Caffe to TensorFlow Conversion and Benchmarking Models

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Abstract

The CarML (Cognitive ARtifacts for Machine Learning) is a platform allowing people to easily deploy and experiment ML (Machine Learning)/DL (Deep Learning) frameworks and models. It allows ML/DL software developers to deploy their software packages, ML model developers to publish and evaluate their models, users to experiment with different models and frameworks, all through a web user interface or a REST api, and system architects to capture system resource usage to inform future system and hardware configuration. In order to compare the accuracy that a model predicts among frameworks, instead of using a existing model from different framework, it is better to use a model in one framework to convert to other frameworks. There are many existing converters for framework conversion; however, none of them is able to convert all kinds of models. Therefore, I researched on how to solve the issues happened when converting from Caffe to TensorFlow, and composed a script to automatically collect and analyze results by inquiring CarML by images.

Introduction

With the rise of popularity of ML/DL, there are numerous converters available online. I adopted two converters **MMdnn** by $Microsoft$, and **caffe-tensorflow** by $ethereo$. Unfortunately, Caffe is far different from TensorFlow. For instance, in the graph of Caffe, each node represents a layer. In TensorFlow, however, each node is a tensor operation (e.g. matrix add/multiply, convolution, etc.). Since the similarity between Caffe and TensorFlow is not as high as Caffe and Caffe2, it needs an indirect state to be converted successfully. The conversion procedure is as $Figure1$:

Figure 1: Conversion from Caffe to TensorFlow with an indirect state Numpy

Besides, although there are many resources (converters) available, most of these them are not perfect. They are either rife with bugs or not supporting Caffe models. The details will be discussed later.

Conversion

Common Layers in Caffe Graphs

The following layers are used mostly in every models I converted:

1. **Convolution**: By weighted moving average, find out edges, corners, or other features.
2. **ReLU (Rectified Linear Units)**: Introduce non-linearity to a system that basically has just been computing linear operations during the conv layers, it is faster than $Tanh$ or $Signoid$ functions. Also alleviate the vanishing gradient problem.
3. **Pooling**: Maxpooling is the most popular. It takes a filter (normally of size 2x2) and a stride of the same length to down-sample by outputs the maximum number in every subregion that the filter convolves around.
4. **Dropout**: This layer drops out a random set of activations in that layer by setting them to zero, in order to help alleviate the over-fitting problem.

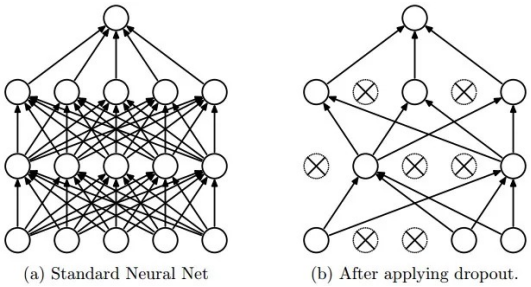

(a) Standard Neural Net (b) After applying dropout.

Figure 2: Mechanism of Dropout

Structure, Features of Models

AlexNet AlexNet is one of the first models which proved the effectiveness of application of CNN (Convolutional Neural Network) on complex model (with error rate 15.3% in ImageNet LSVRC-2012). It consists of 5 convolutional layers followed by 3 fully connected layers as $Figure3$. It adopts ReLU, Dropout, LRN [1], and data augmentation such as image translations, horizontal reflections, and patch extractions, which were innovative then, so that it could increase the accuracy significantly compared to the past.

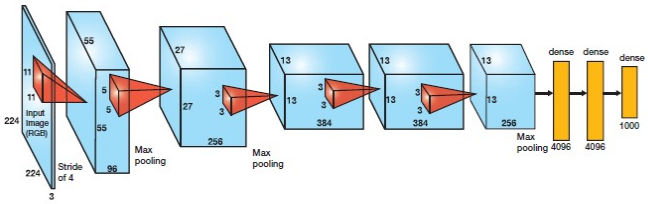
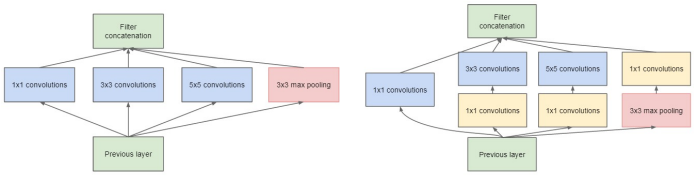


Figure 3: AlexNet Structure.

Inception From $Figure$ 4 we can observe the structures of Inception. The bottom green box is input and the top one is output. The naive version of Inception allows to perform all of the convolution or the pooling operations in parallel. Nonetheless, this would lead to too many outputs. The solution is to add 1x1 convolution operations before the 3x3 and 5x5 layers since 1x1 convolutions [2] provide a way of a method of dimensionality reduction.



(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 4: Inception Structures.

The evolution of Inception:

- **V1 (GoogLeNet) to V2**: Introduce to factorization (factorize convolutions into smaller convolutions). For example, Convolution whose kernel is larger than 3x3 can be expressed more efficiently with a series of smaller convolutions. (As $Figure$ 5)
- **V2 to V3**: A variant of Inception-v2 which adds BN-auxiliary, which is the version in which the fully connected layer of the auxiliary classifier is also-normalized, not just convolutions. Besides, it tears down 3x3 convolution in to 3x1 and 1x3 to reduce parameters. (As $Figure$ 6)
- **V3 to V4**: A streamlined version of v3 with a more uniform architecture and better recognition performance.

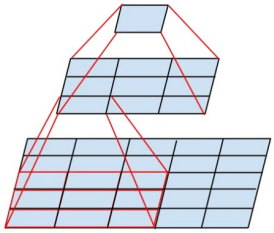


Figure 5: By using smaller kernel, the calculation will be more efficient.

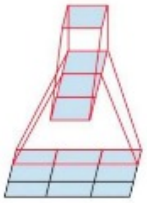


Figure 6: By using 1x3 and 3x1, it can reduce parameter usage.

GoogLeNet The appearance of GoogLeNet proved that with more convolutions, deeper layer, it is more likely to obtain a bettern result (accuracy). It won ILSVRC 2014 with a top 5 error rate of 6.7%, and it was one of the first CNN architectures that really strayed from the general approach of simply stacking convolution and pooling layers on top of each other in a sequential structure. GoogLeNet has 22 layers, which means almost 12x less parameters, so it is faster and less than AlexNet and much more accurate.

When observing the structure of GoogLeNet (as $Figure$ 7), it is obvious that not everything is happening sequentially. Some of pieces of this network which are happening in parallel, which is Inception module actually. GoogLeNet has 9 Inception modules in the entire structure, and with over 100 layers in total. In addition, it did not use fully connected layers, which could save a huge number of parameters. It is important that it combined with Inception module so

[1] LRN layers are used in Alexnet to normalize pixels across channels in the first convolutional layers, in order to to ensure that very bright or dark pixels do not dominate their neighbors.

[2] 1x1 convolutions (Network in Network layer) span a certain depth, so we can think of it as a 1 x 1 x N convolution where N is the number of filters applied in the layer. Effectively, this layer is performing a N-D element-wise multiplication where N is the depth of the input volume into the layer.

that it can have amazing performance and computationally efficiency.

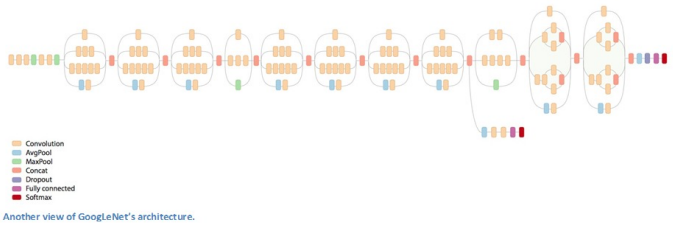


Figure 7: GoogLeNet Structure.

VGG (Visual Geometry Group) The characteristics of VGG are simplicity and depth. Though it did not win the championship of ILSVRC 2014 (it was GoogLeNet), it still performed marvelously with only 7.3% error rate. By utilizing small filters (3x3), it effectively reduces the need of the amount of parameters, and thereby it is able to use more ReLU layers and go deeper. The structure is as $Figure$ 8. The usage of smaller filters influenced some renowned models such as ResNet and GoogLeNet. However, it is time-consuming to train VGG and its weights are large (VGG16 is over 533MB and VGG19 is over 574MB)

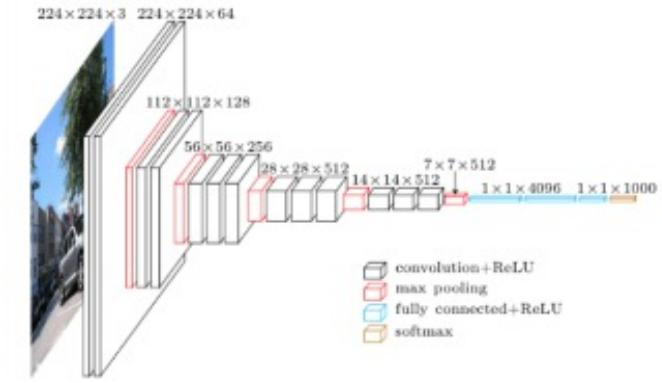


Figure 8: VGG16 Structure.

ResNet ResNet is known for its extremely huge number of layers (can be as large as 269), which helped it won ILSVRC 2015 with an incredible error rate of 3.6%. The reason that it can achieve numerous layers is that it utilize residual block. The idea of residual block is that when the input x was originally going to go through conv-relu-conv series (as $Figure$ 9), instead of going through them, it just bypasses them and go to the output, then add the F(x) to the output to achieve similar result of going through the series. By doing so, a tremendous number of layers is achievable. Also, its fantastic performance inspired people to focus on residual learning.

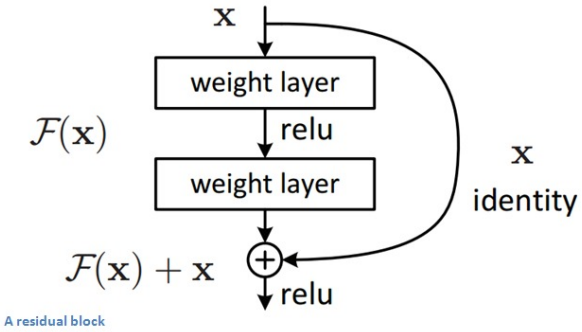


Figure 9: Residual Learning: A Building Block.

The evolution of ResNet is from small number of layers to huge number of layers, so does the performance (accuracy rate). However, it should be noted that ResNet team did try a 1202 layers network, but ended up having lower performance owing to over-fitting.

SqueezeNet Unlike other models which pursue higher accuracy, SqueezeNet was invented to reduce the complexity of network. Although deep residual learning models (e.g., ResNet) have implemented small kernel (3x3), SqueeseNet substituted some of 3x3 kernel to 1x1. This can effectively reduce 9 times smaller parameters. The reason why SqueezeNet did not replace them all is not to cause negative effect on accuracy.

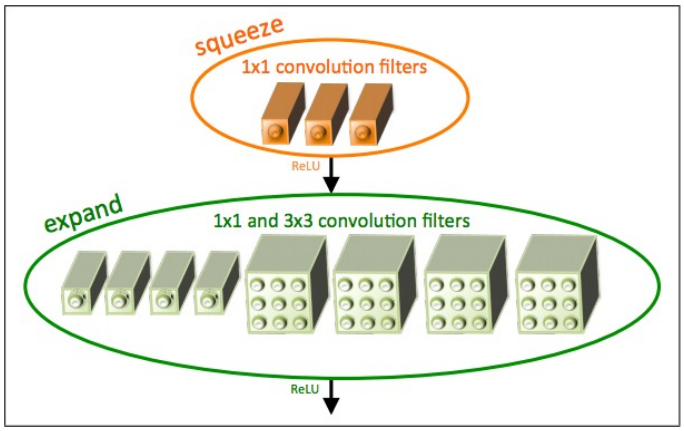


Figure 10: Fire Module

SqueezeNet also reduce the number of inputs for the remaining 3x3 filters. This strategy reduces the number of parameters by basically just using fewer filters. The mechanism behind this is by feeding $squeeze$ layers into what they term $expand$ layers (as $Figure$ 10). By reducing the number of filters in the squeeze layer feeding into the expand layer, they are reducing the number of

connections entering these 3x3 filters thus reducing the total number of parameters. (This is also called $FireModule$)

Finally, it down-samples late in the network so that convolution layers have large activation maps. The principle is to decrease the stride with later convolution layers and thus creating a larger activation/feature map later in the network, classification accuracy actually increases.

SqueezeNet takes advantages of fire module and chains many of these modules together to arrive at a smaller model. $Figure$ 11 shows some variants of this chaining process.

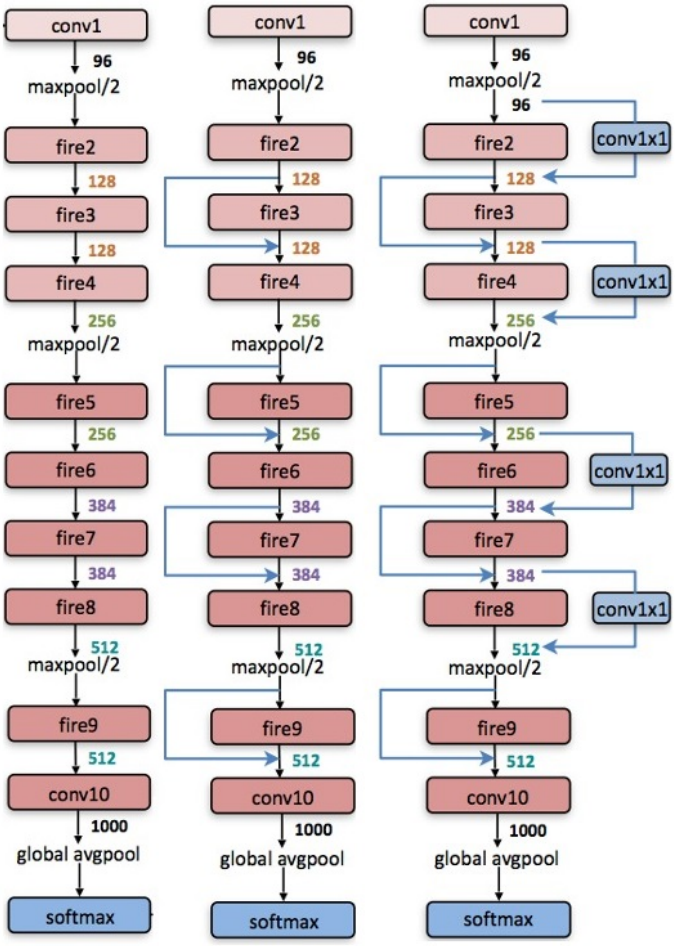


Figure 11: Left: SqueezeNet. Middle: SqueezeNet with simple bypass. Right: SqueezeNet with complex bypass.

Note that SqueezeNet architecture was able to achieve a 50X reduction in model size compared to AlexNet while meeting or exceeding the top-1 and top-5 accuracy of AlexNet. Also, its size is 510x smaller than AlexNet. These results are really encouraging because SqueezeNet shows the potential for combining different approaches for compression

NIN (Network-in-network) NIN is proposed to enhance model discriminability for local patches within the receptive field. Rather than using the conventional convolutional layer, whose linear filters followed by a nonlinear activation function to scan the input, NIN builds micro neural networks with more complex structures to abstract the data within the receptive field. (As $Figure$ 12)

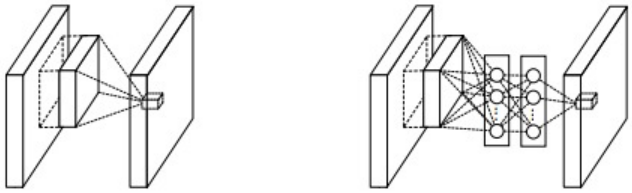


Figure 12: The linear convolution layer includes a linear filter while the mlpconv layer includes a micro network (multilayer perceptron)

The feature maps are obtained by sliding the a multilayer perceptron (MLP) over the input in a similar manner as CNN and are then fed into the next layer. Therefore, the overall structure of the NIN is the stacking of multiple mlpconv layers. (As $Figure$ 13)

Note that the idea of using MLP is adopted by ResNet and Inception.

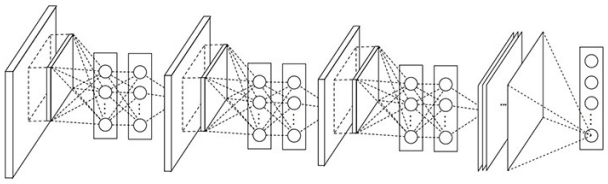


Figure 13: NIN Structure

Xception The Xception model is an extension of Inception. It takes advantage of depth-wise separable convolutions and the residual block from ResNet. By using depth-wise separable convolutions and the residual block, Xception can reduce a huge amount of computational resources, and thus having around 91 MB for its weights. The structure of Xception can refer to $Figure$ 14.

WRN (Wide Residual Networks) To WRN, residual blocks of ResNet tends to provide little amount of information since ResNet is too deep; namely, WRN considers that the success of ResNet was credited to residual block instead of deeper layers. Also, WRN thinks that each fraction of a percent of improved accuracy costs nearly doubling the number of layers, and so training very deep residual

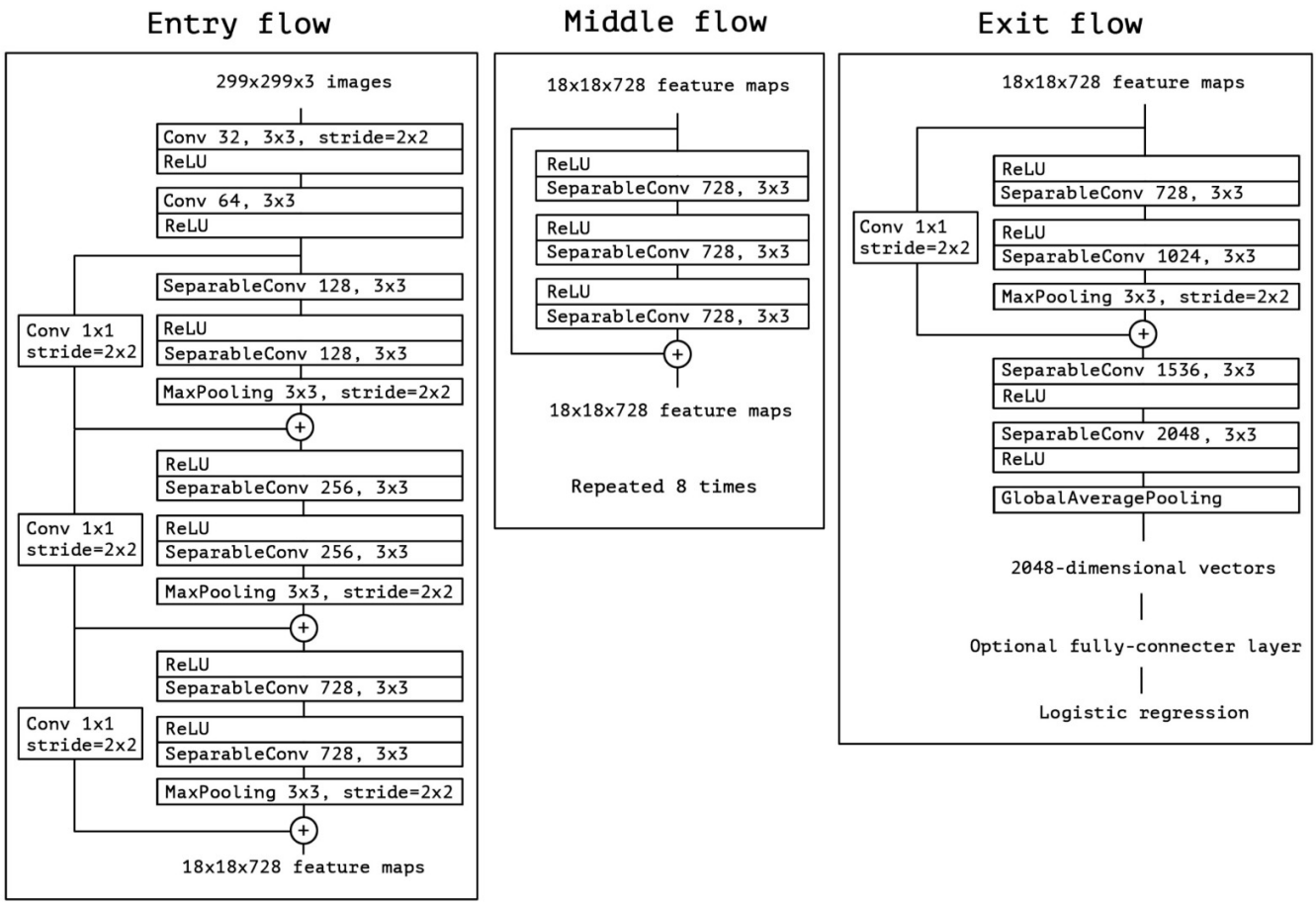


Figure 14: Xception Structure: the data first goes through the entry flow, then through the middle flow which is repeated eight times, and finally through the exit flow. Note that all Convolution and Separable Convolution layers are followed by batch normalization (not included in the diagram). All Separable Convolution layers use a depth multiplier of 1 (no depth expansion).

networks has a problem of diminishing feature reuse, which makes these networks very slow to train.

As a result, WRN decreases depth and increases width of residual networks. To achieve it, WRN utilizes the following three way: More convolution layers; More feature planes; Increment filter size of convolution layers. Besides, with the rise of width, parameters will also be increased by the power of two. To reduce the number of parameters, WRN adopts dropout.

The performance and the number of parameters of WRN40-4 is similar to ResNet1001; however, WRN's training time is less 8 times than ResNet's.

DPN (Dual Path Networks) ResNet focuses on the reuse of the characteristics, but giving up exploring new characteristics. The DenseNet is the opposite. DPN takes

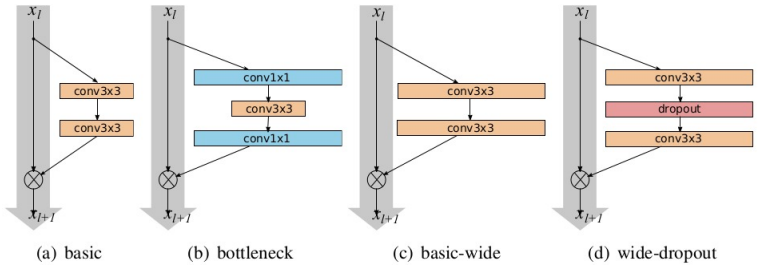


Figure 15: Various residual blocks used by WRN.

advantages of ResNet and DenseNet. As $Figure$ 16 (e), DPN uses ResNet as main body, aided by DenseNet.

Note that DPN won the championship in Object Localization Task in ILSVRC 2017, with all competition tasks within Top 3.

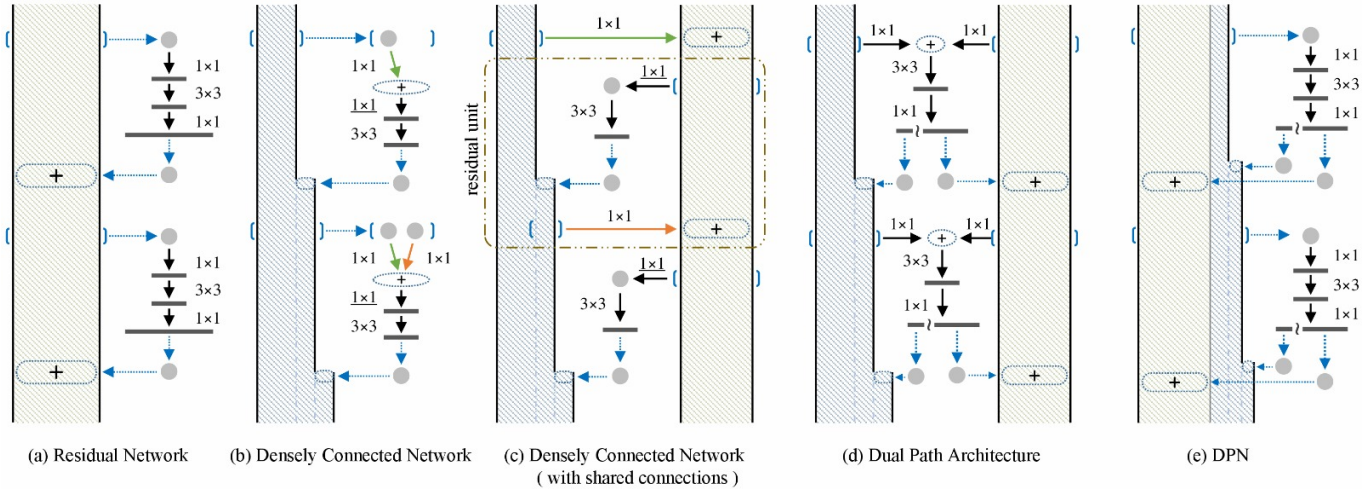


Figure 16:
(a): Residual Network; (b): DenseNet Structure; (c): When sharing all first 1x1 convolutional filter, DenseNet can be in format of the residual block; (d): DPN Structure; (e): DPN Implementation.

FCN (Fully Convolutional Networks) FCN adapts contemporary classification networks (AlexNet, VGG, and GoogLeNet) into fully convolutional networks and transfer their learned representations by fine-tuning to the segmentation task. Then, it defines a novel architecture that combines semantic information from a deep, coarse layer with appearance information from a shallow, fine layer to produce accurate and detailed segmentations

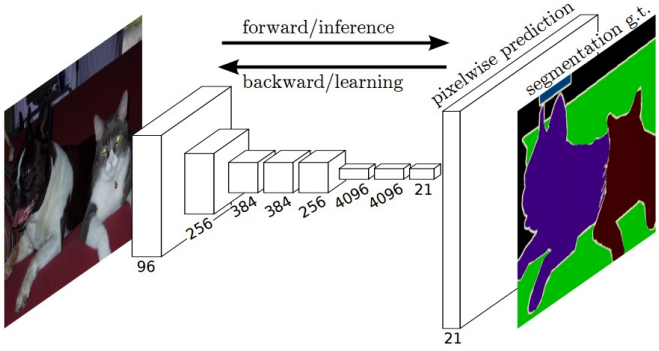


Figure 17: FCN end-to-end dense prediction pipeline.

In FCN, the features are merged from different stages in the encoder which vary in coarseness of semantic information. Also, the up-sampling of learned low resolution semantic feature maps is done using de-convolutions which are initialized with billinear interpolation filters.

For traditional up-sampling, due to the fixed stride, it does not take care of margin, and also limits the scale of detail of the up-sampling output. FCN use skip layer, which will decrease the size of stride around margin area, and incorporate the fine layer and the coarse layer, then do the up-sampling. This method takes care of local and global information. Hence it enhances the performance.

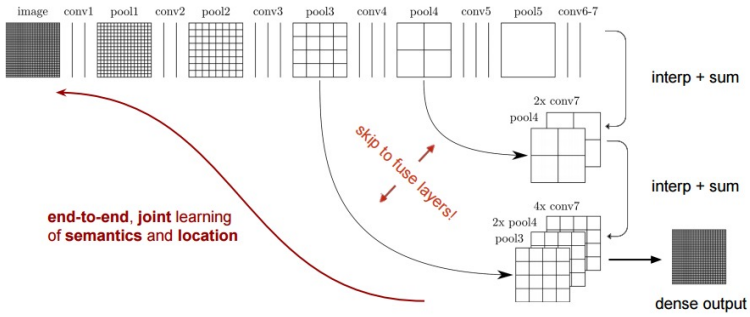


Figure 18: FCN-32s Structure.

Conversion Results

In 31 models, I successfully converted 27 Caffe models into TensorFlow. The 4 failed ones are DPN68, DPN92, voc-fcn16s, and voc-fcn32s. During the conversion, there were many bugs found and fixed. The detail about bug fixing will be elaborated in next section.

From Caffe to Numpy

1. The first issue I encountered was *Unable to determine kernel parameter*. I tried to set lots of break points to find out the cause. Finally, I found that this happened because the converter did not know the input shape when trying to get the stride kernel output shape. The solution is to set the input shape in the

file **layers.py** and **shapes.py** before using layers to get the result.

2. Another issue was $Unknown\ layer\ type\ encountered$. I tried to traced the cause but everything looked well. Then I tried to find resource from the internet, and I noticed that this converter needs a great amount of memory space. I expanded the memory size (from 2GB to 4GB) that the converter can use and solved this issue.

3. Some of the models were out of date so that the converter could not use those models as inputs. The solution is simply to update Caffe models by using the tool in the Caffe Library.

4. One more issue was that parsing slice layer is not implemented in the converter. This one led to DPN and fcn models conversion. I have posted an issue on GitHub and the author replied that he will get it fixed soon.

From Numpy to TensorFlow

1. There was one error message saying that $TypeError$: $Input\ split\_dim\ of Split\ Op\ has\ type\ float32\ that\ does\ not\ match\ expected\ type\ of\ int32$. I tried to change the parameter type before passing to the function; however, this caused other problems that the function wants the original type. Then I set break points trying to figure out what happened. I found out this was nothing to do with type error; instead, when the converter trying to call a function split in python library, it passed the parameters with the wrong order. It happened since the documentation of that function was wrong:

   On the documentation, it shows that the order of the parameter of the function is $tf.split(split\_dim,\ num\_split,\ value,\ name =' split')$. But actually it is defined as $split(value,\ num\_or\_size\_splits,\ axis = 0,\ num = None,\ name = "split")$.

   Since the converter used the function based on the documentation, I changed the order and it worked.

2. Another issue was assertion error. In Caffe, it accepts more types of padding, but TensorFlow only accepts either $SAME$ [3] or $VALID$ [4]. Therefore, when I converted models from Caffe, some of them may have padding type $None$ (i.e., without any padding). After looking for information about $SAME$ and $VALID$, I realized that $VALID$ itself is without padding. So I change $None$ to $VALID$ and resolved the issue.

3. The last one was caused by the dimension of the layers of models. Some of them exceeds the dimension defined in functions of the converter so that there will be negative dimension when doing convolution. This issue happens in the converter **caffe-tensorflow** by $ethereo$. The solution is to observe what is the maximum number of dimension needed by the input, then modified it in the functions of the converter. However, since the converter **MMdnn** by $Microsoft$ has dealt with this situation, we can use it instead, and the problem resolved.

Conclusion Before fixing the bugs, I could only converted 18 models from Caffe to Numpy, and only 13 of them could be converted from Numpy to TensorFlow. Nevertheless, after bugs fixed, I am certainly sure that every Numpy can be converted to TensorFlow, and after MMdnn updates, every caffe should be able to be converted from Caffe to Numpy.

Benchmark

Data Collection Implementation

My script for inference is adapted from $Abdul\ Dakkak$'s script. In his script, when a website of an URL is corrupted, the entire results will be gone. Thus, I tried two methods to improve $Abdul\ Dakkak$'s script for inference:

1. First, I tried to examine the HTTP response code to check if the website is still accessible. By this method I can eliminate many corrupted website. However, I found out even some of the responses are 404, the images on those website are still available. As a result, after checking the HTTP response code, I also try to load the image to validate if the image is available. This will slow down the speed of inference, but this helps a lot since there are many resources showing 404 while the image exists.

   Unfortunately, there are some URLs with HTTP response code 200 (i.e., the request has succeeded.) will also lead to the script crashed and lose the result. What's worse, when trying to check those URLs by inputting them in browser, they just show up normally. Therefore, if we want to use this method, we have to manually take out these URLs.

2. Since the first method was not ideal, I try to utilize another strategy: do inference one URL by one URL. Instead of checking the validation of an URL, I just input it and try to analyze the result on CarML. If this URL is corrupted, pass it and try the next one; if it works, then write the result into output file.

   This method effectively eliminate any possibility of program crash, as well as the lose of results. What's more, without trying to check validation of images by loading the image, this method is far faster than $method$

[3] SAME means the output of convolution is exactly the same size of the input since it will add padding to input.

[4] VALID does not add any padding to input.

1. Therefore, I adopt the second method to do inference and result collection.

Detailed Methodology Used for Benchmarking

Data To analyze the performance of models, first thing is to have sufficient data to input. I used URLs from $ImageNet$. Since sometimes an output from model may have names in the format of scientific name or some unusual name, it is not easy to analyze the statistical result. Thus, I chose images of **Bear** for the most of the outputs of bear include 'Bear'.

Result Collection By using the script, For each output of an input, I will write three results with Top 3 probability to the output file. For example, when there is an output as following:

Name	Probability
Cheeseburger	0.9993
Meat loaf	0.0003
Ice cream	0.0002
Hotdog	0.0001
Guacamole	0.0001

I will only output Cheeseburger, Meat loaf, and Ice cream with their probabilities individually.

Analysis After having sufficient data of results (i.e., around 6000.), I can start analyze. First, I check the name each data of results whether has Bear'.

- If it does not match, then add 0 to the variable $sumProbability$.
- If it matches, choose the highest probability among three results, and also add it into the variable $sumProbability$. Meanwhile, if the result with the highest probability matches, increment $sumAccuracy$ by 1.

After checking 6000 results, we will derive the overall average of the probability and the overall accuracy by the following two equations:

$$OverallAccuracy = \frac{sumAccuracy}{6000}$$

$$OverallProbability = \frac{sumProbability}{6000}$$

By having the overall average of the performance (accuracy) and probability for each model, we will be able to see the difference between models (i.e., which one has higher performance, etc.). The next step is to analyze the same model perform on different frameworks (which framework has higher performance, etc.).

Frameworks →	Caffe		TensorFlow	
Models ↓	Accuracy	Probability	Accuracy	Probability
BVLC-AlexNet	0.820	0.677	0.804	0.688
BVLC-GoogLeNet	0.877	0.783	0.841	0.788
BVLC-Reference-CaffeNet	0.817	0.681	0.778	0.685
DPN68	0.945	0.818	N/A	N/A
DPN92	0.952	0.844	N/A	N/A
Inception-ResNet_v2	0.949	0.926	N/A	N/A
Inception-v3	0.943	0.809	N/A	N/A
Inception-v4	0.950	0.822	N/A	N/A
ResNet101	0.872	0.827	N/A	N/A
ResNet101-v2	0.934	0.881	N/A	N/A
ResNet152	0.877	0.832	N/A	N/A

Table 1: Results of Each Model in Different Frameworks. Caffe has 6000s inputs. TensorFlow has 1000s inputs.

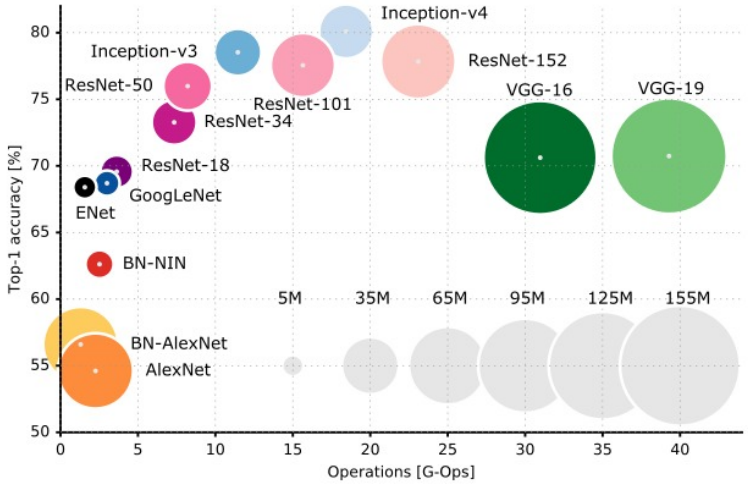


Figure 19: The Expected Performance of Each Model.

Result

Result Analysis From $Table$ 1 and $Figure$ 19, it can be observed that

1. Most of the results are similar to the expected ones. However, some of ResNets have incredible accuracy (i.e., 95%). I believe this is caused by over-fitting since ResNet typically has a hugh number of layers, but it can only pass a small amount of information to the next layer. If using more kinds of input (i.e., using various kinds of images) and calculate the average accuracy, it will reduce the problem with such a high accuracy due to over-fitting.
2. With the improvement of the model (e.g., Inception-v3 to Inception-v4, etc.), the overall accuracy is enhanced.

3. Since AlexNet is the earliest model here and almost every other model is based on AlexNet, its accuracy is relatively low than others.

4. In this result table, we cannot analyze the difference between frameworks since Tensorflow only has $\frac{1}{6}$ inputs compared to Caffe. Nonetheless, it is still somewhat observable that the overall accuracy on TensorFlow is close to one on Caffe.

Difference between Caffe and TensorFlow

- TensorFlow
  - Pros:
    - Python + Numpy
    - Computational graph abstraction
    - TensorBoard for visualization
    - Data and model parallelism
  - Cons:
    - Slower than other frameworks
    - Not many pretrained models
    - Computational graph is pure Python, therefore slow
    - Drops out to Python to load each new training batch
    - Not very toolable

- Caffe
  - Pros:
    - Good for feedforward networks and image processing
    - Train models without writing any code
  - Cons:
    - Need to write C++ / CUDA for new GPU layers
    - Not good for recurrent networks
    - Cumbersome for big networks (GoogLeNet, ResNet)
    - Not extensible, bit of a hairball

Explanation of Insufficient Data The reason that there is only few result is that

1. I used a huge number of inputs for each model. When I tried to run 6000s inputs, it took around 2 hours.

2. The CarML website is not stable. It is easy to crash when receiving a certain number of inferences.

I was told that 1000 inputs is enough for analyzing during the last meeting with $AbdulDakkak$. This is also why there are only 1000 inputs for TensorFlow.

I am confident that my script is perfect, so if I can have enough time (including restarting CarML server), I can get all of results from models on frameworks.

Conclusion/Prospect

Basically, almost every model can be converted from Caffe to TensorFlow, and results of each model can be derived given time.

By using models from one specific framework to convert to other frameworks, it can used to analyze the difference between frameworks since these model is from the same resource instead of re-training on different frameworks. Also, with more and more models available on frameworks on CarML, CarML can be a public platform for analysis of Machine Learning/Deep Learning models!

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