 (MaxPooling2)	(None, 178, 200, 16)	0
conv2d_2 (Conv2D)	(None, 176, 198, 32)	4640
max_pooling2d_2 (MaxPooling2)	(None, 88, 99, 32)	0
conv2d_3 (Conv2D)	(None, 86, 97, 64)	18496
max_pooling2d_3 (MaxPooling2)	(None, 43, 48, 64)	0
conv2d_4 (Conv2D)	(None, 41, 46, 128)	73856
max_pooling2d_4 (MaxPooling2)	(None, 20, 23, 128)	0
flatten_1 (Flatten)	(None, 58880)	0
dense_1 (Dense)	(None, 96)	5652576
dense_2 (Dense)	(None, 2)	194
Total params: 5,750,210.0		
Trainable params: 5,750,210.0		
Non-trainable params: 0.0		

Figure 6: Convolutional Neural Network used as benchmark.

used can be seen in figure 6. More information about the metric calculation can be obtained in the subsection “Metrics” of section 1.

The results obtained using the benchmark CNN are the following:

	LogLoss	Accuracy
Benchmark CNN	0.17	0.87

To have a reference point in the confusion matrix given of the other models, the confusion matrix of this model is given below:

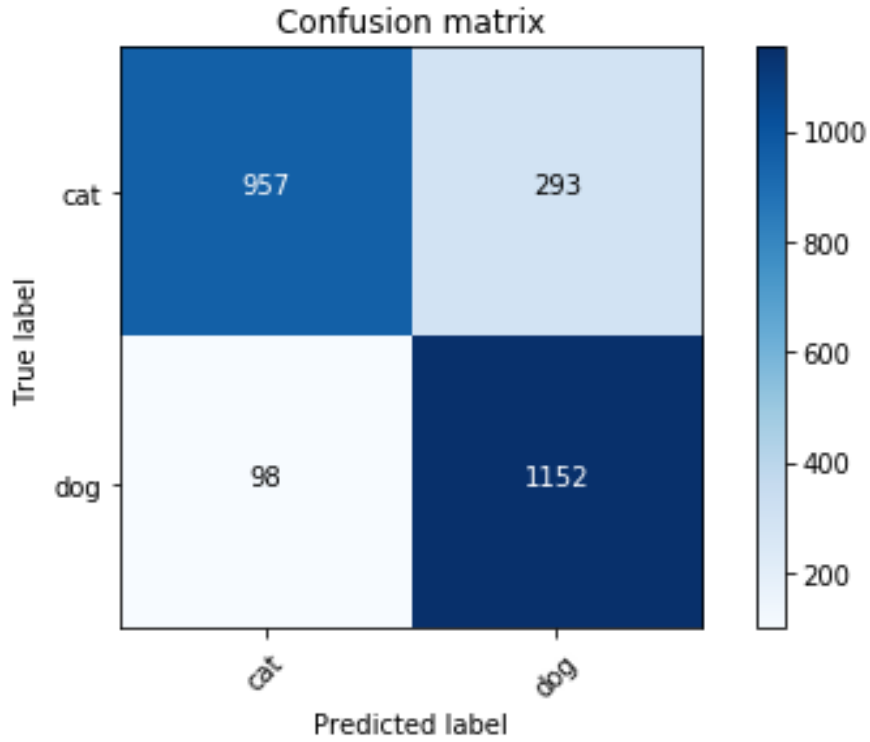


Figure 7: Confusion matrix of the benchmark model results.

III. Methodology

Data Preprocessing

The dataset consist of labelled data with the following convention for each image:

data/train/CLASS.id.jpg

The class of each image is given in the file name. In this capstone keras.preprocessing.image library is going to be used, to do so, we need the folder structure to be:

```
data/train/CLASS/image-name.jpg.
```

An script was written to convert between the two formats. It can be found in the repository of the project.

There was not need to preprocess the images of the dataset. The only preprocessing technique applied to the images was normalization, each value of each RGB image was divided by 255.

The technique of data augmentation was also used during the training step. During this step of data augmentation, the techniques used where to flip the images horizontally. Shear and zoom with an angle of 0.2 radians was also used.

Implementation

All the implementation was done using the keras labrary with tensorflow as a backend.

The implementation of the convolutional neural network used to obtain the benchmark is documented in the following code snippet:

```
inputs = Input(shape = (IMAGE_SIZE[0], IMAGE_SIZE[1], 3))

# First CNN Layer
x = Convolution2D(16, (3, 3),
                  activation='relu',
                  data_format="channels_last",
                  kernel_initializer="he_uniform")(inputs)

x = MaxPooling2D(pool_size=(3, 3),
                  strides=(2, 2),
                  data_format="channels_last")(x)

# Second CNN Layer
x = Convolution2D(32, (3, 3),
                  activation='relu',
                  data_format="channels_last",
                  kernel_initializer="he_uniform")(x)

x = MaxPooling2D(pool_size=(2, 2),
                  strides=(2, 2),
                  data_format="channels_last")(x)
```

```

# Third CNN Layer
x = Convolution2D(64, (3, 3),
                  activation='relu',
                  data_format="channels_last",
                  kernel_initializer="he_uniform")(x)
x = MaxPooling2D(pool_size=(2, 2),
                 strides=(2, 2),
                 data_format="channels_last")(x)

# 4 CNN Layer
x = Convolution2D(128, (3, 3),
                  activation='relu',
                  data_format="channels_last",
                  kernel_initializer="he_uniform")(x)
x = MaxPooling2D(pool_size=(2, 2),
                 strides=(2, 2),
                 data_format="channels_last")(x)

x = Flatten()(x)

x = Dense(96, activation='relu', kernel_initializer="he_uniform")(x)
predictions = Dense(2, activation='softmax')(x)

```

The creation and load of weights of the InceptionV3 model can be seen bellow:

```

from keras.applications.inception_v3 import InceptionV3
# create the base pre-trained model
base_model = InceptionV3(weights='imagenet', include_top=False)

```

The creation and load of weights of the ResNet50 model can be seen bellow:

```

from keras.applications.resnet50 import ResNet50
# create the base pre-trained model
base_model = ResNet50(weights='imagenet', include_top=False)

```

The creation and load of weights of the VGG16 model can be seen bellow:

```

from keras.applications.vgg16 import VGG16
# create the base pre-trained model
base_model = VGG16(weights='imagenet', include_top=False)

```

On top of each of the pre-trained convolutional networks a simple FCN was used as a classifier:

```
#####
# FCN layer
#####
from keras.layers import Dense, Dropout, GlobalAveragePooling2D
# add a global spatial average pooling layer
x = base_model.output
x = GlobalAveragePooling2D()(x)
# let's add a fully-connected layer
x = Dense(64, activation='relu')(x)
x = Dropout(0.3)(x)
# and a logistic layer
predictions = Dense(2, activation='softmax')(x)
```

Adding this FCN on top of each of the base models (the one already pre-trained) we obtain each network used in the capstone, the snippet of code below shows how this is done:

```
#####
# complete model
#####
from keras.models import Model
# this is the model we will train
model = Model(inputs=base_model.input, outputs=predictions)
```

Stochastic Gradient descent was used as an optimizer to train all the network, a snippet of code show how it was configured:

```
OPTIMIZER_LEARNING_RATE = 1e-2
OPTIMIZER_DECAY = 1e-4
OPTIMIZER_MOMENTUM = 0.89
OPTIMIZER_NESTEROV_ENABLED = False
from keras.optimizers import SGD
optimizer = SGD(lr=OPTIMIZER_LEARNING_RATE,
                decay=OPTIMIZER_DECAY,
                momentum=OPTIMIZER_MOMENTUM,
                nesterov=OPTIMIZER_NESTEROV_ENABLED)
```

The learning rate was decreased for the fine-tuning step.

During the development of the capstone, pre-computed features of each model were tried to be computed, with the idea of use this pre computed features as an input to the FCN. This technique proved complicated, because of the size of the dataset and the amount of RAM memory available in the system used to run the process.

IV. Results

Model Evaluation and Validation

VGG16 pre-trained results

The results obtained evaluation the pre-trained vgg16 model on the cats and dogs dataset are the following:

	LogLoss	Accuracy
Pre-trained VGG16	0.335	0.9

The confusion matrix can be seen in Figure 8. There are more errors classifying cats as dogs than dogs as cats.

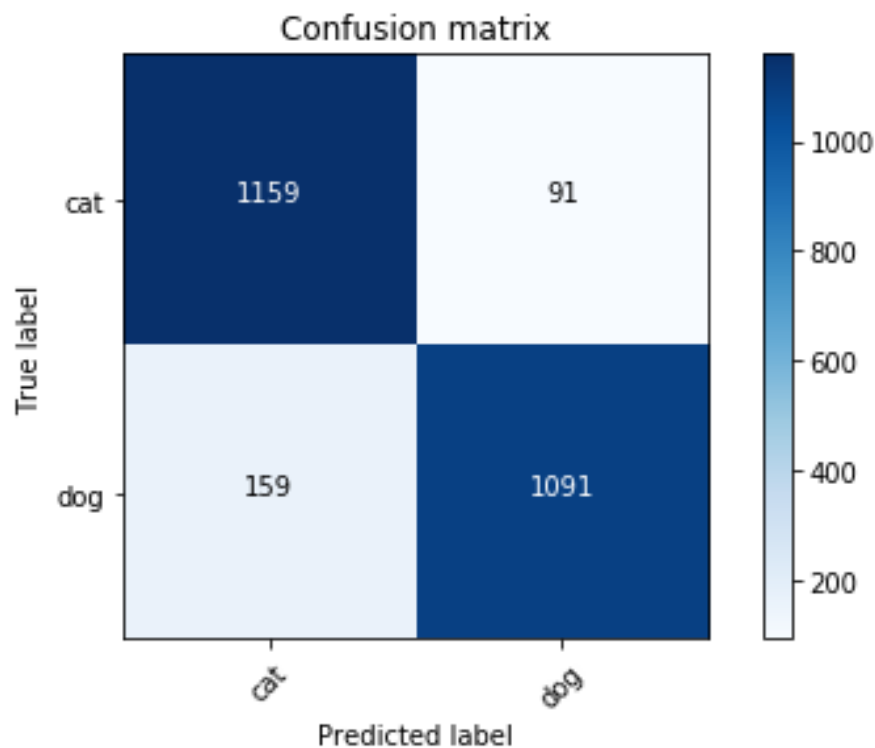


Figure 8: Confusion matrix of the VGG16 pre-trained model results.

A few examples of positive classification can be seen in Figure 9 and Figure 10.

A few examples of erroneous classification can be seen in Figure 11 and Figure 12. We can see that these are not particularly difficult examples.

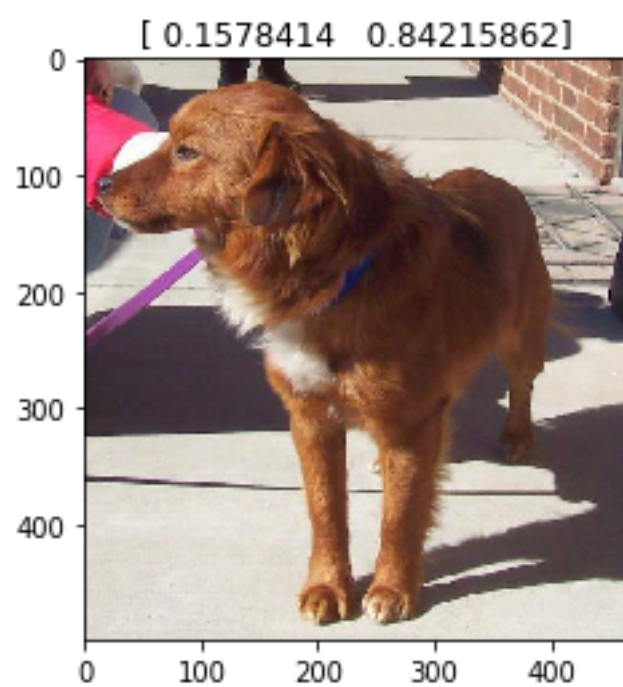


Figure 9: Confusion matrix of the VGG16 model results.



Figure 10: Confusion matrix of the VGG16 model results.

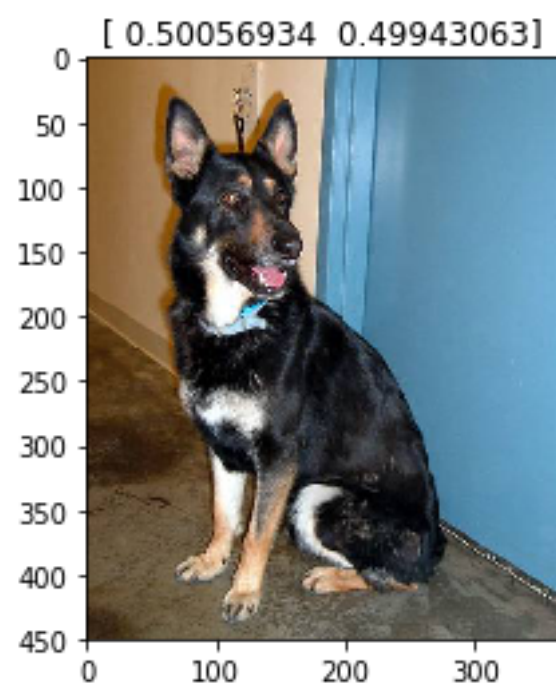


Figure 11: Confusion matrix of the VGG16 model results.

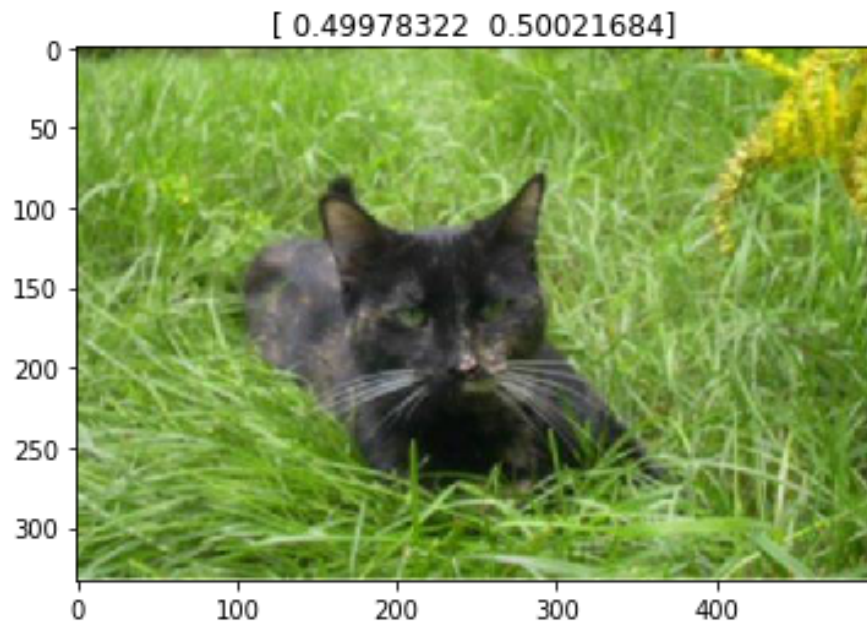


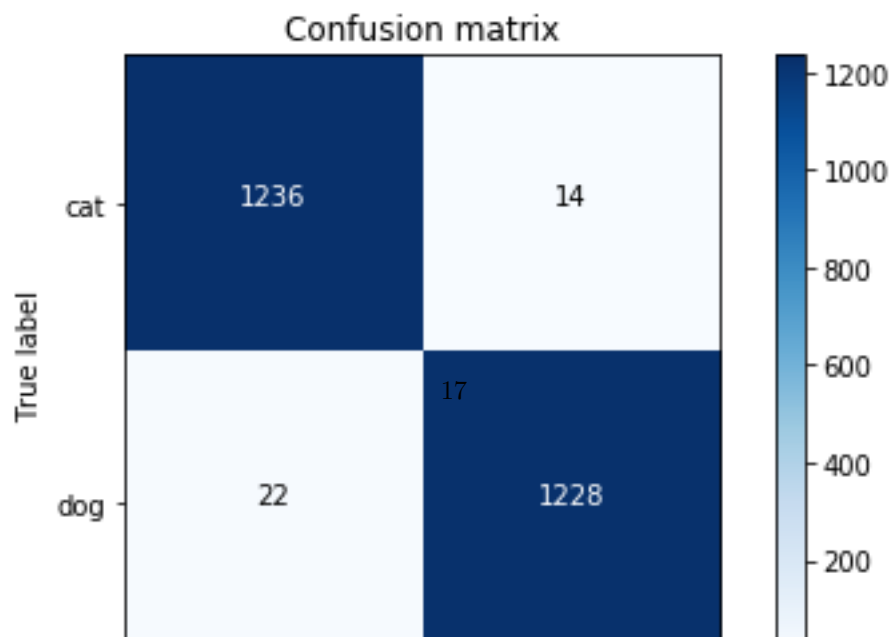
Figure 12: Confusion matrix of the VGG16 model results.

ResNet50 pre-trained results

This model was extremely successful with the new dataset. The results obtained evaluation the pre-trained ResNet50 model on the cats and dogs dataset are the following:

	LogLoss	Accuracy
Pretrained ResNet50	0.045	0.98

The confusion matrix can be seen in Figure 13. There are more errors classifying cats as dogs than dogs as cats.



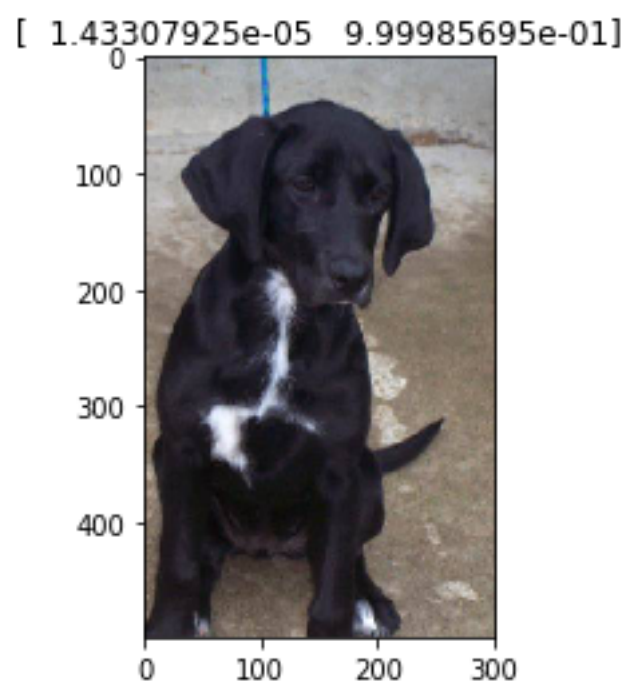


Figure 14: Confusion matrix of the ResNet50 model results.

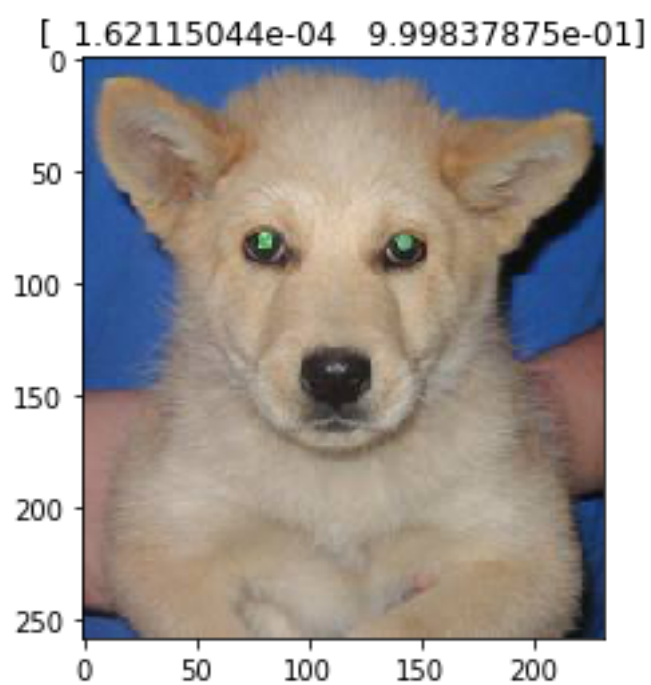


Figure 15: Confusion matrix of the ResNet50 model results.

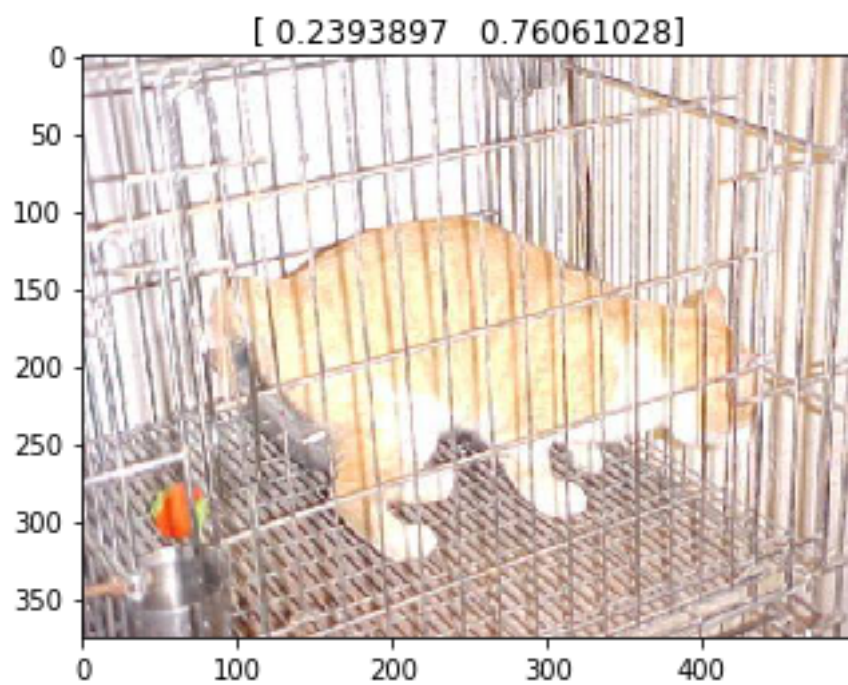


Figure 16: Confusion matrix of the ResNet50 model results.



Figure 17: Confusion matrix of the ResNet50 model results.

InceptionV3 pre-trained results

This model was extremely successful with the new dataset. The results obtained evaluation the pre-trained InceptionV3 model on the cats and dogs dataset are the following:

	LogLoss	Accuracy
Pretrained InceptionV3	0.046	0.97

The confusion matrix can be seen in Figure 18. There are more errors classifying cats as dogs than dogs as cats.

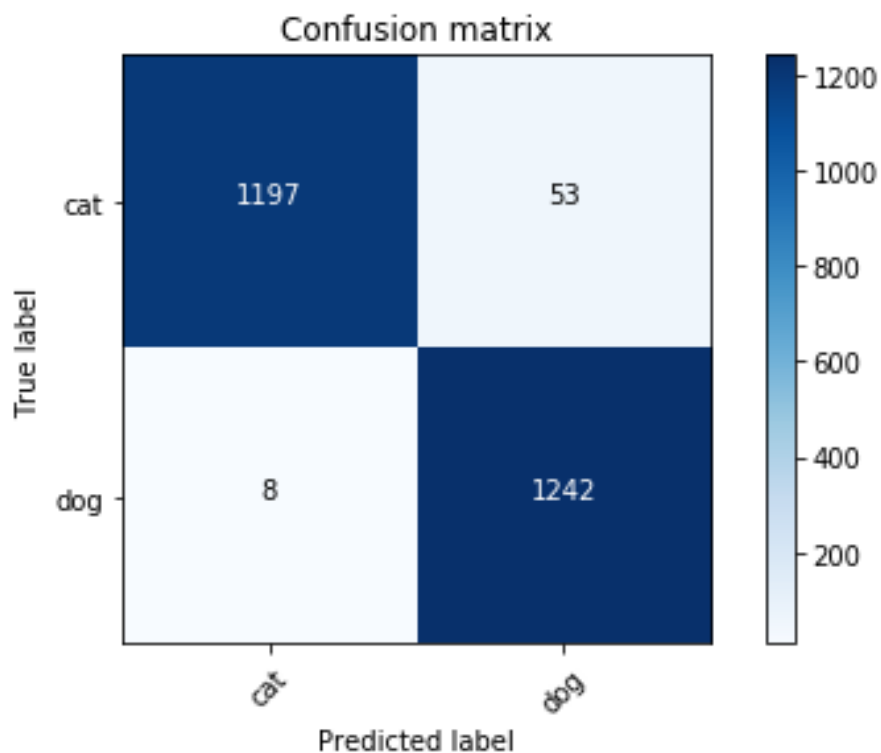


Figure 18: Confusion matrix of the InceptionV3 pre-trained model results.

Afew examples of positive classification can be seen in Figure 19 and Figure 20.

Afew examples of erroneous classification can be seen in Figure 21 and Figure 22. We can see that these are not particularly difficult examples.

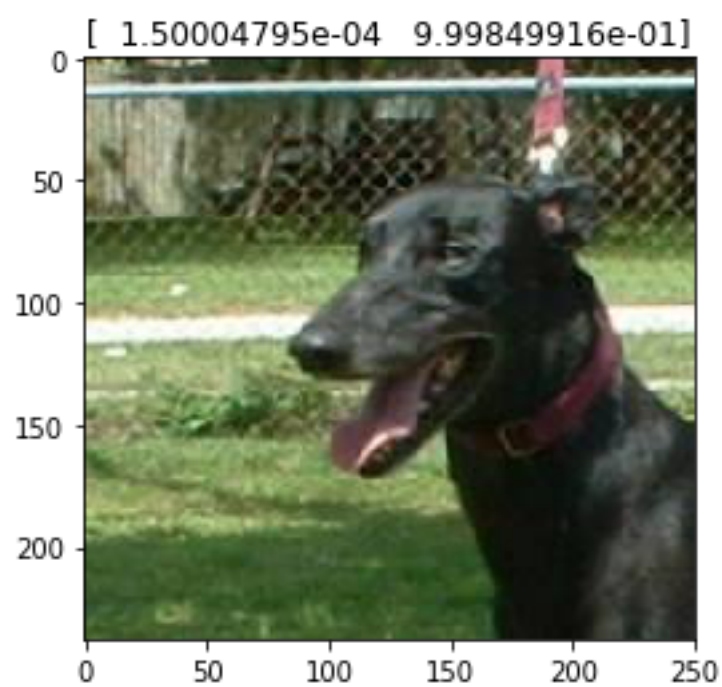


Figure 19: Confusion matrix of the InceptionV3 model results.

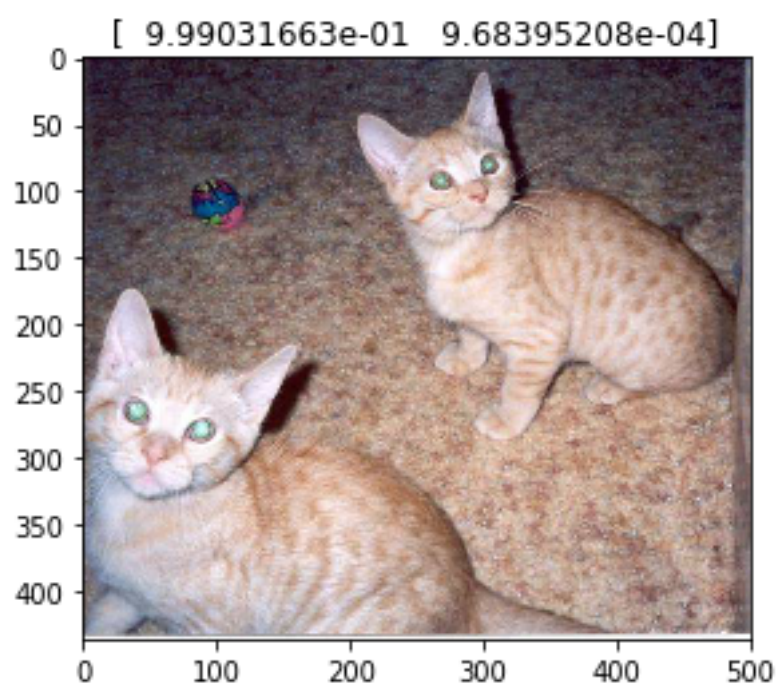


Figure 20: Confusion matrix of the InceptionV3 model results.



Figure 21: Confusion matrix of the InceptionV3 model results.



Figure 22: Confusion matrix of the InceptionV3 model results.

Justification

We offer a comparison of the results obtained using the benchmark model and the pre-trained models. These results were obtained in a test dataset not seen before by any of the model.

	LogLoss	Accuracy
Benchmark CNN	0.358	0.87
Pre-trained VGG16	0.335	0.9
Pretrained ResNet50	0.045	0.98
Pretrained InceptionV3	0.046	0.97

Although the VGG16 pre-trained model offer an improve over the benchmark model, the pre-trained InceptionV3 and ResNet50 models show an improve by an order of magnitud. We have seen that the errors commited by these two models are really difficult images.

V. Conclusion

Reflection

In this capstone we have created and trained a model from scratch and used the predictions on the test dataset as a benchmark. Despite of being good results, best performance can be obtained using transfer learning. With regard with transfer learning, we have shown three pre-trained models, previously trained with ImageNet dataset. These pre-trained models were used to predict unseen data from the test dataset, it has been shown that the results are an order of magnitude better than the benchmark. The models that perform particularly better are InveptionV3 and ResNet50. The results indicate that the features extracted by the pre-trained convolutional neural networks are very powerful. This features can be used in another not previously seen dataset.

It has been shown that using only a few lines of code we obtain better results than training a model from scratch. We shown that only 15 lines of code are required to implement a pre-trained model using the facilities offer by libraries like Keras. Transfer learning should be used as an easy way to obtain a benchmark to any new task, and improve from there.

In regard of the time of training, using a pre-trained model with take advantage of the hours of training done by the teams that create and trained the show models. This is an important point because the time and economics resource used in training the models can be leverage to new task.

One of the difficult aspects of the project was to manage a large amount of images in RAM, this can be hard deppending on the computer resources used.

Improvement

The way the images are read and used in the project can be improved. The important aspects to be taken into account are the amount of memory used while reading and training.

Another improvement proposed is to use more models in the comparison in future work. Using more models could give more insight into transfer learning.

Possibly, another dataset has to be used. The best models shown here did extremely well, so a more difficult dataset could be taken into account in future work.