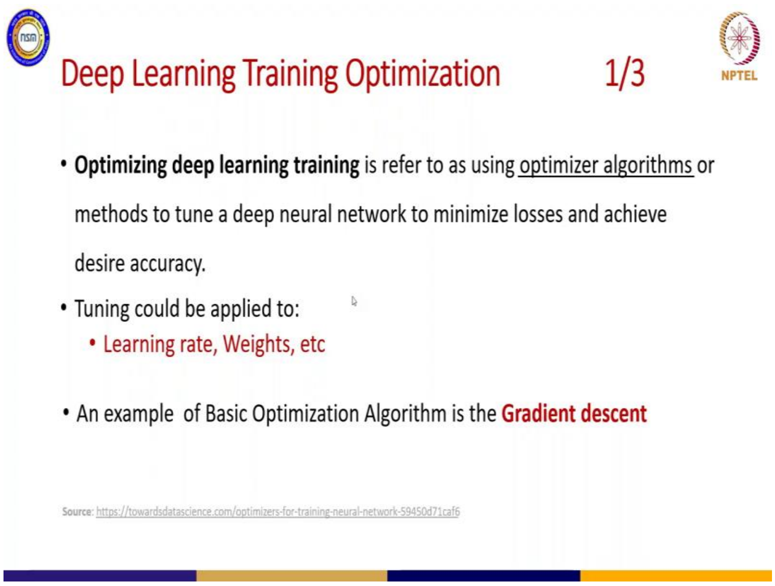
Applied Accelerated Artificial Intelligence
Dr. Tosin Adesuyi
Department of Computer Science and Engineering
Indian Institute of Technology, Madaras

End to End Accelerated Date Learning
Lecture - 30
Optimizing Deep Learning Training: Automatic Mixed Precision Part - 1

Welcome everyone to the session 2 of end to end Accelerated Deep Learning and so, this particular session would be taken by Dr. Tosin; Tosin is working as a GPU Advocate at NVIDIA and is based out in Korea and over to you Tosin for taking the session today.

Thank you Bharat. Hi everybody, I welcome you to this section which is based on end to end Accelerated Data learning and today, we will be talking about Optimizing Deep Learning Training and we will focus on Automatic Mixed Precision. So, that is what we will focus on today.

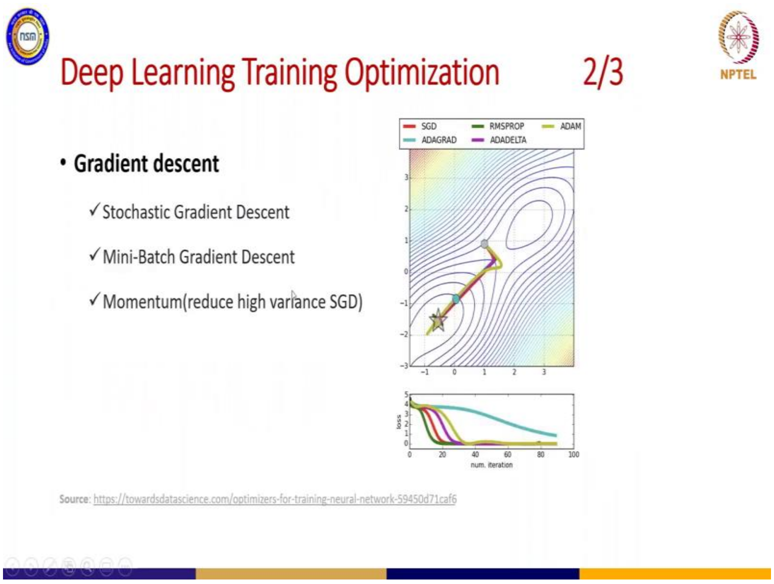
(Refer Slide Time: 01:08)



First of all, I will be talking about Deep Learning Training Optimization. So, what do we refer to as a deep learning training optimization? So, we are talking about optimization algorithm which is used during the training of a deep neural network, in order to achieve a desired goal and in a nutshell, you are worth reducing the loss to a minimal level. So, this is commonly used when we are training a deep neural network. So, these optimizers that have been used. So, this optimizer, they help us to the deep neural network to be able to reach a convergence level faster.

And so, what is actually been tuned in the deep neural network? The learning rates and the weights that one have been tuned and also, the other parameters which also been tune like the the batch size also they have been tuned. So, an example of optimization algorithm is the gradient descent. So, the gradient decent is commonly used and we have types of gradient descent that are used.

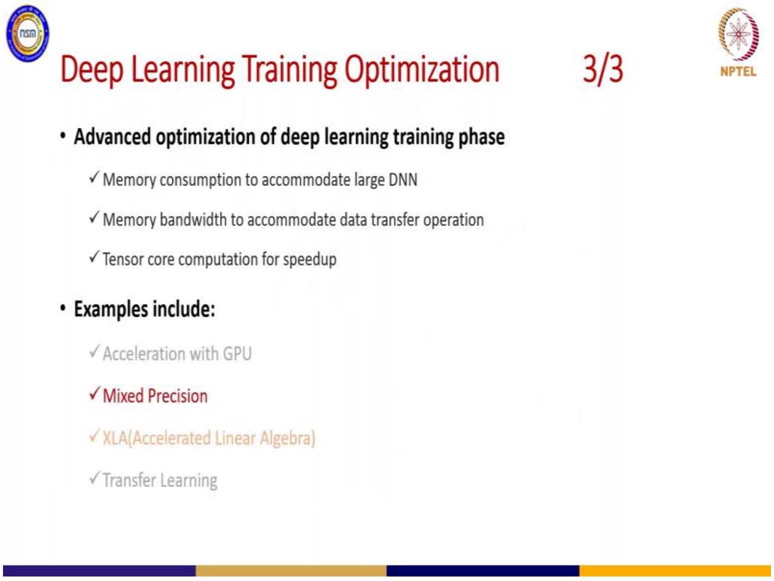
(Refer Slide Time: 02:38)



So, I have listed three here; you we have these stochastic gradient descent which have been used. This stochastic what it does is that what it picks the data in batches in terms of what randomly using probability. Also, there is the mini batch gradient descent as well. These big chunks of the batches, it feed them into the momentum.

And also, there is what we call the momentum. So, this momentum is used to reduce the high variance in the stochastic gradient distance. There are other examples of optimizer like the ADAMs, the ADAGRAD and ADADELTA and many of them have been used which I know many of us are familiar with this. So, in the event, where training model are becoming more complex, researchers are trying to solve complex tasks, it require larger models to be built and also, more data are also required to be used to build these models.

(Refer Slide Time: 03:49)

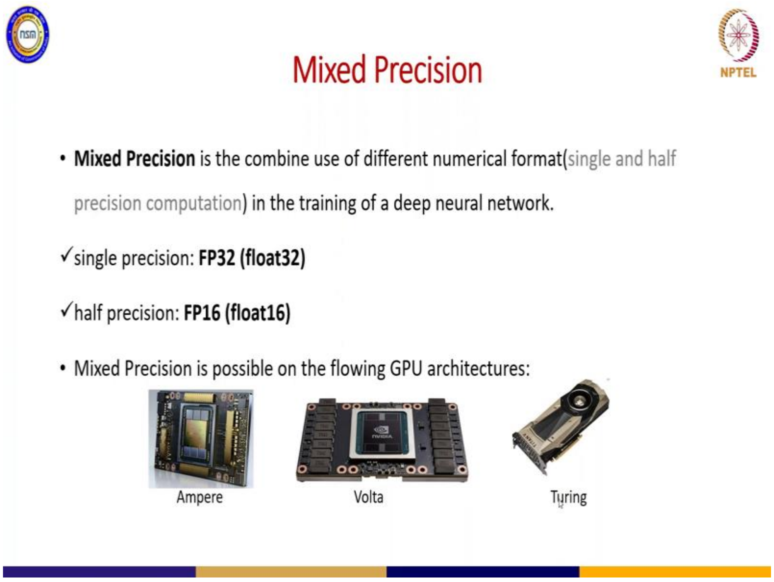


So, in this lights, there is a need for what we call the advanced optimization for deep learning training phase. So, and when you want to go through this level, there are things which you may need to consider. So, you will be looking at the memory consumption to accommodate large DNN model and also, you will be looking at the memory bandwidth also which will be required to transfer data and you know large model might require large data and there is transfer here and there that will be needed during the training phase.

Also, you are looking at the word speed up in terms of computation and which would require some tensor core. So, now you make use of advanced optimization that can give you all these attributes. So, example is what you use GPU, you accelerate which GPU that is one level of advanced optimization and another one is the mixed precision which we are going to focus on today and there is also an aspect called the XLA which is accelerated linear algebra, this is from tensor flow a special compiler and also there is the transfer learning.

So, we will talk about transfer learning in our subsequent a course. So, we focus first of all on the mixed precision.

(Refer Slide Time: 05:21)

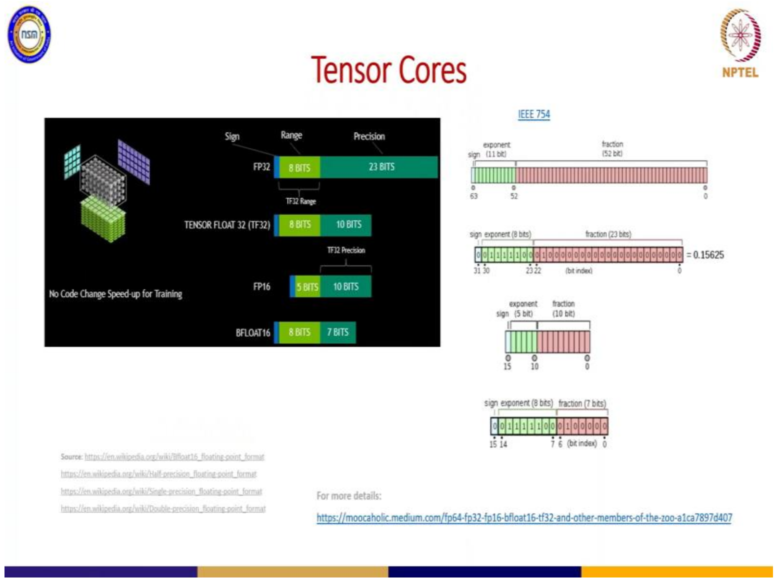


So, what do we refer to as mixed precision? A mixed precision is a using different numerical format with respect to deep learning, we can say mixed precision is the use of single and half precision for computation during the training of deep neural network. And what the word refer to as single precision? Single precision is simply the float 32 is what we refer to as single precision. Why half precision is float 16, which we call FP16?

So, we are looking at a scenario, where in the training of a deep neural network, these two precision data type are being used. So, it is an high level optimization process and how for you to use this mixed precision, there are requirement that is to look at the resources that the usage of this precision are possible. So, you must consider the GPU architecture which facilitate the use of these mixed precisions.

First of all, the one we have is the ampere. So, it is possible if your GPU is ampere architecture, you can use mixed precision is possible. For volta architecture, mixed precision is also possible and also, for tuning architecture, mixed precision is also possible.

(Refer Slide Time: 07:11)



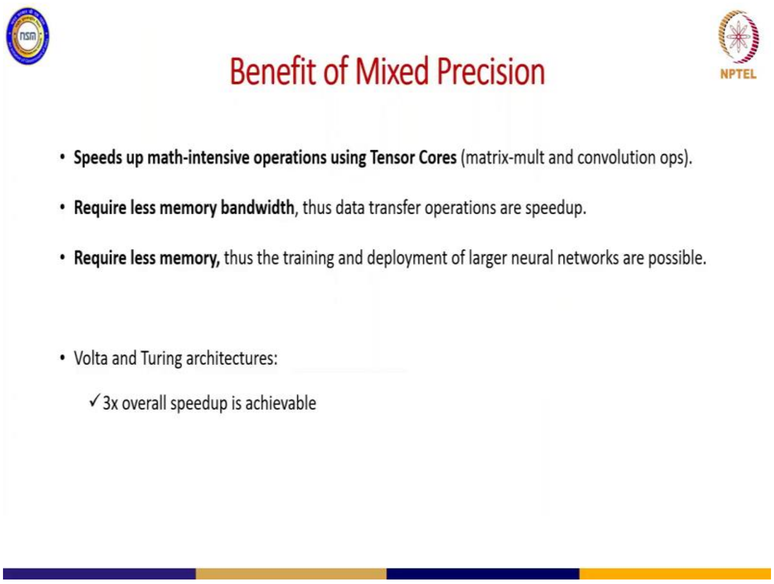
So, we would like to talk about tensor core. So, in those architecture, how is it possible for mixed precision to be used? It is possible based on the tensor core that exists in those architecture. So, and what are tensor core, these are just dedicated cores for matrix multiplication that goes on in the deep neural network. The deep neural network itself is made up of matrix multiplication and convolution and this convolution and this multiplication are the those tasks can be handled by the tensor core.

So, and we will be talking about mixed precision, we talk about FP32 and FP16. So, the tensor core, they have data type which are fits into FP32, FP16 BFLOAT 16. So, we will be able to see that computation will be much easier because we have calls that are dedicated for that computation and in doing that, it does not require you changing any code and the at the later hand, you get a maximum speed up with that.

And we can also look at the IEEE standard for that which is the 754 IEEE standard, the first one you can see here is that is for FP64, this is for FP 32. Then, there is the one for FP16, the floating point 16 and there is the BFLOAT.

So, why the BFLOAT? The BFLOAT comes because there is a dynamic range issue which FP16 which the BFLOAT is able to work to overcome that. But however, with those dynamic rate issue using a method called scaling can make our FP16 perform better to overcome the dynamic range issue. So, for more, you can check this link; you can get more on that. But I would not want to put out more into these details because I want to focus on the empirical side of it, which is the practical side.

(Refer Slide Time: 09:26)

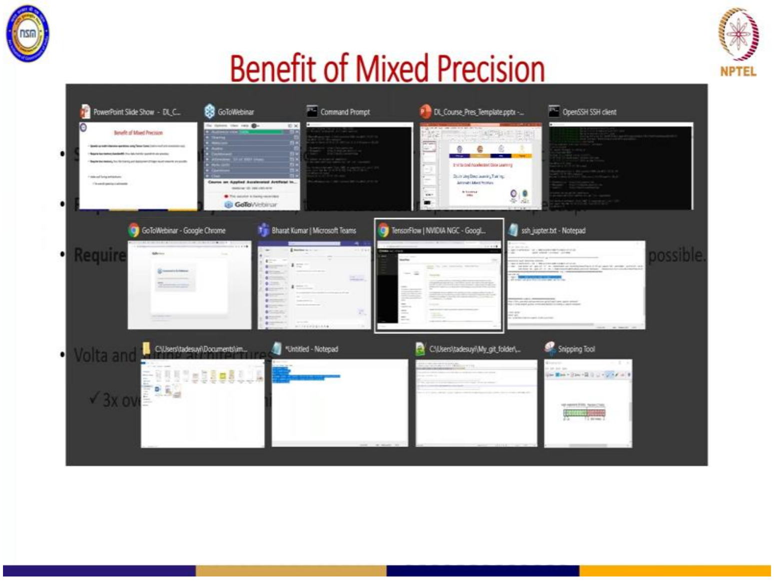


So, what are the benefit of mixed precision? The first thing is that with mixed precision, you are able to perform matrix multiplication and convolution. Convolution operations in your deep neural network with maximum speed up that is mass intensity operations are being performed using the tensor core. Like I said before that the tensor core is dedicated for such operation and also, it require less memory bandwidth.

So, when it requires less memory bandwidth, then you can transfer more data operation can be done. So, in a short time, then it require lesser memory. Why? Because it require lesser memory in the sense that operations are being performed in half precision mode. So, if those operation have been performed in half precision mode, either it require lesser memory and thus, you can train large models very well.

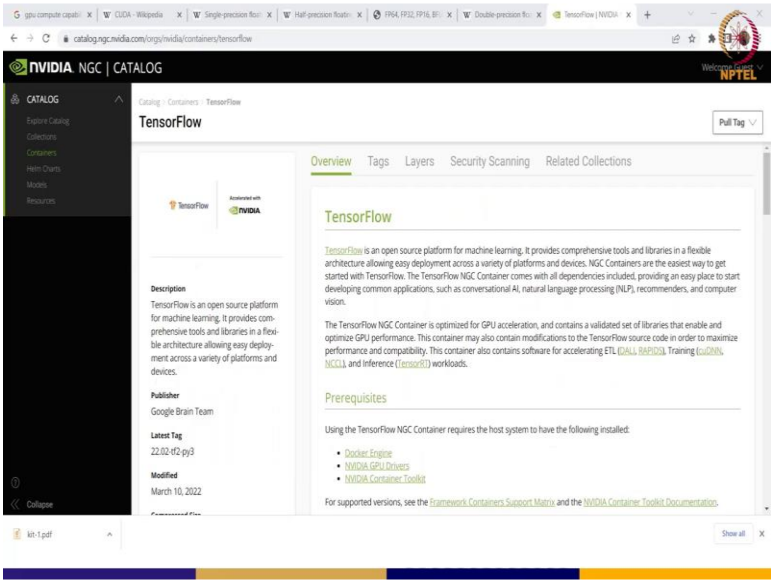
So, and after using mixed precision, so what are the benefits you can also get from there is that you get minimum of 3x speedup based on volta architecture and also, Turing architecture, if these are the GPU architecture you used. So, based on that, you can gets 3x speedup. If you use ampere, you will get definitely get more than that.

(Refer Slide Time: 11:05)

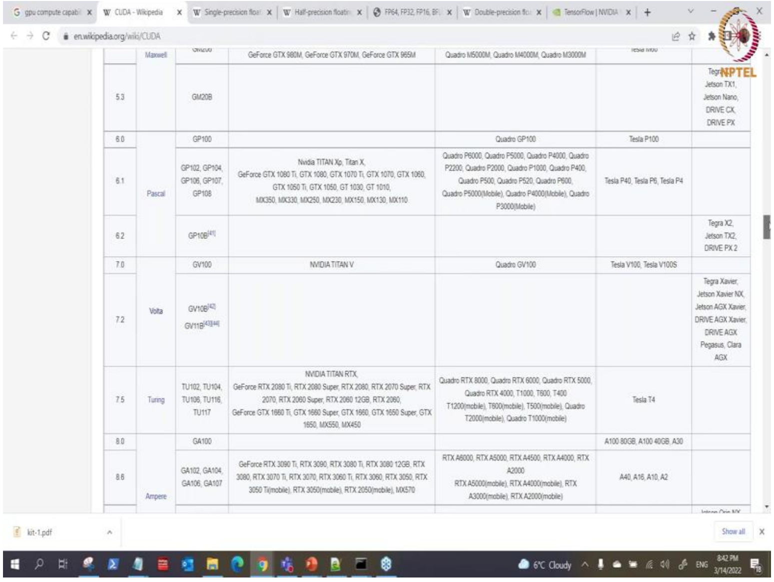


There are many if you want to know the classes of your architecture of your GPU. So, you can check online, there are several of them online which you can check on.

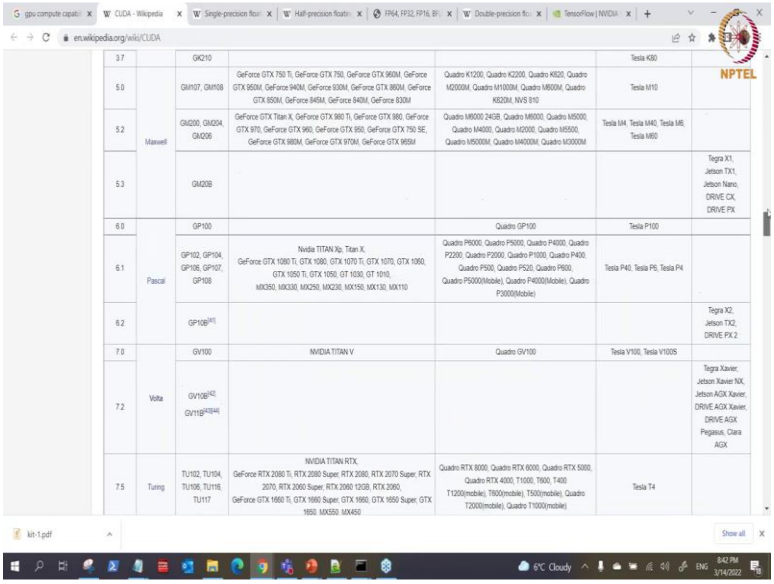
(Refer Slide Time: 11:15)



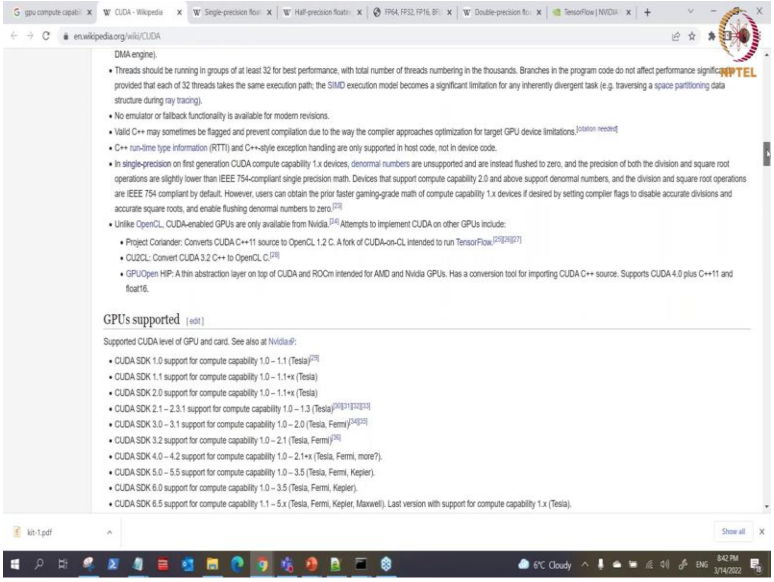
(Refer Slide Time: 11:18)



(Refer Slide Time: 11:19)

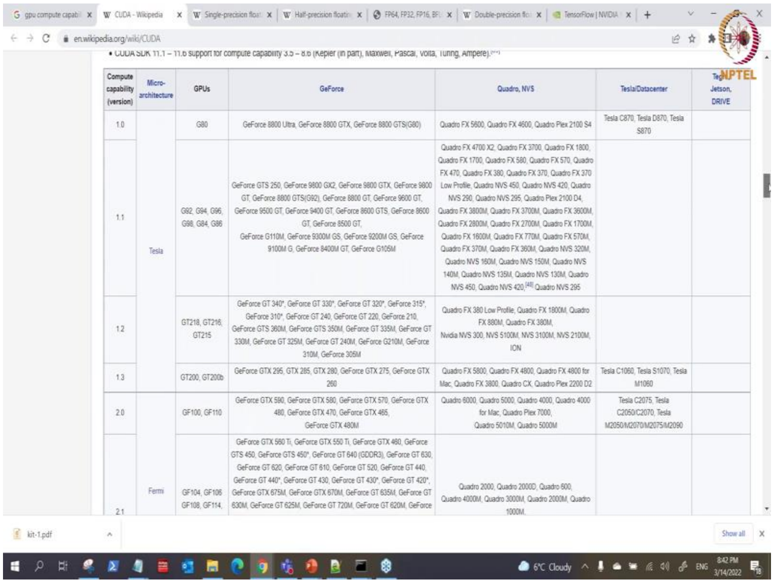


(Refer Slide Time: 11:20)



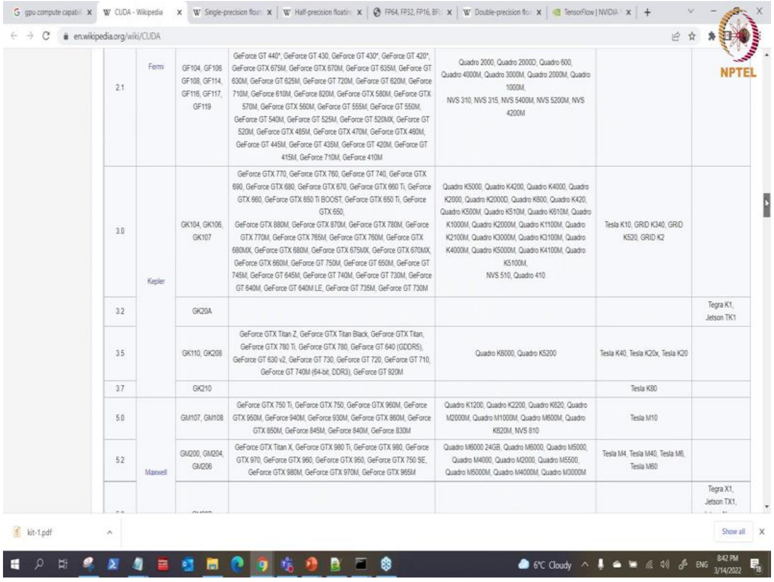
I think I look up somewhere.

(Refer Slide Time: 11:22)

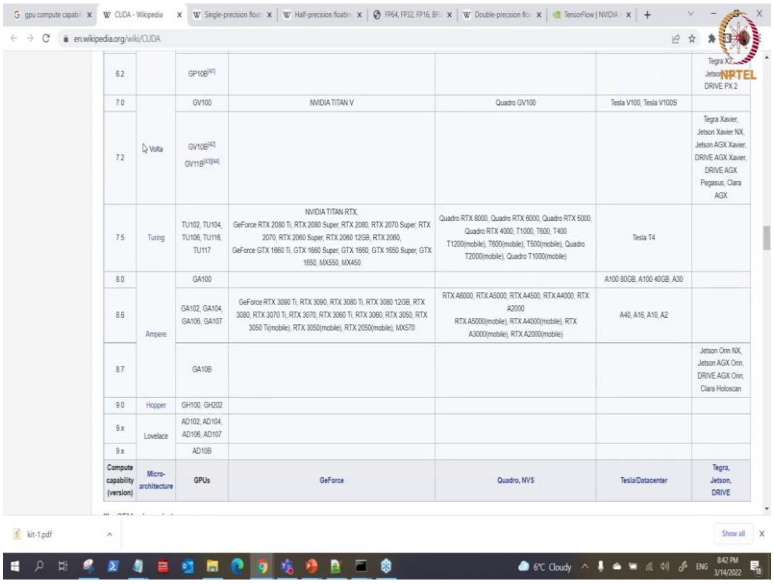


So, if you check Wikipedia for that, you can see this is a compute capacity here.

(Refer Slide Time: 11:26)

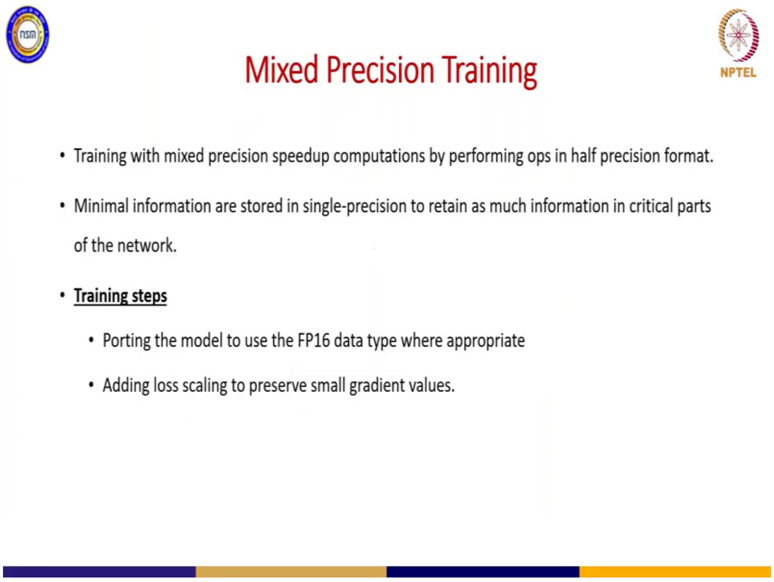


(Refer Slide Time: 11:35)



So, you can you be able to know that type of your architecture used. This is you can see Kepler, you can see Pascal, we have Volta, here the GPUs, that are there Turing, you can see the classes of the GPU that you use, you also have Ampere here, the classes of GPU that belongs to that you can have all of them.

(Refer Slide Time: 11:48)

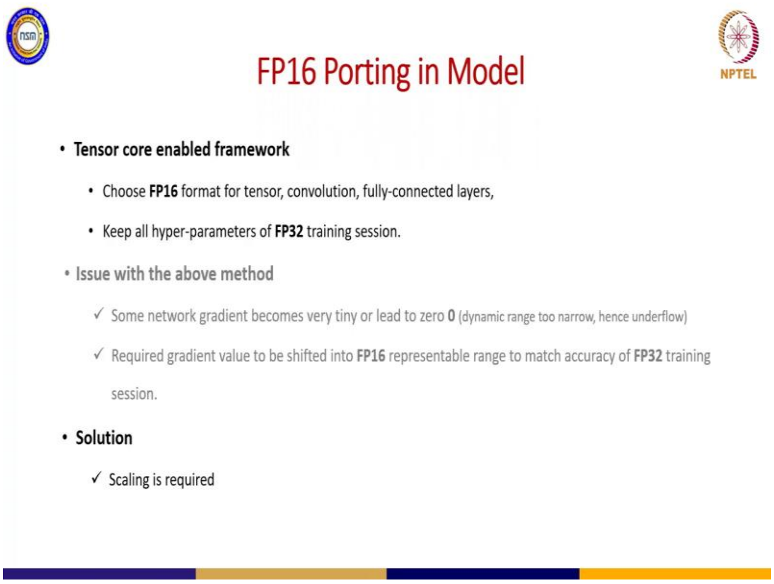


Then, mixed precision training. So, after, while you do train your model using mixed precision, so ideally the training with mixed precision will help you to speed up computation. Because those operations they are performed in half precision format. That is its performed those operation using float 16, FP16 and then, the minimal information are being stored in FP32 which is the single precision. So, the process is that you are using both FP16 and you are using FP32 as well.

So, during the training, what are the steps you need to take during the training is that you need to port your model to use the FP16 data type, where it is appropriate. The only place you will not use the FP16 is if your model may be your dealing with multi-classification tasks, where you might want to use Softmax activation function. So, at the Softmax activation function, you have to use FP32 there. Then, the other part you will be you will be able to use FP16.

And the second part, step is that you need to add a loss scaling to preserve small gradient. So, why this is that? When you use mixed precision because of the computation that happen with FP16, it usually leads to small gradients which is we call it on the float such that during the gradients computation, the gradient is so small that sometimes it leads to 0 value and those 0 values affect the accuracy of the model. So, you will not be able to get the accuracy, you will get if you are using only FP32. So, then the loss of your model has to be scaled and how do you scale? You scale by multiplying loss with a particular value.

(Refer Slide Time: 14:04)



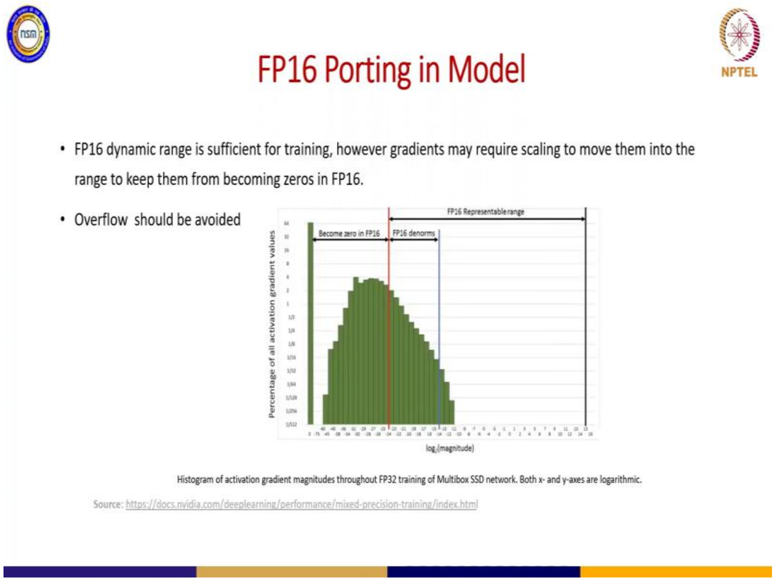
So, during FP16 porting in your model, so how do you how will you be able to achieve this is that? You use frameworks that tensor core are enabled because the that is being performed actually by tensor core. So, because those tensor core they also have precisions which is based on FP16 and FP32.

So, you choose FP16 format for a tensor which helps you to do the matrix multiplication are there, the convolution operation also it works with the fully connected layer and also, you keep all the hyper parameters of FP32 that is the floating point 32 training section there.

Now, like I said earlier, there are issues with this; but the issue that will not arise there is that FP16 has a way of what we call dynamic range being too narrow and it leads to what we call the underflow. So, gradient become very small that leads to you may have 0 gradient and this will affects your training. So, it requires a gradient, it requires such that you need to shift do some kind of shifting into FP16 representable range to match the accuracy of FP32 that you have.

So, now, how do you achieve that is the solution is that you use what we call scaling and scaling which we I have mentioned before is that you multiply by a particular threshold, you multiply your loss by a particular threshold. And what you get there is what we call scaling, but I will still explain further as we continue.

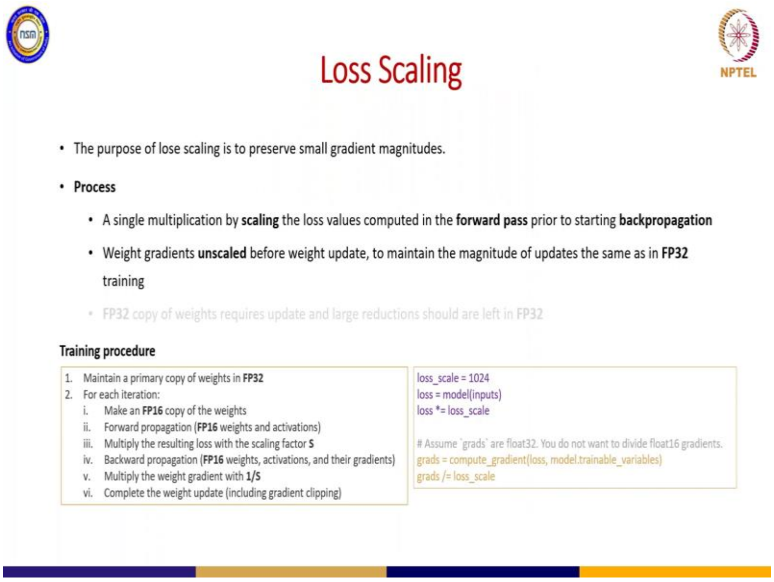
(Refer Slide Time: 15:58)



So, FP16 as a dynamic range which is sufficient for you to train and it does this in a way that it is affects the gradients of your deep neural network and so, what you need to do is to what to do scaling like I said; but while doing the scaling there is an issue that will arise as well.

Because when you scale you multiply by a particular threshold value, it can result to what we call overflow and what we mean by overflow? Overflow in the sense that you will be having values that may lead to infinity or NAND value that will lead there. So, that is what happened in that sense.

(Refer Slide Time: 16:44)



So, and the next phase is Loss scaling. So, how do you perform loss scaling and what is the reason for loss scaling? The reason for lo scaling is that you want to preserve this small gradient. How do you preserve it such that you are able to train your model as if you are using FP32 only.

So, the first thing you do is to what? You make a single multiplication by scaling the loss value. So, when you scale the loss value at the forward pass. So, what do you mean by forward pass? This is like the forward propagation that is you when your model forced to run your deep neural network, when it runs and it eats the output; before it comes back again which is what feeding the output, it get feeding it back to deduct from the weight.

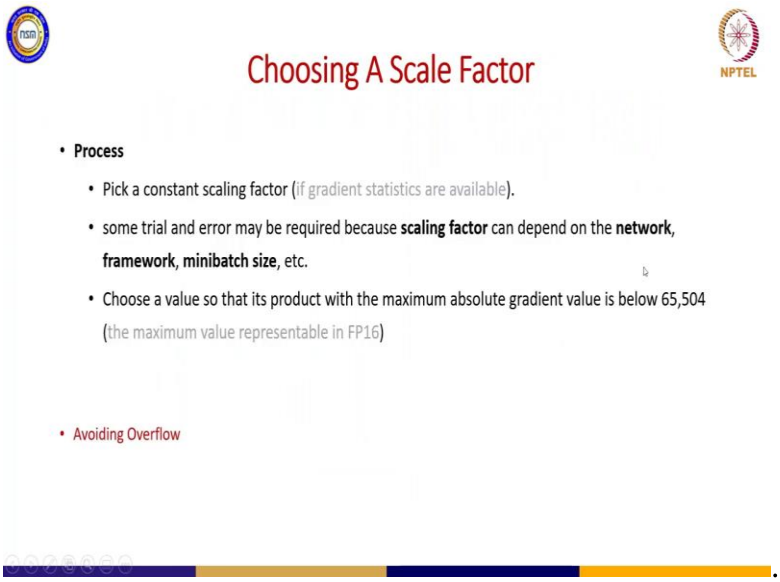
So, which is the word the process of back propagation. So, the first thing what I am trying to say is that you multiply your loss scale For example, if I assigned 1024 my loss as my loss scale, I can compute my model here get the loss and then, most of use the loss scale which is 1024 to multiply and add to the loss. So, this is what we call scaling.

So, this is done at the forward pass of your model, when your model initially run the first time. So, then you compute the gradient. Secondly, that is what you do; you compute the gradients. So, after you compute the gradient, then you on scale back again, you want scale back. So, or scale back. So, add you scale back, you divide the gradient which you computes by the value you use to scale initially. So, when you do that, then you can now updates the weights.

So, there is a procedure for doing that this is a simple algorithm to do that I would can see here. So, the first one, the first line is what you maintain a primary copy of your weight. Your weight will be in FP32, then during the iteration. So, this iteration this is what happens while you are training your deep neural network, where you can have the step and the iterations that are there. So, within that step and iteration, you can make an FP16 copy of your weights and after then, so that F16 copy of your weight, you perform that with what the forward propagation that is the initial runs.

Then, so, you scale. So, how do you scale which I have explained here, you scale you multiply the resulting loss with a scaling factor x. So, the scaling factor x is what you have here. Then you cannot do your back propagation. So, after the back propagation is performed, then you on scale back that is you divide the gradient you get there by the value of the scale and then, you cannot proceed to updates the weights.

(Refer Slide Time: 19:46)

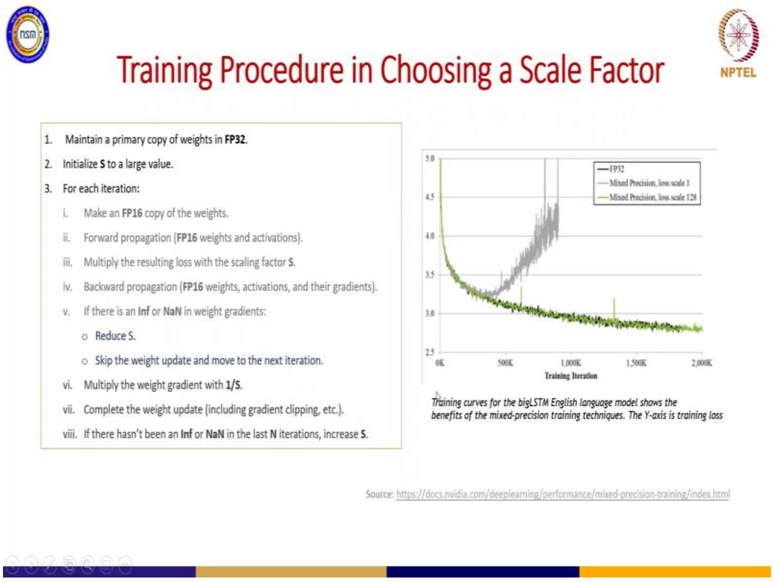


So, here how do we know; how do we pick a scaling factor? Like ok, do we just pick 1024 or we just pick one just pick to how do you know how to pick that? So, there is a process for that is that the first one is you can pick a constant value scaling value and that is can only be done if you have the statistical gradient value for your gradient. If you have the statistics for your gradient that is when that is possible or you can use some brute force method which you refer to as trial by error to test.

If this particular scaling value that you pick, if it will not run into overflow, so you can use trial by error. Now, why do you have to use trial by error? It is because this scaling factor is dependent on some other attributes or factors like the your network size that is your model size, the framework you are using, whether you are using tensor flow or you are using pytorch or you are using mx, also the mini batch also the size of your minibatch, it also depend on that.

So, that is why you have to try to you able to get the right scaling factor for the kind of tasks you are doing and also, you can choose a value which will not exceed the maximum value which is represented in FP16 and that maximum value is the 65,400. These value have been proved to be efficient and work well and in research that it is if your value is below this range your scaling value. Then, your model would definitely do well; but while doing this, you must avoid what we call the overflow.

(Refer Slide Time: 21:44)



So, how do we now train because why you are trying to pick up scaling value, you need to test it during your training see that ok, this value scaling well and it is not leading to overflow or you are not experiencing an underflow. So, the first thing you do this is an algorithm here is that you maintain the primary copy of your weight which is in FP32.

So, how do you have this is that your model variable data type by default will be FP32? Then, you initialize your scaling value to a large value, you pick just pick a large value which is less than the value I mentioned here which the result will be less than this. So, you pick that. Then, in your iteration, so you make a copy of your FP16 weights, then you perform forward propagation with it, then you scale using with the value.

Then, after you scale you perform your model perform the backward propagation. So, after the backward propagation is performed, so what you need to do is what you have to check, you check if that does not resort to overflow that is infinity or NAND in your weights your gradient weights.

So, if that on call, what you need to reduce what? You need to reduce the value of that scaling factor x, you reduce it from the initial one then. You would skip the weight update; you would not update because you can update with an infinity or a none value in your weight. So, you skip that.

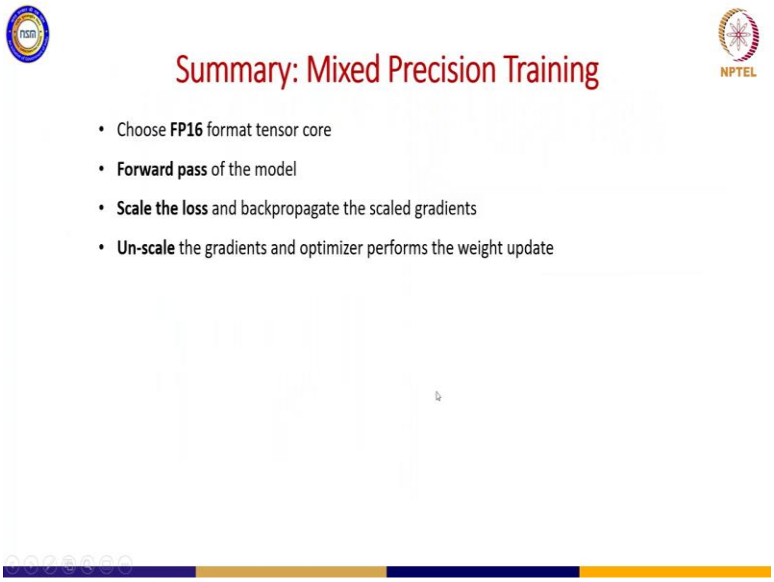
So, when you skip that, after you have reduced then you start all over again. But if that is not the case then what you need to do is you on scale back your gradient by dividing it with the scale factor value that you pick and then, you complete your weight update. So, when you complete your weight update then, so after that has been successful, you check your model; I mean the iteration fully run.

So, and if you if why the iteration fully run, you check that oh there is no infinity or none value existing in between the iteration. Then, you can also increase your scaling value since your iteration the iteration have performed, there is no overflow. So, you can increase it. So, when there is an over overflow, you reduce its and to able to get a value where overflow does not occur anymore and that after that value, a slight increase in that value may lead to overflow.

So, at exact point, you can use that particular scaling factor and this is an example here which is perform on big using big LSTM. So, what you can see here is that the FP32, the loss this the y axis is the loss; the loss this is the black one you see the loss decrease, it decreased steadily; then the mixed precision used when the loss scale is at 1, you can see its decreased and suddenly rises again.

So, which does not give good loss function, it does not give good loss. So, because the loss is increasing again. then our accuracy will be down. So, when the mixed precision loss is scaled at 128, we can see which is the green one its give the same result as if we were using FP32. So, it is it was able to achieve the same result as FP32. However, the were able to use it to train larger models, it require less memory would gain speedup as well.

(Refer Slide Time: 25:41)

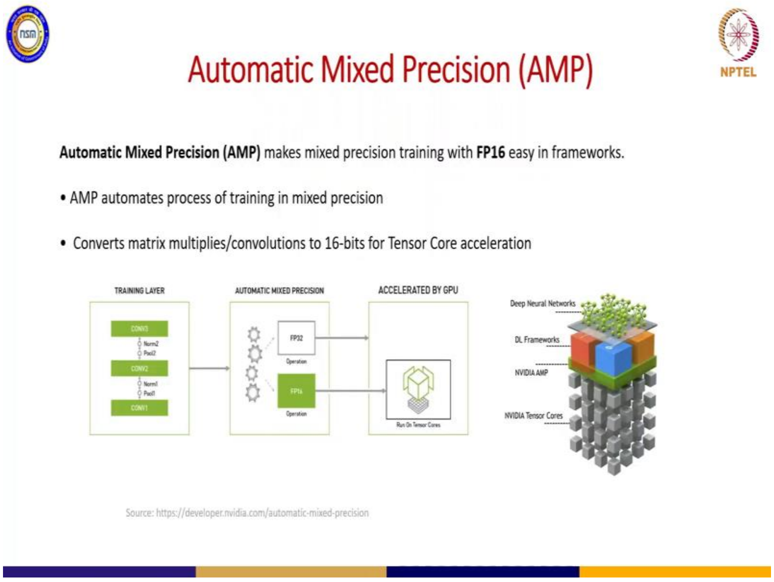


So, in summary, the mixed precision training is that you have to pick choose a floating point of FP16 format, then you perform your forward pass in your model. After that you scale the loss and then, do your back propagation of the scale gradient and then, you will scale back the gradients and the optimizer performs the weight update. These are just the summary of all what have been seen.

(Refer Slide Time: 26:11)

So, is there a simpler way with all this more of theoretical scale, unscale and do that. I would say yes, there is a simpler way.

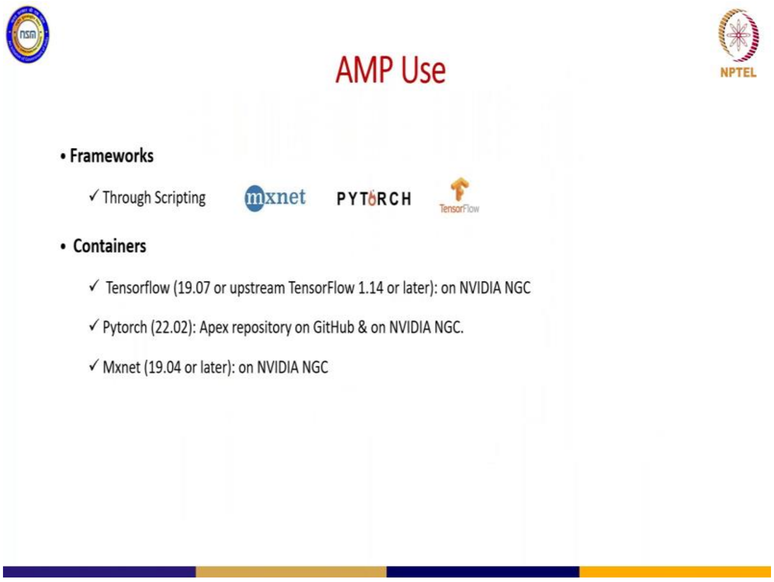
(Refer Slide Time: 26:23)



So, the simplest way this available method is what we call the Automatic Mixed Precision; AMP. Now, the automatic mixed precision make things easier. So, you can perform your training using FP16 within the framework. So, you do not have to do all the manual job again. So, the automatic mixed precision automate the process of training in mixed precision. It does the automation for you. It converts the matrix then and the convolution into 16 bits for your tensor.

So, for example, what we have let us say this is our training layer, the convolution layer that you can see here. So, the training is being done using what automatic mixed precision which is both FP32 and FP16 as well and the computation that will go within the FP16, I will be run on the tensor core. And for example, this is an example here that you have your deep neural network here, the DL, the frameworks are here and the another framework is embedded with enabled with automatic mixed precision here. So, which will be handled by the tensor core.

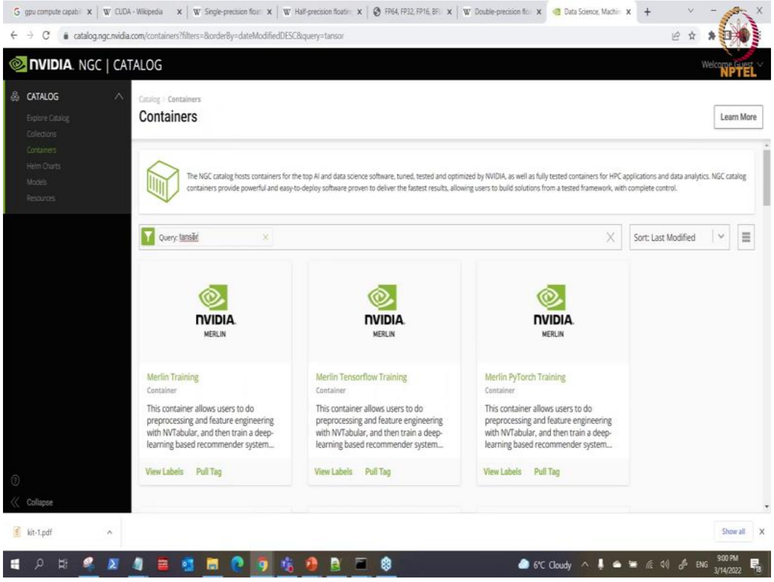
(Refer Slide Time: 27:37)



So, automatic mixed precision use how do we use the automatic mixed precision, we can use it using our frameworks through scripting. So, it exists here in mxnet, pytorch also, you can use tensor flow as well. And then, you can use container. However, in the container, I must say for tensorflow you can use it is only possible with tensorflow version 1 that is only where you can use the automatic mixed precision.

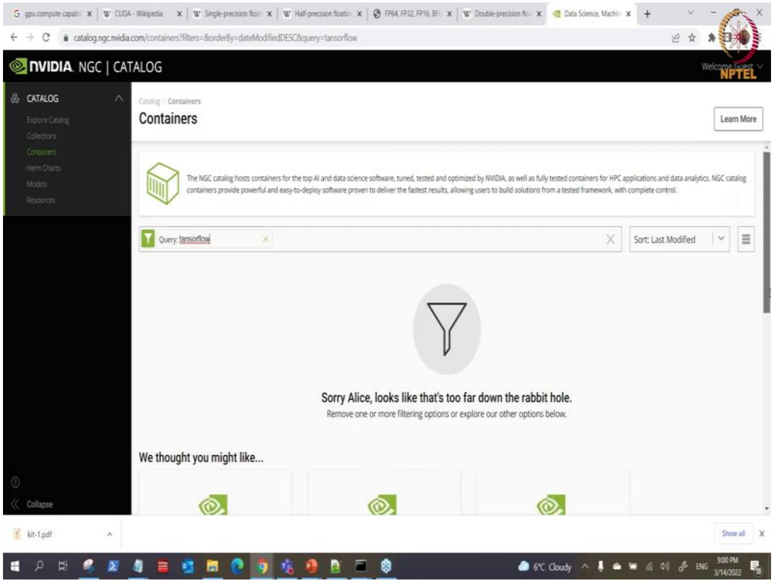
If you want to use a mixed precision, automatic mixed precision with tensorflow version 2, it might not be possible. I tried it there are so many errors that you can you might visit from there. Also, you can use pytorch, also mxnet as well. So, all of these you can pull them on the NVIDIA NGC. So, if you go to NVIDIA NGC here. So, from here so this is tensor flow. Let me come to catalog here ok; yeah.

(Refer Slide Time: 28:50)



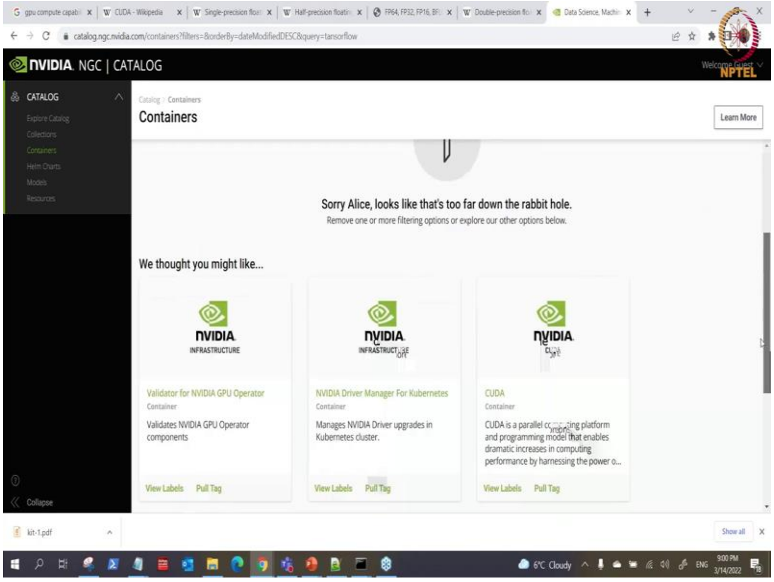
So, you can search, you can search for tensorflow or you search for pytorch.

(Refer Slide Time: 28:58)

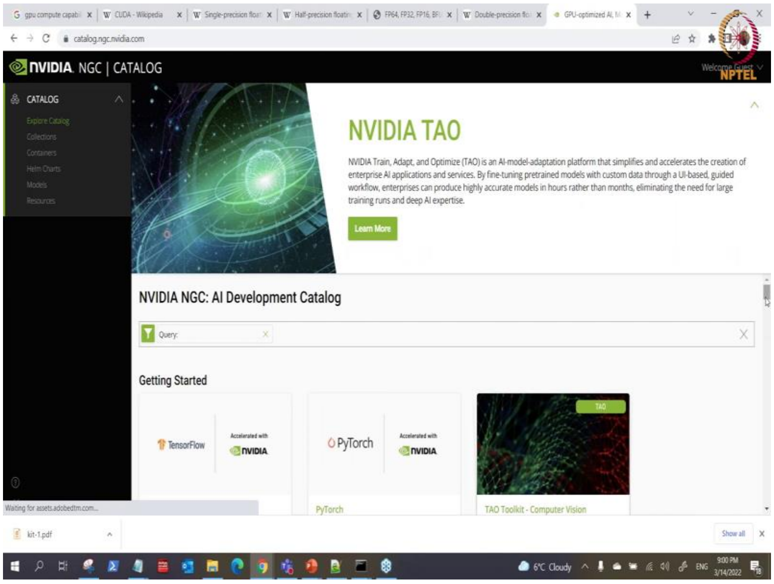


So, if you search all of that, come in ok alright.

(Refer Slide Time: 29:02)

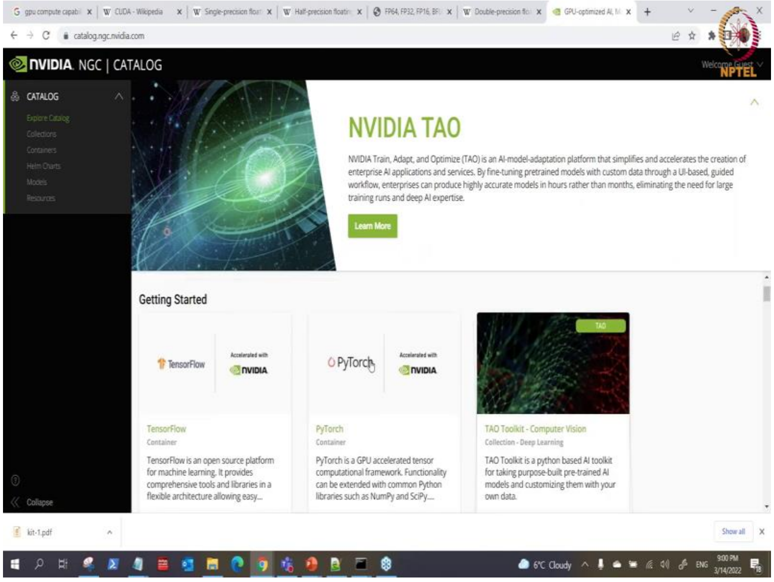


(Refer Slide Time: 29:08)

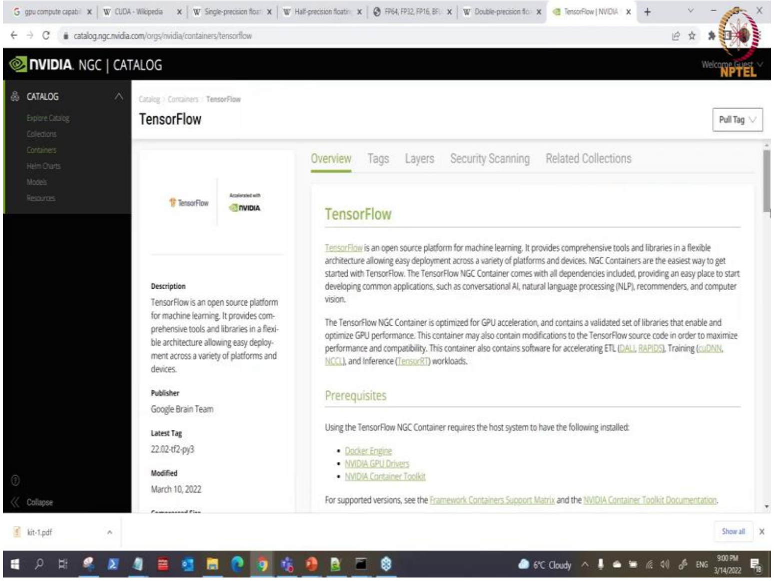


So, yeah they yeah you can just click you search for them, you can see this is tensorflow this is pytorch.

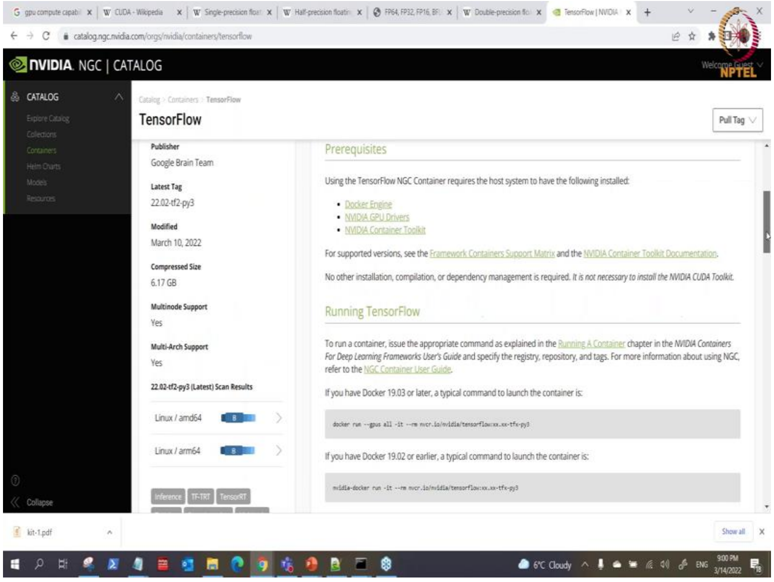
(Refer Slide Time: 29:13)



(Refer Slide Time: 29:19)

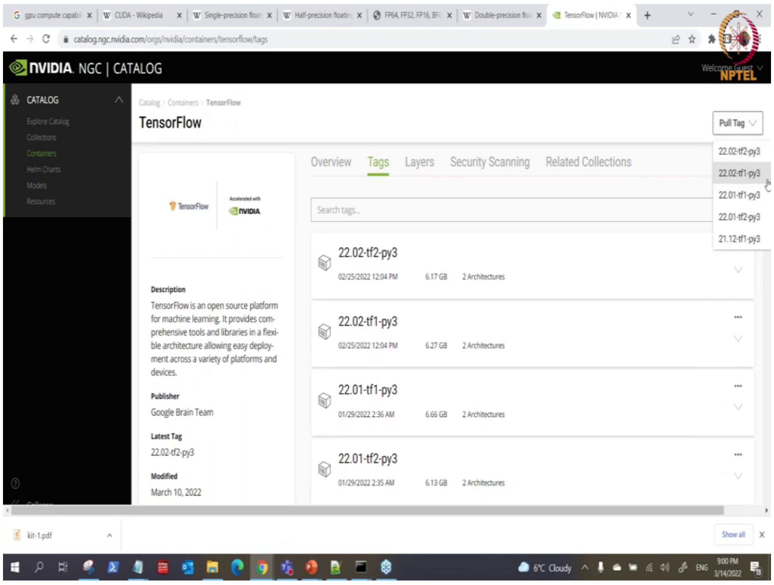


(Refer Slide Time: 29:21)

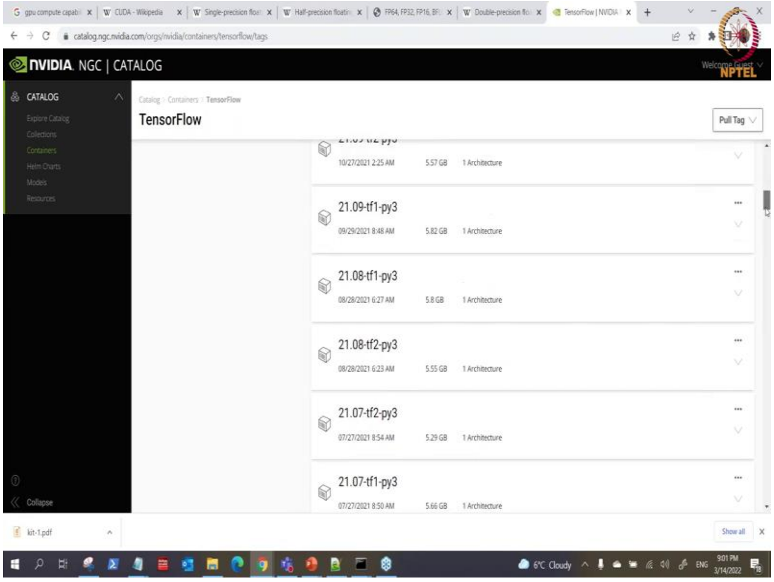


If you click on them, you can get here; you will pick. So, you can pull there are several versions here. Again, you can pull from there, but if you need to use if you are using this these are tensorflow version 2. So, here you can only use mixed precision; you cannot use automatic mixed precision.

(Refer Slide Time: 29:42)

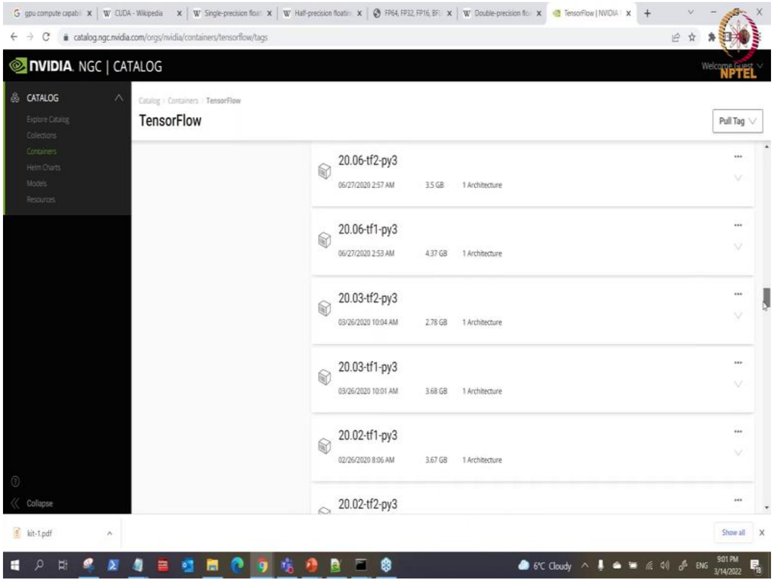


(Refer Slide Time: 29:51)

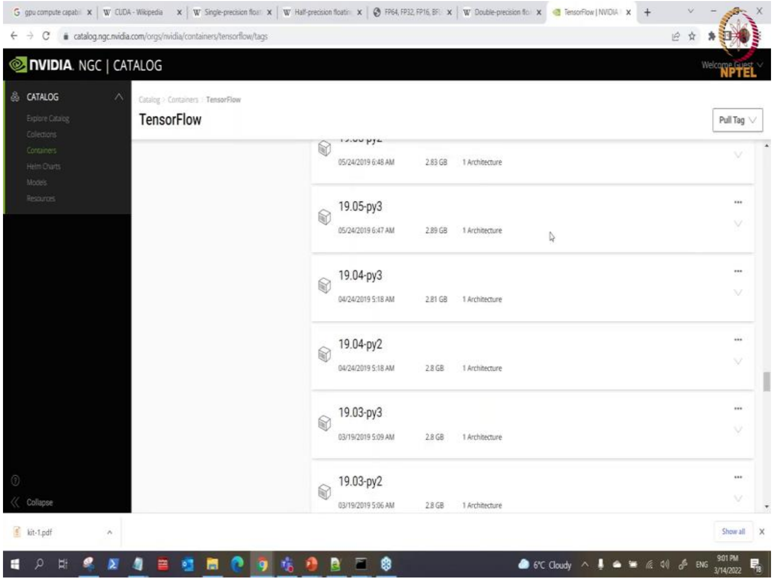


For you to use automatic mixed precision, so you click on the tag here, you come here there is a version there is version 19 here.

(Refer Slide Time: 29:55)



(Refer Slide Time: 29:57)



Version go to 19 07. So, yes, if you pull this one, this is version you will pull this. So, you just need to click here, then you pull and you can you know use that for your automatic mixed precision.