(https://www.nvidia.com/en-us/deep-learning-ai/education/)

Training a Semantic Segmentation Network Ready for Deployment in the Car

Lab created by Oliver Knieps

Before we begin, let's verify WebSockets (http://en.wikipedia.org/wiki/WebSocket) are working on your system. To do this, execute the cell block below by giving it focus (clicking on it with your mouse), and hitting Ctrl-Enter, or pressing the play button in the toolbar above. If all goes well, you should see some output returned below the grey cell. If not, please consult the Self-paced Lab Troubleshooting FAQ (https://developer.nvidia.com/self-paced-labs-faq#Troubleshooting) to debug the issue.

NOTE: It is highly recommended to use Google Chrome as the web browser to run this lab.

In [32]:

```
The answer should be three: 3
```

Let's execute the cell below to display information about the GPUs running on the server.

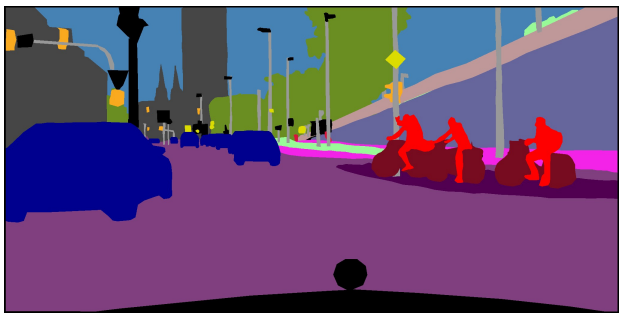
In [33]:

```
Sat Feb  2 05:38:01 2019
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 387.34                 Driver Version: 387.34                    |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  Tesla K80           On   | 00000000:00:1E.0 Off |                    0 |
| N/A   58C    P0    61W / 149W |  10945MiB / 11439MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                       GPU Memory |
|  GPU       PID   Type   Process name                             Usage      |
|=============================================================================|
+-----------------------------------------------------------------------------+
```

1. Introduction

Real-time scene understanding based upon camera images is a major part in nowadays' perception modules for mobile robotics and self-driving cars. In the DNN domain, this can be solved by Fully Convolutional Networks (FCNs) that perform semantic segmentation in a single forward-pass (Long et al., 2015). As the name suggests, a semantic segmentation FCN assigns each pixel of the input image to one of the predefined classes such as "road" or "sky": This output from the perception stage can effectively be fed into localization and path-planning modules.

To give you a first impression of the task environment within this lab, look at the following frame and its pixel-wise, hand-labeled annotation from the Cityscapes dataset (Cordts et al., 2016), a poplular Semantic Segmentation dataset that we will be using (this frame has been captured in Cologne, and you actually see the Cologne Cathedral on the horizon). For now, just think of every color in the image to the right as a different class (you may be able to guess the color-to-class mapping):

This lab takes a classification network as a baseline and shows how to turn it into an FCN architecture that will be trained on a down-scaled subset of Cityscapes for several epochs.

A Neural Network such as an FCN is nothing else than a long series of computations depending on each other from layer to layer – knowing a network's topology allows us to estimate how many operations are needed to perform one or more predictions. This information is very useful to meet practical requirements, given by e.g. the embedded platform we develop for, how many images we need to process in a specific use case, and/or what minimum detection performance is needed. In this lab, the target hardware will be DRIVE PX 2, and you will work on meeting the set of requirements for **Task 1** as outlined in the table below. The other two task configurations are optional thought exercises.

Task number	Scenario	Number of classes	Number of cameras	Frame rate for processing	Required accuracy	Computational budget on platform
1)	Parking scenario	7 classes: Sky, Infrastructure, Road, Sidewalk, Vehicles, Vulnerable Road Users, Void	4 cameras	Medium frame rate: 15 fps	Medium accuracy	Low budget on platform (70 Giga operations per second)
2)	Urban scenario	7 classes: Sky, Infrastructure, Road, Sidewalk, Vehicles, Vulnerable Road Users, Void	4 cameras	High frame rate: 30 fps	Medium accuracy	High budget on platform (300 Giga operations per second
3)	Rural scenario	2 classes: Road, Not Road	1 camera	High frame rate: 30 fps	High accuracy	Medium budget on platform (120 Giga operations per second)

Note: 1 Giga operation = 10^9 operations. You will get an introduction on how we define "accuracy" in a Semantic Segmentation context later in this lab.

We will learn how to design DNNs for Semantic Segmentation with moderate accuracies on Cityscapes, and then develop an understanding of the available budget for deployment on the target platform.

2. Approach

With this lab, we intend to shed light into creating a suitable FCN for a real-life Semantic Segmentation use case. To that end, we will modify an existing CNN architecture, MobileNets (Howard et al., 2017), to perform pixel-wise classification in TensorFlow. We will familiarize ourselves with a down-scaled and simplified version of the Cityscapes dataset, which has a fully labeled training, validation and test set at an original color image resolution of 2048 by 1024 pixels. *Note that we will stick to the TensorFlow convention for dimensionality order of [height x width x channels], so that our original dataset's image size is [1024 x 2048 x 3].* In a "real" automotive scenario for Semantic Segmentation, images ingested into a DNN architecture are typically much larger than the one used in our toy example in order to have a better granularity of the predictions. This granularity is especially relevant when segmenting areas that are very distant from the camera. A small image size helps you speed up the CNN training process, so that you can spend more time on the important content of this lab.

Important note about chapters marked blue:
This is a lab at 'Advanced' level and presents many topics at a high level of detail, especially in the "Theory and MobileNets" chapters. Not all of this information is required to complete this lab; if some contents are totally new to you and you feel that you are stuck, don't skip but just skim through the corresponding chapters marked blue. There will be some time to re-read them during the training stage for your network. The same applies to blue exercises.

- 3. Theory: The next chapter covers the theoretical background needed for building a Fully Convolutional Network fitting into a previously known computational budget. The content of this chapter is targeted on a more proficient understanding and includes some questions. It first shows how to calculate the computational costs of a CNN in 3.1 Counting operations in a CNN (blue), then introduces 3.2 Fully Convolutional Networks for Semantic Segmentation (partially blue) and eventually presents two metrics for assessing an FCN architecture's quality in 3.3 Measuring performance: Pixel-wise accuracy vs. Intersection over Union (partially blue).
- 4. MobileNets: An adjustable CNN as the fully convolutional stem: You would rarely start from scratch when designing a Convolutional Neural Net for a specific purpose, and rather re-use successful architectures from academia and research. During this lab, we will make use of a subsets of the MobileNets topology. MobileNets, whose base version is designed for classification tasks, are interesting to us because they are generally not too resource-hungry and also give us a convenient parameter for scaling our computational needs – to the expense of a potentially lower performance. We will get to know MobileNets in general in 4.1 MobileNets basics (partially blue), and then identify the subset which we can re-use for an FCN architecture in 4.2 Preparing MobileNets for a Semantic Segmentation task.
- 5. Attaching a simple FCN head for Semantic Segmentation: Having derived a subset of scalable MobileNets as our FCN "stem" and also having the background on FCN architectures from the Theory chapter, all we need to do now is to connect those dots. During the fifth chapter, we will turn FCN theory into practice and attach a simple FCN "head" to the MobileNets stem which allows us to train the resulting overall topology on a Semantic Segmentation task.
- 6. Preparing the dataset and importing it into DIGITS: We will train the FCN architecture generated in the preceding chapter in DIGITS, using its TensorFlow back-end. Before that, we will have to modify a down-sampled version of the Cityscapes dataset – reducing its labels to the number of classes given in your scenario – and then import it into DIGITS.
- 7. Putting everything together: Training in DIGITS: This is the final part of the lab where all the previously introduced parts come together. Having in mind the specific use case you have been assigned to, you will first explore which MobileNets can potentially meet your scenario's budget constraints, attach an FCN head and train it on the previously modified Cityscapes dataset. Since we are collecting performance numbers from other participants at the end of this lab, you will get a feeling for the trade-off between resource consumption and performance in a CNN setting.

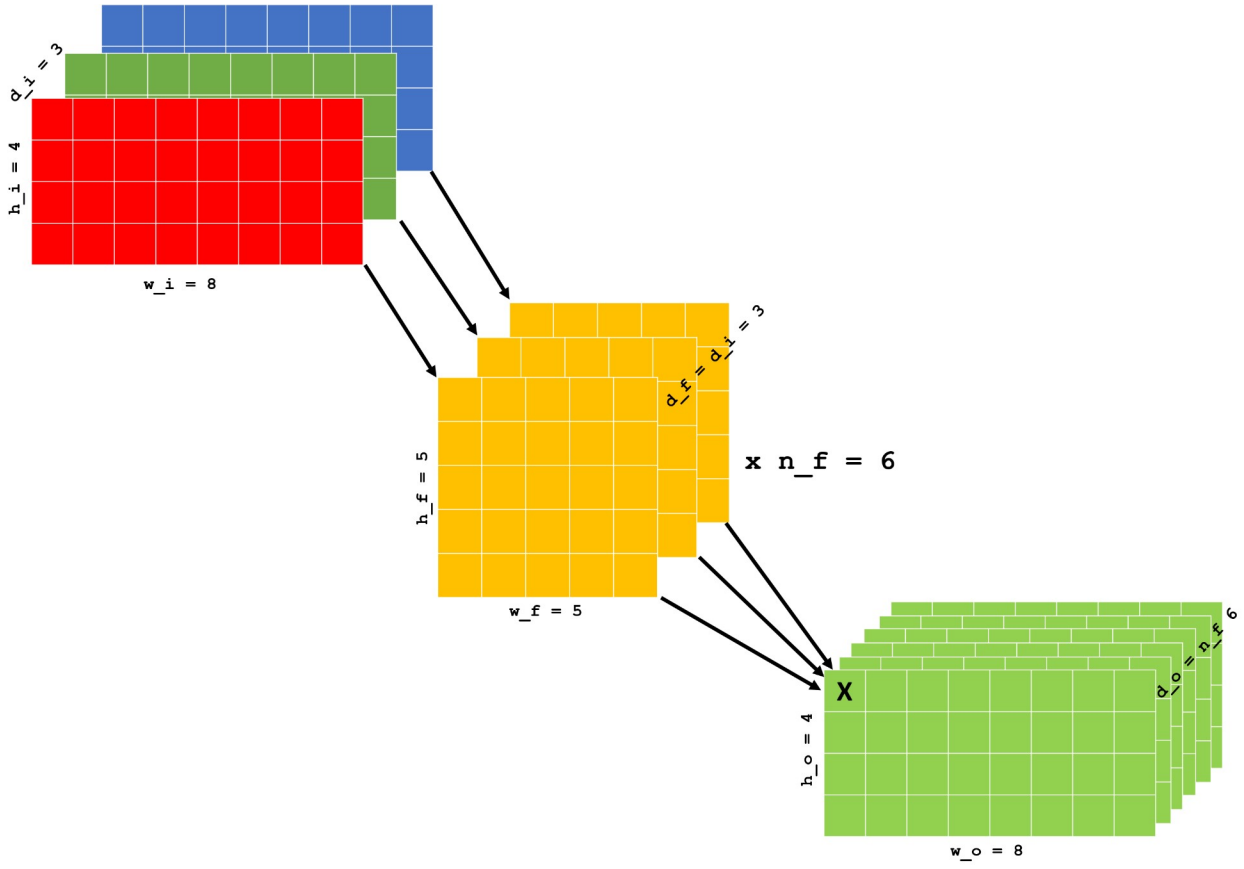
3. Theory

3.1 Counting operations in a CNN

State-of-the-art Convolutional Neural Networks require millions and billions of operations for a single prediction (even more for the back-propagation step during training). Since CNNs are that resource hungry and at the same time of paramount importance to nowadays' AI applications, they have become one of the favorite benchmarks for measuring a hardware's performance.

The costliest as well as most frequent operation of CNNs – consuming easily more than 95% of the total computation time – is contained in their convolution layers (we will refer to this as "Classical Convolution", because you will get to know a less hungry convolution variant later). Let's understand how many operations Classical Convolution requires with the help of a simple example. It is not too important that you understand every detail of it, but it is key that you understand from which inputs the formula at the bottom of this paragraph can be derived:

Consider you want to process an input color image with one red, one green and one blue channel ($c_i = 3$) at a height of $h_i = 4$ pixels and a width of $w_i = 8$ pixels through a Classical Convolution layer (without adding the bias term). The convolution shall use $n_f = 6$ square filters with a height of $h_f = 5$ pixels and a width of $w_f = 5$ pixels. We also do not want to skip any input pixel and set the stride to $s = 1$. To facilitate the calculation a bit, let's assume that we will zero-pad our input image with $(5 - 1)/2 = 2$ pixels on all its borders, so that our output image has the same spatial dimensions as our input image: $h_o = h_i = 4$ and $w_o = w_i = 8$ (with a stride of 2, we would skip every other pixel and have a spatial output dimensionality of 2 by 4 pixels). Since each filter will create one output feature map of the previously mentioned spatial dimensions, we also know the output depth: $d_o = n_f = 6$. Here is a brief sketch of the input feature maps, one of the 6 filters/kernels, and the output feature maps:

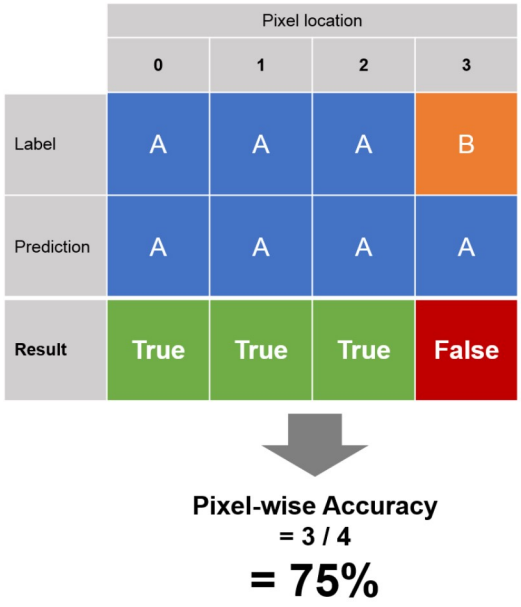


That means every pixel, for example, the one marked with an 'X', of the 3-dimensional output volume with size (h_o x w_o x d_o) = (4 x 8 x 6) is the result of one convolution operation. Such operation is nothing else than multiplying $h_f * w_f * d_i = 5 * 5 * 3 = 75$ input pixels with the $h_f * w_f$ filter weights and accumulating them to a single value: That means it takes $h_f * w_f * d_i = 75$ multiplications and $h_f * w_f * d_i = 75$ additions, which yields $2 * h_f * w_f * d_i = 150$ operations per convolution. On a modern GPU, this can be performed especially efficiently because it can typically calculate

3.3 Measuring performance: Pixel-wise accuracy vs. Intersection over Union

3.3.1 Pixel-wise accuracy

When classifying pixel-wise, you could treat each pixel prediction similarly to how you would for a "traditional" classification task. This would mean, if we had an image row of 1 x 4 pixels with the three leftmost pixels labeled as Class A and the rightmost pixel labeled as Class B, a single wrong prediction of the rightmost pixel would result in an accuracy of $3/4 = 75\%$.



In other words, if we predicted all 4 of the pixels to be class A, we would still achieve a relatively good accuracy of 75%! Class imbalances are very common in Semantic Segmentation annotations: Think of an urban dataset taken from forward-looking camera mounted on a car where a huge portion of the pixels in *every* frame would be labeled as 'Sky', and comparably few pixels would be labeled as 'Pedestrian' in only those frames where pedestrians are visible. This is equivalent to our class A and class B example.

We hence need a stricter metric which is often preferred in a Semantic Segmentation task: Intersection over Union, which is used in the popular Pascal VOC Challenge ((Everingham et al., 2010), for instance.

3.3.2 Intersection over Union

While we can calculate the pixel-wise accuracy directly through comparison of the expected output (the label) and the predicted output of a pixel-wise classifier, Intersection over Union is first calculated for all classes separately, and then averaged over all classes for achieving the overall Intersection over Union score. This allows for a balanced analysis of all present classes; in practice, knowing that some classes are more relevant to the particular use case than others, weighted averages are also often used. In this lab, we will consider all classes as equally important, and just use the arithmetic mean over N classes:

$$IoU_{total} = \frac{\sum_{i=1}^{N} IoU_i^{class}}{N}$$

Let's now explore how to calculate the class-wise Intersection over Union score IoU^{class} : Looking at prediction results for each class separately turns the problem into a binary classification with True Positives (TP), False Negatives(FN), False Positives (FP) and True Negatives (TN). In case you do not remember how to determine these outcomes, we have listed them here for the class in focus:

Label	Prediction	Outcome
Class in focus ($True$)	Class in focus($True$)	True Positive (TP)
Class in focus ($True$)	Different class ($False$)	False Negative (FN)

4. MobileNets: An adjustable CNN as the fully convolutional stem

Within the concept of Fully Convolutional Networks, we will use MobileNets (Howard et al., 2017) as the encoder responsible for distilling a "raw" input image into a much lower resolution one, containing hundreds of learned features per pixel.

4.1 MobileNets basics

Often design choices in the embedded domain are driven by computational requirements, just like your target use case – with MobileNets (notice the plural form: it is rather a set of networks than a single DNN), we are given a scalable concept for designing convolutional networks at different levels of fidelity, depending on the requirements of the task at hand.

4.1.1 Depth-wise Convolutions

Before looking at MobileNets' scalable nature, let's spend some time on understanding another key concept they make use of to keep the workload low and still achieve considerably good results: **Depth-wise Convolutions** (Chollet, 2016). Unlike the "classical" convolutions used in popular network topologies such as VGG (Simonyan and Zisserman, 2014), GoogLeNet (Szegedy et al., 2015) or ResNet (He et al., 2016), a single kernel from a Separable Convolution layer (e.g. at a size of 3x3 pixels) convolves over all input feature maps separately in a first step – instead of convolving at the full depth of all input feature maps. This first step, also called Separable Convolutions, will always produce the same number of output feature maps as input feature maps and does not "mix" them; Separable Convolutions involve MAC^{SC} multiply-accumulates:

$$MAC^{SC} = h_o * w_o * c_i * h_f * w_f$$

To overcome the deficiencies of not being able to choose the number of output feature maps and having no option for channel mixing, Separable Convolutions are followed by so-called Point-wise Convolutions (there are actually batch normalization and ReLU activation layers attached to them, but this does not affect the number of operations too much). This second step of Depth-wise Convolutions is simply a convolution layer with a spatial kernel size of 1x1 pixel, convolving over all "stacked" output feature maps of the Separable Convolution step. We can thus use the the formula for calculating multiply-accumulates of Classical Convolution from earlier, setting the kernel height and size to 1 so that our output resolution stays at h_o x w_o, and keeping c_i from the calculation of MAC^{SC}:

$$MAC^{PW} = h_o * w_o * c_i * n_f * 1 * 1 = h_o * w_o * c_i * n_f$$

Hence Depth-wise Convolutions require the following number of multiply-accumulates and operations:

$$MAC^{DW} = MAC^{SC} + MAC^{PW}$$

$$MAC^{DW} = h_o * w_o * c_i * h_f * w_f + h_o * w_o * c_i * n_f$$

$$MAC^{DW} = h_o * w_o * c_i * (h_f * w_f + n_f)$$

$$ops^{DW} = 2 * MAC^{DW} = 2 * h_o * w_o * c_i * (h_f * w_f + n_f)$$

That means our reduction factor r of operations for using Depth-wise Convolutions instead of Classical Convolution is:

$$r_{ops} = \frac{2 * h_o * w_o * c_i * h_f * w_f * n_f}{2 * h_o * w_o * c_i * (h_f * w_f + n_f)} = \frac{h_f * w_f * n_f}{h_f * w_f + n_f}$$

Question 4.1.1

Let's consider the following:

We have an input layer with [h_i x w_i x c_i] = [4 x 4 x 5]
We will use $n_f = 8$ kernels with [h_f x w_f x c_f] = [3 x 3 x 5], and a padding of $p = 1$ (`'SAME'` output resolution as input resolution)

What is the shape of the expected output assuming Classical Convolution? What is the reduction factor r_{ops} of using Depth-wise Convolutions instead of Classical Convolution?

4.2 Preparing MobileNets for a Semantic Segmentation task

The above table describes MobileNet architecture as found on page 4 of the paper (https://arxiv.org/abs/1704.04861): *"MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications"* (authored by Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam).

The rest of MobileNet paper is optional reading material for your interests. In the table above, we see a listing of layers and their respective input sizes in the leftmost column. What we really care about for convolutionalizing MobileNets is a layer's output size, which is unfortunately not explicitly listed: Here, an output size [h_o x w_o x c_o] at layer n implies that the following layer $n+1$ has a corresponding input size. We can ignore the number of channels (the last factor in the rightmost column) for now, since we are primarily interested in the downsampling factor from layer to layer. For example, the first convolution layer "Conv / s2" ("s2" stands for a stride of two, skipping every other pixel during convolution) produces an output of half the spatial size of its input: [112 x 112].

We require a specific (fully convolutional) subset of MobileNets that we can re-use for our Semantic Segmentation task in mind. Luckily, the creators provide us with a handy function for constructing custom MobileNets. During this lab, not all of the optional arguments are of importance – we occluded the less relevant and focus on the following three:

- Of course, it is necessary to specify a tensor containing the image data in **`inputs`** so that the spatial dimensions can iteratively be adjusted from layer to layer (you can specify tensors of input sizes other than [224 x 224 x 3])
- The construction of our custom MobileNet instance will terminate at the layer with the string identifier **`final_endpoint`**. For instance, you could let your MobileNet creation stop after the first layer by filling in `'Conv2d_0'`, which is the only "classical" convolutional layer with kernel size 3 x 3 and a stride of 2.
- As described earlier, the parameter **`depth_multiplier`** dictates how many filters of the specified size are learned in **all convolutional layers**, and is therefore a useful measure to adjust the computational needs and the capacity of your network topology. By default, it is set to `1.0`. In the first layer `'Conv2d_0'`, this default setting results in 32 filter maps. Lowering `depth_multiplier` to e.g. `0.5` would reduce the number of filter maps to 16 for `'Conv2d_0'` – reducing the layer's computational requirements as well as its capacity – and correspondingly halve all other convolution layers' number of filter maps, too.

Take a brief look at the reduced version of the function, and pay special attention to the options for `final_endpoint`:

```
def mobilenet_v1_base(inputs,
                      final_endpoint='TheLayerYouChoose',
                      depth_multiplier=1.0)
  """Mobilenet v1.

  Constructs a Mobilenet v1 network from inputs to the given final endpoint.

  Args:
    inputs: a tensor of shape [batch_size, height, width, channels].
    final_endpoint: specifies the endpoint to construct the network up to. It
      can be one of ['Conv2d_0', 'Conv2d_1_pointwise', 'Conv2d_2_pointwise',
      'Conv2d_3_pointwise', 'Conv2d_4_pointwise', 'Conv2d_5'_pointwise,
      'Conv2d_6_pointwise', 'Conv2d_7_pointwise', 'Conv2d_8_pointwise',
      'Conv2d_9_pointwise', 'Conv2d_10_pointwise', 'Conv2d_11_pointwise',
      'Conv2d_12_pointwise', 'Conv2d_13_pointwise'].
    depth_multiplier: Float multiplier for the depth (number of channels)
      for all convolution ops. The value must be greater than zero. Typical
      usage will be to set this value in (0, 1) to reduce the number of
      parameters or computation cost of the model.

  Returns:
    tensor_out: output tensor corresponding to the final_endpoint.
    end_points: a set of activations for external use, for example summaries or
                losses.

  Raises:
```

Exercise A

As mentioned before, MobileNet's strided convolution layers are responsible for gradually reducing the spatial input sizes to the network. Look at the table on page 4 of the MobileNet paper for answering the following questions:

Question 4.2.1

Until which layer can we consider the network topology (with an input size of [224 x 224 x 3]) as a 'fully convolutional neural network', preserving spatial information from its input image?

The network is considered fully convolutional neural network until before the average pooling layer is applied.

Question 4.2.2

In the largest fully convolutional subset of MobileNet, by which factor do we "downsample" the input image's spatial dimensions? Compare the input dimensions to the network and the output dimensions of the FCN subset.

We 'downsample' input image's spatial dimensions 32 times.

Exercise B

Verify your assumptions from Exercise A by playing around with the following code snippet and answering the following questions:

Question 4.2.3

If we want to encode the input image to a spatial representation at $\frac{1}{32}$ of both the input height and the input width (from an input dimensionality of [224 x 224 x 3]), which layers can we select as an end point? Similarly, which layers can we choose as an endpoint if we want to "downsample" by a factor of 16? Modify `my_endpoint` .

either Conv2d_12_pointwise or Conv2d_13_pointwise

Question 4.2.4

If you were to change the input size to e.g. [360 x 480 x 3], do we achieve the same downsampling factor for input height and the width if we set `my_endpoint` to `'Conv2d_13_pointwise'` ?

No, height has different downsampling factor

In [34]:
```
import tensorflow as tf
from tensorflow.contrib import slim
from mobilenet_v1 import *

## Modify these lines for Question 4.2.4
######################################################################
height = 360 # The height of one input image
width = 480 # The width of one input image
######################################################################

# We will replace this placeholder with our training images later
my_image_tensor = tf.placeholder(tf.float32, shape=(1, height, width, 3))


######################################################################
# Choose an appropriate endpoint for creating a custom MobileNet.
# hint: Have a closer look at mobilenet_v1_base documentation above.
my_endpoint = "Conv2d_13_pointwise"
######################################################################

# To prevent multiple graphs being active during one session, we reset the default graph every
tf.reset_default_graph()
my_mobilenet,my_endpoints = mobilenet_v1_base(inputs=my_image_tensor,
                  final_endpoint=my_endpoint,
                  depth_multiplier=1.0)
input_shape = my_image_tensor.get_shape().as_list()
output_shape = my_mobilenet.get_shape().as_list()
print('Input dimensions: ' + str(input_shape))
print('Output dimensions: ' + str(output_shape))
print('Height downsampling factor: %.1f' % (input_shape[1]/output_shape[1]))
print('Width downsampling factor: %.1f' % (input_shape[2]/output_shape[2]))
```

```
Input dimensions: [1, 360, 480, 3]
Output dimensions: [1, 12, 15, 1024]
Height downsampling factor: 30.0
Width downsampling factor: 32.0
```

5. Attaching a simple FCN head for Semantic Segmentation

We have derived a fully convolutional MobileNet stem whose computational complexity and capacity we can modify with the Depth Multiplier parameter. As we had learned earlier, this will not be sufficient to semantically segment an input image. We still require an "appendix" to the stem which classifies pixel-wise via (1x1) Point-wise Convolution and also up-samples to our original input image size through Transposed Convolution.

5.1 A bilinear distribution for initializing Transposed Convolution kernels

First of all let's elaborate on the layer type used for upsampling in an FCN that we learned about in the Theory chapter: Transposed Convolution. As we remember, the kernel weights act as a kind of "brush" distributor of an input pixel's value, and we found a good setting for overlapping sliding window positions with

$$\theta(x) = (s, k, p)^T = (x, 2x, x/2)^T,$$

x being the factor we want to upsample by, and s, k, p being the stride, kernel size, and padding parameters of the Transposed Convolution layer, respectively.

According to the brush analogy, if we set all the weights within a Transposed Convolution kernel to the same value, we would achieve a drawing pattern similar to a marker pen: We would color all output pixels in the sliding window with the same intensity, which is derived from the corresponding input pixel.

From the fully convolutional MobileNet base topology, we found out that we downsample by a factor of 32 horizontally and vertically. Correspondingly, in order to reach a classification granularity of one distinct class per pixel, we would have to eventually upsample by exactly the same factor. That means we can use the configuration for s, k and p that we calculated earlier.

This implies that we have rather large square kernels with an edge length of $k = 64$; instead of using a marker pen, we would actually prefer a "real" brush shape where we paint more color in central regions than in the surroundings. If you are working with image processing libraries such as OpenCV or OpenVX, this strategy is often referred to as upsampling with bilinear interpolation (Prashanth et al., 2009), and it can also be used for Fully Convolutional Networks Long et al. (2015).

Within the terminology of Transposed Convolution, we could interpret this as a setup where the pixels within a moving window on the output feature map being further away from the central input pixel contribute less to the final prediction than closer ones.

Exercise C

Question 5.1.1

Linking all of the knowledge above together, we will use a bilinear distribution as the weights initializer for the Transposed Convolution kernels of our FCN architecture. The initial weights are created in the following code block; inspect the implementation, modify `nclasses` to the number of classes from your use case, modify `kernel_dims` to your calculated value from Question 3.2.3, and then run the cell to visualize your initialized weights:

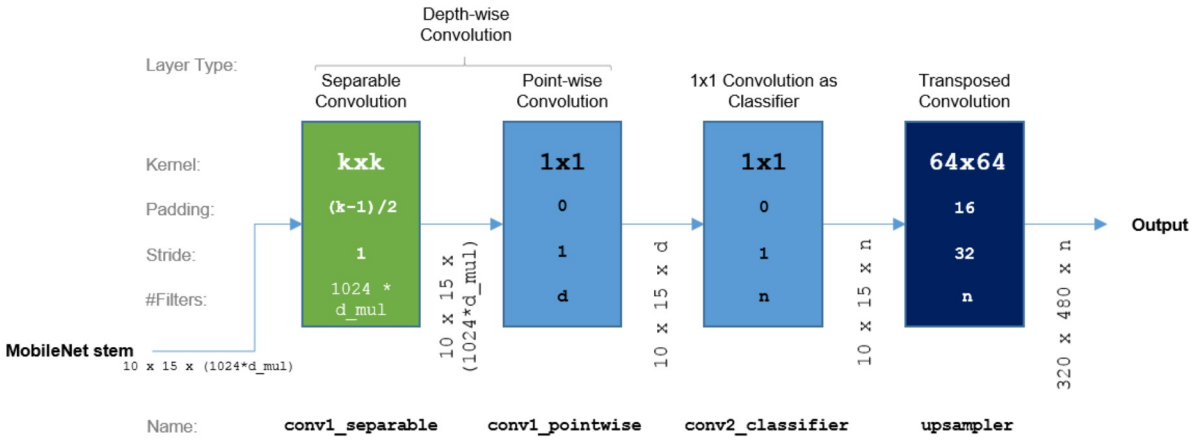
In [25]:
```
import numpy as np
import warnings
with warnings.catch_warnings():
    warnings.simplefilter("ignore")
    import matplotlib.pyplot as plt
%matplotlib inline


# Adjust the following:
######################################################################
kernel_dims = [64,64]
nclasses = 7
######################################################################


def create_bilinear_kernels(num_classes, kernel_dims):
    """Creates a 2D bilinear distribution for initializing the weights for transposed convolut
    """Output: NumPy array with dimensions: [kernel_dims[0] x kernel_dims[1] x num_classes x n
    def find_params(size):
        """For odd size: take the mid pixel as the center, for even size: take two adjacent pi
        divisor = np.floor((size + 1) / 2.0)
        if size%2==0:
            center = divisor - 0.5
        else:
            center = divisor - 1
        return divisor,center

    # note the expected shape of kernel_dims variable
    height, width = kernel_dims

    # Determine the center and the divisor for height and width
    divisor_height,center_height = find_params(height)
    divisor_width,center_width = find_params(width)

    # Create one kernel with ones in the center, and decrease the value further away we move f
    grid = np.ogrid[:height, :width]
    filter_coefficients = (1.0 - abs(grid[0] - center_height) / divisor_height) * (1.0 - abs(g
    # Now put everything into a NumPy array in the required float32 precision (shape: [height
    one_plane = np.array(filter_coefficients, dtype=np.float32)
    # For each input feature map to each output feature map,
    # we will use transposed convolution with a kernel of [height x width].
    # There are num_classes input feature maps and also num_classes output feature maps.
    # Hence we will first initialize a NumPy array with dimensionality [height x width x num_c
    all_planes = np.zeros((height,
                width,
                num_classes,
                num_classes), dtype=np.float32)

    # ... and then copy one_plane to all num_classes x num_classes entries in the last two dim
    for i in range(num_classes):
        for j in range(num_classes):
            all_planes[:, :, i, j] = one_plane
    return all_planes



# Draw the weights for initializing one kernel
bilinear_kernels = create_bilinear_kernels(nclasses, kernel_dims)
plt.imshow(bilinear_kernels[:,:,0,0])
plt.suptitle("One kernel with dimensions %d x %d" %(kernel_dims[0],kernel_dims[1]), fontsize=1
plt.show()

# Draw the miniatures of the weights for initializing all kernels
fig, axes = plt.subplots(ncols=nclasses, nrows=nclasses)
fig.suptitle(("All %d x %d kernels" %(nclasses,nclasses)), fontsize=15)
for row in range(nclasses):
    for col in range(nclasses):
        axes[row, col].imshow(bilinear_kernels[:,:,row,col])
        axes[row, col].get_xaxis().set_visible(False)
```

5.2 A complete FCN head for Semantic Segmentation with a MobileNet stem

In this section, we combine many learnings from earlier parts of this notebook. So read carefully and check for yourself if you have understood everything.

We will construct a very simple Fully Convolutional Network (Long et al., 2015) head to our MobileNet stem that enables training the overall architecture for a Semantic Segmentation task. Even though this FCN head is very basic – do not expect to win any competitions with it – it will do an adequate job on our Cityscapes dataset and can serve as solid learning material.

Here is the architecture of mentioned FCN head that we will subsequently implement (note that we have omitted the activation and batch normalization layers for all convolution layers):



- As you can see, we append it to a pruned MobileNet with a spatial output dimensionality of 10 x 15, whereas the depth of the MobileNet output is determined by `1024*d_mul` (making use of the Depth Multiplier parameter, here `d_mul`, that we previously described). **In the code below, `d_mul` is referred to as `depth_multiplier`.**
- The head's first convolution layer is there to replace the average pooling layer of the classification MobileNet topology with a window size of 7x7 (remember your findings from Exercise A). For this layer, we have to choose a kernel size `k`, while we use TensorFlow's `'FULL'` padding policy and a stride of 1 so that our resolution does not change. The greater the value for `k`, the greater the receptive field of the network, which basically represents the size of an area on the input image that is responsible for the prediction of one output pixel. To keep the computational needs within that layer low, we use the Depth-wise Convolution concept that is prominently present in MobileNets (if you are interested, you can calculate how many operations are required if we used Classical Convolution with a kernel size of `k=7` if you have 1024 input features and 1024 filters – as you may guess, a lot). Correspondingly, we have first have the Separable Convolution layer `conv1_separable`, producing `1024*d_mul` output feature maps, which is followed by a Point-wise Convolution layer, which we will describe in the following bullet point. **In the code below, `k` is referred to as `kernel`.**
- The Point-wise Convolution layer `conv1_pointwise` has a 1x1 kernel and `d` filter maps, so that the output feature map depth is equal to `d`. **In the code below, `d` is referred to as `depth`.**
- In the subsequent layer `conv2_classifier`, we intend to classify each of the 10x15 pixels received from the previous layer into `n` classes. We hence use another 1x1 convolution layer with `n` filters. **In the code below, `n` is referred to as `num_classes`.**
- In principle, the output feature maps from the previous 1x1 convolution layer could already serve for a very coarse-grained Semantic Segmentation task where a region of 32x32 input pixels would be processed to a prediction of a single pixel. Our goal is to output predictions at a (single-)pixel granularity; we will therefore make use of the Transposed Convolution layer `upsampler` with the parameters from the question you answered earlier and initialize the weights with the function we got to know in Exercise C. All the previous layers are initialized with the Xavier weight filler.

Exercise D

Question 5.2.1

In [35]:
```
def add_fcn_head(net, num_classes, input_shape, is_training, kernel=[7,7], depth=1024):
    """Adds a very simple fully convolutional head to the network specified with net."""
    """num_classes defines the target output depth of the upsampling layer and the last point-
    """input_shape shape is needed for determining the target dimensionality after upsampling.
    """is_training indicates if we have to initialize the weights."""
    """kernel determines the size of the first convolution layer's filter."""
    """depth is the parameter for the number of the point-wise convolution layers' filters in

    # This is the Depth-wise Convolution block:
    # First the Separable Convolution layer with the specified kernel,
    # taking the output from the MobileNet stem as an input...
    # Input shape: [10 x 15 x (1024*depth_multiplier from MobileNet stem)]
    # Output shape: [10 x 15 x 1024*depth_multiplier from MobileNet stem)]
    conv1_separable = slim.separable_conv2d(net, None, kernel,
        depth_multiplier=1.0,
        stride=[1,1],
        normalizer_fn=slim.batch_norm,
        scope='conv1_separable')
    # ... and the following Point-wise Convolution layer.
    # Input shape: [10 x 15 x (1024*depth_multiplier from MobileNet stem)]
    # Output shape: [10 x 15 x depth]
    conv1_pointwise = slim.conv2d(net, depth, [1, 1], 1, scope='conv1_pointwise')

    # Let's use Dropout layer with a common Dropout ratio of 0.5 for regularization.
    # Input shape: [10 x 15 x depth]
    # Output shape: [10 x 15 x depth]
    dropout_keep_prob=0.5
    dropout = slim.dropout(conv1_pointwise, dropout_keep_prob, is_training=is_training, scope=

    # The 1x1 Convolution layer, used as a classifier with num_classes output feature maps.
    # Input shape: [10 x 15 x depth]
    # Output shape: [10 x 15 x num_classes]
    conv2_classifier = slim.conv2d(dropout, num_classes, [1, 1], 1, scope='conv2_classifier')

    # The Transposed Convolution Layer, upsampling from 10 x 15 to the original input image re
    # Input shape: [10 x 15 x num_classes]
    # Output shape: [320 x 480 x num_classes]

    # This is a fixed setting which can only upsample by a factor of 32.
    # Let's first assert that this condition is met:
    current_shape = net.get_shape().as_list()
    factor_height = input_shape[1]/current_shape[1]
    factor_width = input_shape[2]/current_shape[2]
    upsampling_factor = 32
    assert(factor_height==factor_width==upsampling_factor)

    # upsample_kernel_size = upsampling_factor * 2
    upsample_kernel_size = 64

    if is_training:
        # Only initialize the kernel weights with a bilinear distribution if we start from scr
        filter_coefficients = create_bilinear_kernels(num_classes, [upsample_kernel_size, upsa
    else:
        # Otherwise, just use zeros because we will reuse the pre-trained weights of a snapsho
        filter_coefficients = [0]

    # upsample_stride = upsampling_factor
    upsample_stride = 32

    upsampler = slim.conv2d_transpose(conv2_classifier, num_classes,
        kernel_size = [upsample_kernel_size, upsample_kernel_size],
        stride=[upsample_stride, upsample_stride],
        scope='upsampler',
        padding='SAME', # Note: With slim.conv2d_transpose, the padding will be calculated aut
        weights_initializer=tf.constant_initializer(filter_coefficients),
        trainable=True,
        activation_fn=None) # Softmax will only be applied during training. For inference, we
    return upsampler
```

Question 5.2.2

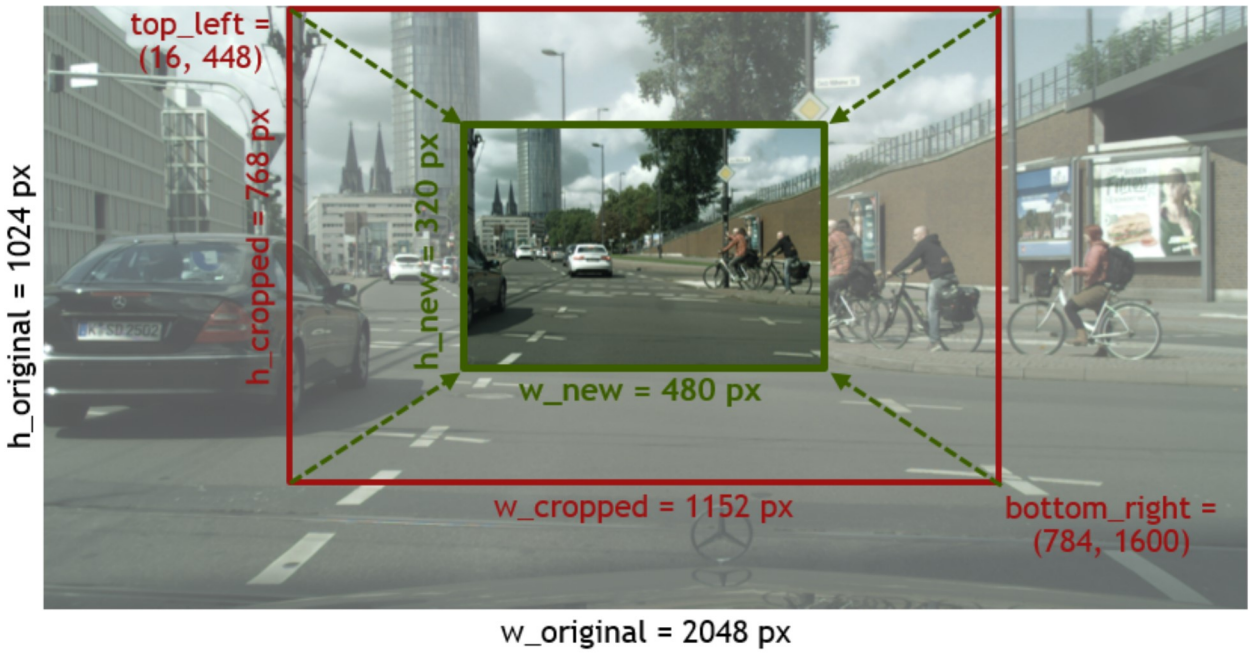
What are the two regularization methods that are applied in the code defining the network? Type your answer in this Markdown cell.

Dropout, Weighted regularization

6. Preparing the dataset and importing it to DIGITS

Originally, the Cityscapes dataset (Cordts et al., 2016) actually contains images at a resolution of $[1024 \text{ x } 2048]$ pixels with pixel-wise annotations for 30 classes, but we use a version downsized to $[320 \text{ x } 480]$ in order to keep your training cycle times low. In the following, we will show you how we cropped and downs-sampled the images.

As mentioned, the dimensions $[1024 \text{ x } 2048]$ of our dataset are not really suitable for the given time frame within this lab. Additionally, the hood of the vehicle that Cityscapes has been recorded with is present at the bottom of all images. Also "blurry" borders can be seen on top of the images, which is the result of rectifying them according to the camera's lens properties after recording. We hence first cropped a central region from the original image and its corresponding annotation to the dimensions $[768 \text{ x } 1152]$, and then downsampled it to $[320 \text{ x } 480]$. This process is shown with our example frame to give you an impression of the actual proportions we will be operating with:



By default, Cityscapes contains 3475 file pairs of camera images with their corresponding pixel-wise annotations (the 1525 test samples are unlabeled), out of which 2975 pairs belong to the training set taken in 18 German cities (one of them being Cologne) and 500 to the validation set taken in Frankfurt, Münster and Lindau. These original sets have been restructured as shown in the following table:

Original set	New set	Original #samples	New #samples	Comment
Training set	Training set	2975	900	On average, drew $900/2875 \approx 30\%$ from all 18 training cities (evenly distributed).
Validation set (Münster)	Validation set	174	100	Using 100 out of 174 samples from the validation set taken in Münster as the new validation set (randomly sampled).
Validation set (Lindau)	Test set	59	59	Using all 59 images from the (fully labeled) validation set taken in Lindau as the new test set. The original Cityscapes test set does not contain labels.

We have ordered the pre-processed Cityscapes dataset in the following way: It consists of one features folder and one labels/annotations folder for each of the training, validation and test sets, totaling 6 folders.

The features folders contain color images of size $[360 \text{ x } 480 \text{ x } 3]$ with 8-bit RGB values. For example, a pixel showing the sky in the upper central part of image `train/cologne_000012_000019.png` (the cropped one we see above) has the values `[194 210 210]`.

The annotation folders contain pixel-wise label images of size $[360 \text{ x } 480 \text{ x } 1]$ with 8-bit gray-scale values. The corresponding label for `train/cologne_000012_000019.png` is given the same file name, but logically resides in a different folder: `trainannot/cologne_000012_000019.png`. The pixel in the label image corresponding to the previously mentioned sky

6.1 Class reduction of Cityscapes

Go through the following exercise and study the code block below.

Exercise E

Question 6.1.1

First study, then modify the following code snippet to match your use case – pay special attention to the number of classes you want to detect, as defined in your use case scenario. The output classes are predefined, however, you will have to figure out a mapping from the old classes to the 7 and 2 classes, respectively. Then run the script to crop all images to a resolution of 320 x 480 and perform the class re-mapping. The processed output files will be stored in `/data/Cityscapes_preprocessed`.

In [27]:
```
import os
import distutils
from distutils import dir_util
from scipy import misc

# Old classes:
# 0: Unlabeled
# 1: Ego vehicle
# 2: Rectification border
# 3: Out of roi
# 4: Static
# 5: Dynamic
# 6: Ground
# 7: Road
# 8: Sidewalk
# 9: Parking
# 10: Rail track
# 11: Building
# 12: Wall
# 13: Fence
# 14: Guard rail
# 15: Bridge
# 16: Tunnel
# 17: Pole
# 18: Polegroup
# 19: Traffic light
# 20: Traffic sign
# 21: Vegetation
# 22: Terrain
# 23: Sky
# 24: Person
# 25: Rider
# 26: Car
# 27: Truck
# 28: Bus
# 29: Caravan
# 30: Trailer
# 31: Train
# 32: Motorcycle
# 33: Bicycle


# New class names for a class number of 7:
# 0: Sky
# 1: Infrastructure
# 2: Road
# 3: Sidewalk
# 4: Vehicles
# 5: VRU (Vulnerable Road Users)
# 6: Void


def reduce_classes(mapping_list, src_folder, dst_folder):
    """Walks iteratively through src_folder and crops all feature and label images to a height
    """Identifies label images if they have only one color channel and applies label conversio
    """Stores new files in dst_folder with the same folder topology as src_folder."""
    for root,dirs,files in os.walk(src_folder):
        print('Started to process all images in %s...' % str(root))
        dst_subfolder = os.path.join(dst_folder,root.split('/')[-1])
        # Check if the current directory is a labels folder, if yes: perform label conversion.
        if str(root).endswith('annot'):
            for f in files:
                if str(f).endswith('.png'):
                    filename_src = os.path.join(root,f)
                    image = misc.imread(filename_src)

                    filename_dst = os.path.join(dst_subfolder,f)
                    if not os.path.exists(dst_subfolder):
                        os.makedirs(dst_subfolder)
```

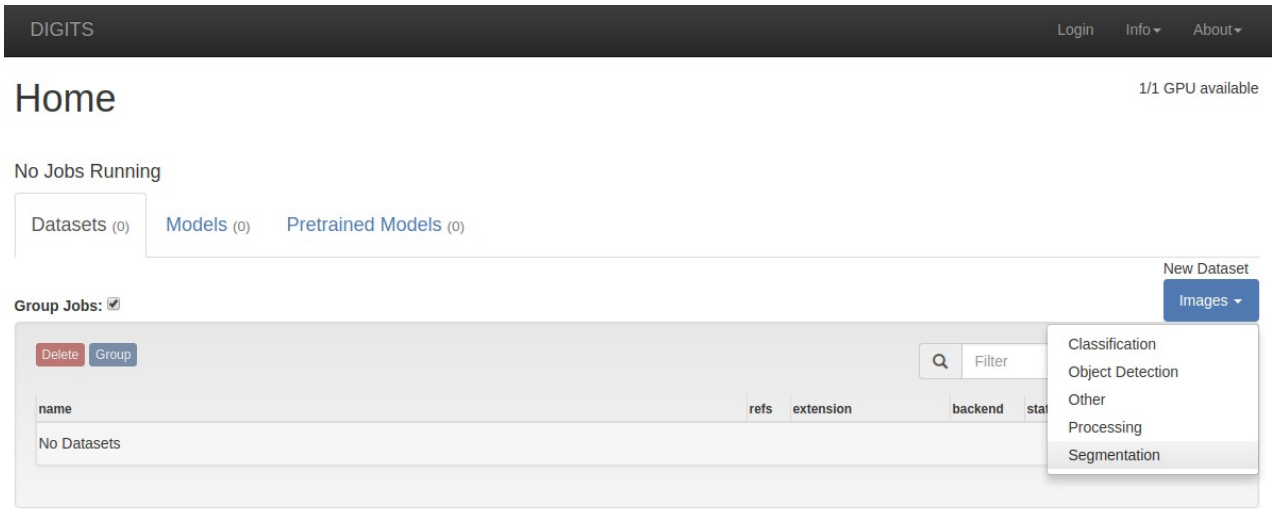
6.2 Importing the modified Cityscapes dataset into DIGITS

Now that we have the Cityscapes dataset in the resolution we require and have reduced the pixel-wise annotations to the number of classes specified in the scenario from the Introduction, we can go ahead and import everything into DIGITS.

Open DIGITS (/digits/) in a separate window first.

In case you are new to DIGITS, take a brief look at the overview given on the NVIDIA website (https://developer.nvidia.com/digits). Independent of the back-end framework you use DIGITS with (we will use TensorFlow), you may create datasets that can be interpreted by any of them and visualize the learning process as well as the inference results on selected input images in the same way.

At first, click on the leftmost `Datasets` tab, then open the `New Datasets` drop-down menu to the right and select `Segmentation`.



DIGITS is specifically designed for multiple users using the same hardware. Even though you will be the only user on the server instance that you run this Jupyter notebook on, create your personal user alias:

Now specify the paths to both the input images and the labels of your training and validation set by copying all settings shown in the screen shot below (do not forget to tick `Separate validation images`).

In case you do not want to type the paths, here a table you can copy-paste from:

Field	Path
`Feature image folder`	`/data/Cityscapes_preprocessed/train`
`Label image folder`	`/data/Cityscapes_preprocessed/trainannot`
`Validation feature image folder`	`/data/Cityscapes_preprocessed/val`
`Validation label image folder`	`/data/Cityscapes_preprocessed/valannot`

For `Class Labels`, choose the correct file corresponding to the number of classes from your use case:

Number of classes	Path for `Class Labels`
2	`/data/label_lists/cityscapes_labels_2classes.txt`

7. Putting everything together: Training in DIGITS

7.1 Exploring the parameter space for a suitable FCN architecture

Before we start training, let's explore the available design space in terms of the four parameters we intend to modify:

`DEPTH_MULTIPLIER` , which is the depth multiplier for your MobileNet stem.
`CLASSIFIER_KERNEL` , which is the kernel size for the Separable Convolution layer of the FCN head.
`CLASSIFIER_DEPTH` , which is the depth of the (first) Point-wise Convolution layer of the FCN head.
`NUMBER_CLASSES` , which is is the class number from your use case.

While `NUMBER_CLASSES` is predefined in the use case scenario, we will have to modify the other 3 parameters to meet the most restrictive requirement: The available budget of Giga operations **per second**.

Per second is an important indication here: In the Theory section, we learned how to calculate the number of operations for a single CNN forward pass at a given input size. But now we need to perform multiple predictions for potentially multiple cameras with number `n_cameras` , and this process is expected to be repeated at the frequency `fps_per_camera` . That means we have a total throughput of `images_per_second = n_cameras * fps_per_camera` images per second.

If we do know the computational requirements for processing one image in Mega (10^6) operations with `megaops_per_image` , we can thus calculate the total requirements in Giga (10^9) operations per second:

```
gigaops_per_second = images_per_second * megaops_per_image / 1000
```

We now know the target output that should stay within our budget constraints, and also know which 3 parameters we can tune to reach that: In a first step, we would probably first choose a **`DEPTH_MULTIPLIER`** for defining the MobileNet stem: This will be the hungriest part of our Fully Convolutional Network.

From the architecture of the FCN head, we see that the depth of the two final layers' depends on `NUMBER_CLASSES` , which we can directly fix according to the use case. The parameters **`CLASSIFIER_KERNEL`** and **`CLASSIFIER_DEPTH`** thus show the only potential for tuning the computational needs of the FCN head. Before we proceed to the final code blocks within this notebook:

Take a look at this spreadsheet on Google Drive: https://docs.google.com/spreadsheets/d/1cxCgM6XNZkF4Zj1jowypBk-LMau9MC2l2w0fHVjcWlM/edit?usp=sharing (https://docs.google.com/spreadsheets/d/1cxCgM6XNZkF4Zj1jowypBk-LMau9MC2l2w0fHVjcWlM/edit?usp=sharing).

On top, you see a table listing the number of Mega operations needed for a forward pass in the MobileNet stem, with different **`DEPTH_MULTIPLIER`** settings at an input size of [320 x 480 x 3].

The lower two tables are correspondingly indicating the number of Mega operations for the FCN head, which is upsampling from [10 x 15 x (1024* `DEPTH_MULTIPLIER`)] to [320 x 480 x `NUMBER_CLASSES`] with values for `CLASSIFIER_KERNEL` and for `CLASSIFIER_DEPTH` .

Exercise F

Question 7.1.1

Take pen and paper and estimate which parameter settings for **`DEPTH_MULTIPLIER`** , **`CLASSIFIER_KERNEL`** and **`CLASSIFIER_DEPTH`** are candidates for meeting the budget requirements of your use case. Hint: The spreadsheet indicates numbers in Mega (10^6) operations per single prediction while your budget is given in Giga (10^9) operations per second, and you will have to make use of the formula for calculating `gigaops_per_second` . **It is recommended to use** **`DEPTH_MULTIPLIER`** $\in \{0.25, 0.50, 0.75, 1.0\}$.

Calculated that for case 1, images_per_second = 15 * 4. The budget allows 70 gops. Therefore, depth_multiplier = 0.5, classifier_kernel = [7,7], and classifier_depth = 1024 should be within budget

In [37]:
```
from calculate_ops import get_megaops

# Modify these values:
######################################################################
DEPTH_MULTIPLIER=0.5 # note 0.25 was used to avoid errors while training
CLASSIFIER_KERNEL=[7, 7]
CLASSIFIER_DEPTH=1024
NUMBER_CLASSES=7
######################################################################


my_image_tensor_fcn = tf.placeholder(tf.float32, shape=(1, 320, 480, 3))
tf.reset_default_graph()
my_mobilenet_fcn = mobilenet_fcn(
            input_tensor=my_image_tensor_fcn,
            num_classes=NUMBER_CLASSES,
            depth_multiplier=DEPTH_MULTIPLIER,
            classifier_kernel=CLASSIFIER_KERNEL,
            classifier_depth=CLASSIFIER_DEPTH
        )

output_shape_fcn = my_mobilenet_fcn.get_shape().as_list()
print('Output dimensions: ' + str(output_shape_fcn))

megaops_per_image = get_megaops(my_mobilenet_fcn, verbose=True)
# Modify these values according to your use case:
######################################################################
n_cameras = 4
fps_per_camera = 15
######################################################################

images_per_second = n_cameras * fps_per_camera

gigaops_per_second = images_per_second * megaops_per_image / 1000
```

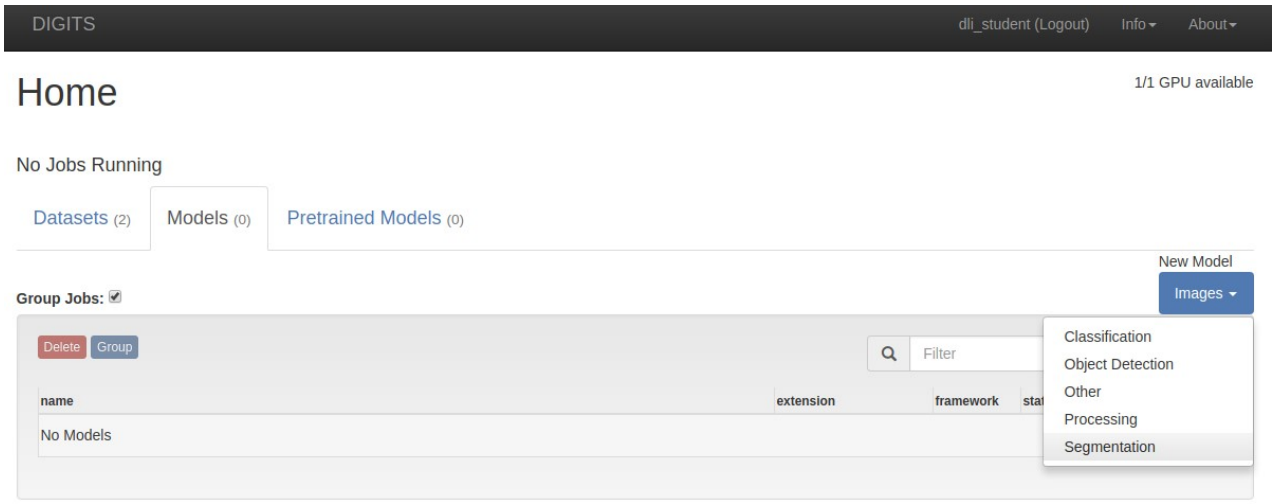
```
Output dimensions: [1, 320, 480, 7]
Layer name                                    MFLOPS      %
--------------------------------------------  --------  -----
MobilenetV1/Conv2d_0/convolution                33.2    2.9
MobilenetV1/Conv2d_1_depthwise/depthwise        11.1    1.0
MobilenetV1/Conv2d_1_pointwise/convolution      39.3    3.4
MobilenetV1/Conv2d_2_depthwise/depthwise         5.5    0.5
MobilenetV1/Conv2d_2_pointwise/convolution      39.3    3.4
MobilenetV1/Conv2d_3_depthwise/depthwise        11.1    1.0
MobilenetV1/Conv2d_3_pointwise/convolution      78.6    6.9
MobilenetV1/Conv2d_4_depthwise/depthwise         2.8    0.2
MobilenetV1/Conv2d_4_pointwise/convolution      39.3    3.4
MobilenetV1/Conv2d_5_depthwise/depthwise         5.5    0.5
MobilenetV1/Conv2d_5_pointwise/convolution      78.6    6.9
MobilenetV1/Conv2d_6_depthwise/depthwise         1.4    0.1
MobilenetV1/Conv2d_6_pointwise/convolution      39.3    3.4
MobilenetV1/Conv2d_7_depthwise/depthwise         2.8    0.2
MobilenetV1/Conv2d_7_pointwise/convolution      78.6    6.9
MobilenetV1/Conv2d_8_depthwise/depthwise         2.8    0.2
MobilenetV1/Conv2d_8_pointwise/convolution      78.6    6.9
MobilenetV1/Conv2d_9_depthwise/depthwise         2.8    0.2
MobilenetV1/Conv2d_9_pointwise/convolution      78.6    6.9
MobilenetV1/Conv2d_10_depthwise/depthwise        2.8    0.2
MobilenetV1/Conv2d_10_pointwise/convolution     78.6    6.9
MobilenetV1/Conv2d_11_depthwise/depthwise        2.8    0.2
MobilenetV1/Conv2d_11_pointwise/convolution     78.6    6.9
MobilenetV1/Conv2d_12_depthwise/depthwise        0.7    0.1
MobilenetV1/Conv2d_12_pointwise/convolution     39.3    3.4
MobilenetV1/Conv2d_13_depthwise/depthwise        1.4    0.1
MobilenetV1/Conv2d_13_pointwise/convolution     78.6    6.9
conv1_separable/depthwise                        7.5    0.7
conv1_pointwise/convolution                    157.3   13.8
conv1_pointwise/BiasAdd                          0.2    0.0
```

7.2 Creating a MobileNet-FCN model in DIGITS

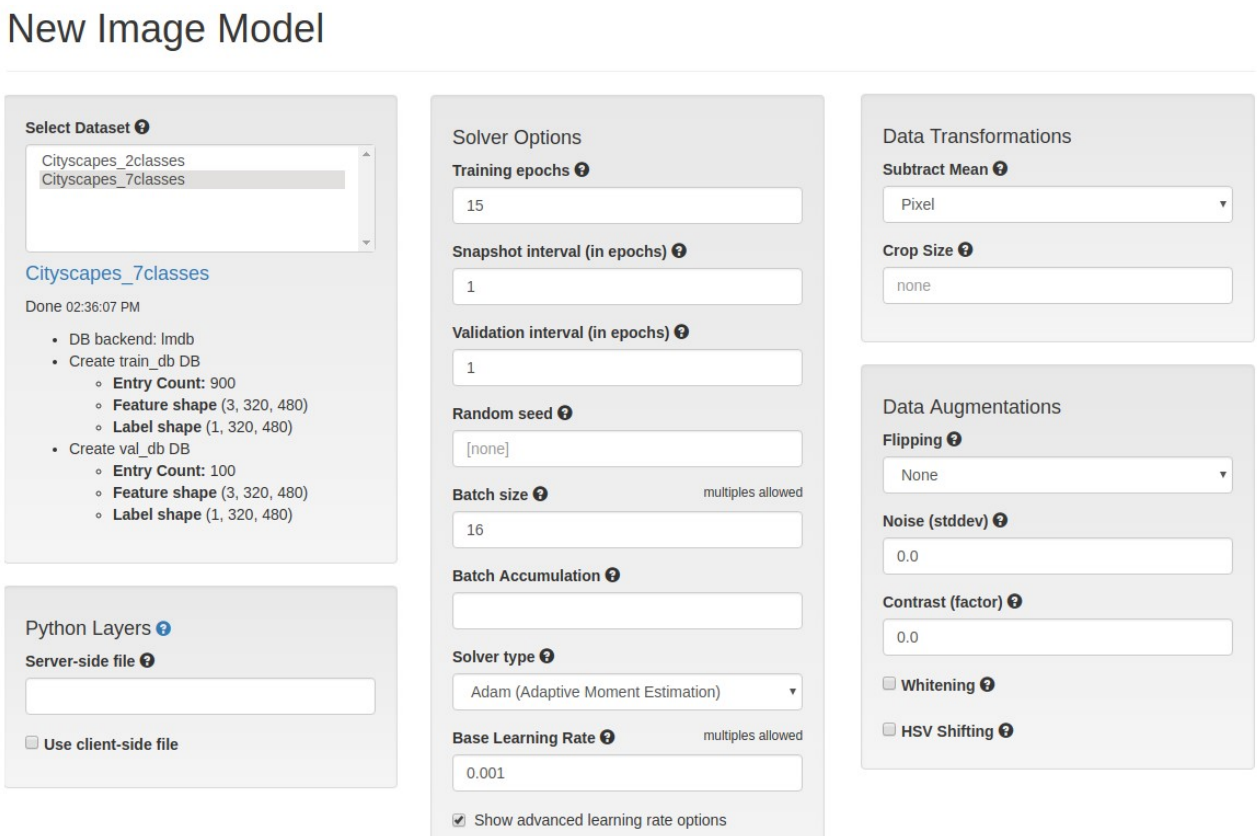
Now we can finally make use of the dataset we previously created in DIGITS, and train our MobileNet-FCN architecture!

Open DIGITS (/digits/) in a separate window again.

Similar to the dataset creation process, click on the `Models` tab, then open the `New Model` drop-down menu to the right and select `Segmentation`.



As shown below, select your dataset in the top left box, and copy the following settings in the `Solver Settings` box. We will use the `Adam` solver (Kingma and Ba, 2014) with a `Fixed` (change to this mode from `Step` in the corresponding drop-down menu, which appears after checking the `Show advanced learning rate options` box) learning rate of `0.001`, the recommended setting from the classification MobileNet version we derived "our" MobileNet-FCN. In the `Data Transformations` box, select `Pixel`: This will subtract the same RGB value from all pixels for all input images. For now, we do not apply any data augmentations but you are invited to experiment with these settings outside of this lab:



In [20]:
```
from model import Tower
from utils import model_property
import tensorflow as tf
import tensorflow.contrib.slim as slim
import utils as digits
import mobilenet_v1

import sys
sys.path.append('/notebooks')

from mobilenet_fcn_from_notebook import add_fcn_head, iou_score

#Copy the values from above into the following field, then copy all contents of this cell into
######################################################################
DEPTH_MULTIPLIER=0.25
CLASSIFIER_KERNEL=[7, 7]
CLASSIFIER_DEPTH=1024
NUMBER_CLASSES=7
######################################################################

def create_fcn_model(x, num_classes, is_training, depth_multiplier, kernel_classifier, depth_c
    input_shape  = x.get_shape().as_list()
    net,_ = mobilenet_v1.mobilenet_v1_base(x, scope='MobilenetV1', final_endpoint='Conv2d_13_p
    net = add_fcn_head(net, num_classes, input_shape, is_training, kernel=kernel_classifier, d
    return net

class UserModel(Tower):

    @model_property
    def inference(self):
        # The expected number of classes is defined first (we do not read this from the datase
        self.nclasses = NUMBER_CLASSES
        # The input batch has to be in the shape [batch_size x height x width x channels] ("NH
        x = tf.reshape(self.x, shape=[-1, self.input_shape[0], self.input_shape[1], self.input
        # Use the following settings for layers of types slim.conv2d and slim.separable_conv2d
        with slim.arg_scope([slim.conv2d, slim.separable_conv2d],
                            weights_initializer=tf.contrib.layers.xavier_initializer(),
                            weights_regularizer=slim.l2_regularizer(1e-6),
                            padding='SAME'):
            fcn = create_fcn_model(x, self.nclasses, self.is_training, DEPTH_MULTIPLIER, CLASS
            if self.is_inference:
                # If we use the network's prediction for visualization in DIGITS, let's conver
                fcn = digits.nhwc_to_nchw(fcn)
        return fcn

    @model_property
    def loss(self):
        predictions = self.inference # Load the inference network from above
        labels = tf.to_int64(self.y) # Make sure that the labels are integers
        # Reshape the predictions from [batch_size x 320 x 480 x 7] to a matrix of [(batch_siz
        predictions_reshaped = tf.reshape( predictions, [-1, self.nclasses] )
        # Reshape the labels from [batch_size x 320 x 480] to a a vector with size [(batch_siz
        labels_reshaped = tf.reshape( labels, [-1] )
        # Let the reshaped predictions run through a Softmax layer, and then calculate the cro
        loss = digits.classification_loss(pred=predictions_reshaped, y=labels_reshaped)
        # Calculate the Intersection over Union score. Ignore the last class ID and make it vi
        iou = iou_score(predictions_reshaped,labels_reshaped,skip_classes=[NUMBER_CLASSES-1])
        self.summaries.append(tf.summary.scalar(iou.op.name, iou))
        # Calculate the pixel-wise accuracy and make it visible during training.
        accuracy = digits.classification_accuracy(pred=predictions_reshaped, y=labels_reshaped
        self.summaries.append(tf.summary.scalar(accuracy.op.name, accuracy))
        return loss
```

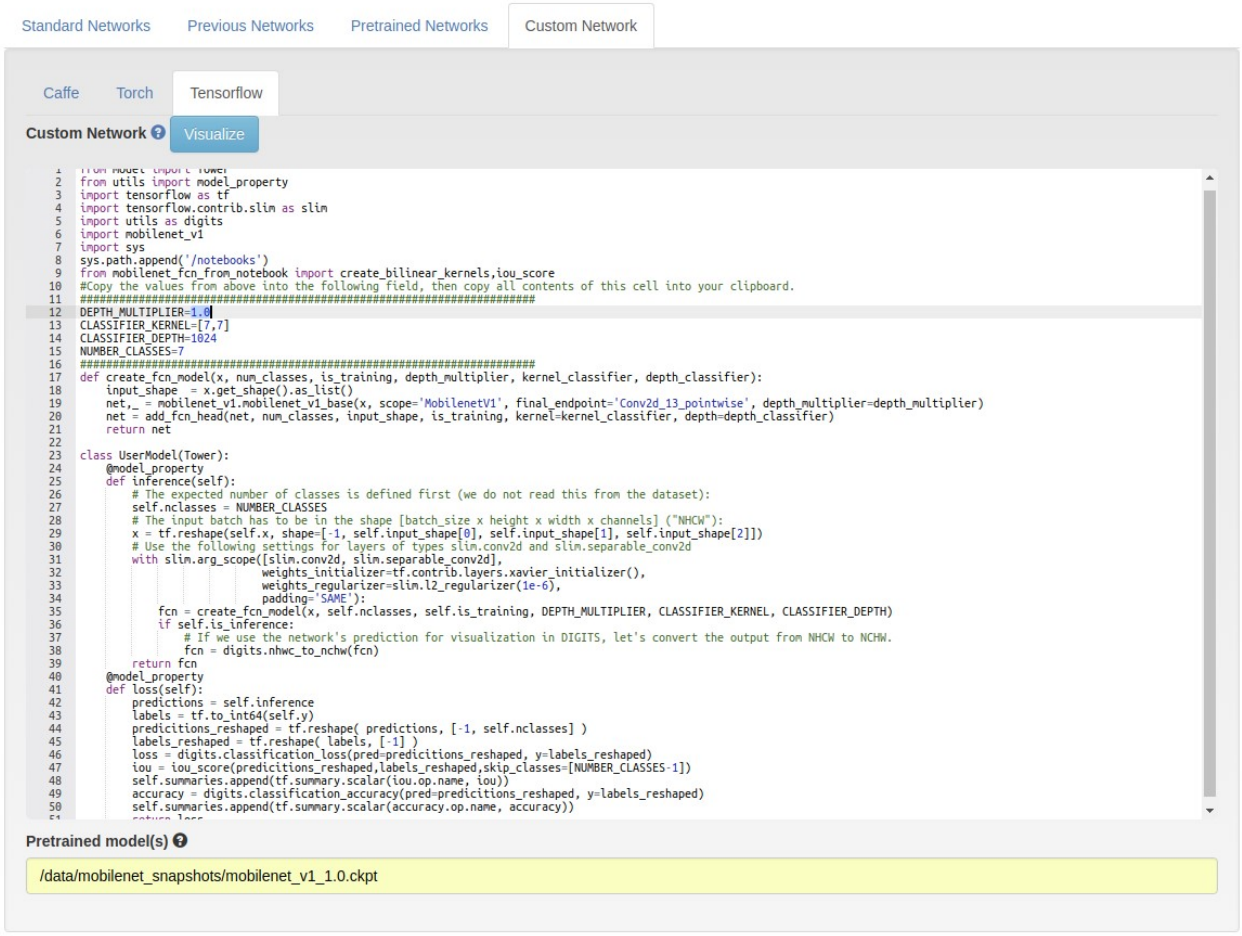
```
ImportErrorTraceback (most recent call last)
<ipython-input-20-2b7ac5ef0e2a> in <module>()
----> 1 from model import Tower
      2 from utils import model_property
      3 import tensorflow as tf
      4 import tensorflow.contrib.slim as slim
```

Now scroll down, click on `Custom Network` , and then on `TensorFlow` . **Then paste the previously copied contents from your clipboard into the text box as shown below.**

If you are using Google Chrome (which is highly recommended), sanity-check if DIGITS can properly interpret your TensorFlow-based DNN by clicking on `Visualize Network` .

If you chose a MobileNet base architecture with a `DEPTH_MULTIPLIER` $\in \{0.25, 0.5, 0.75, 1.0\}$, you can use the weights of a pre-trained classification for initialization; to do that, fill in the corresponding path in `Pretrained Model(s)` , as also shown in the image:

`DEPTH_MULTIPLIER`	Path in `Pretrained model(s)`
0.25	`/data/mobilenet_snapshots/mobilenet_v1_0.25.ckpt`
0.50	`/data/mobilenet_snapshots/mobilenet_v1_0.50.ckpt`
0.75	`/data/mobilenet_snapshots/mobilenet_v1_0.75.ckpt`
1.0	`/data/mobilenet_snapshots/mobilenet_v1_1.0.ckpt`



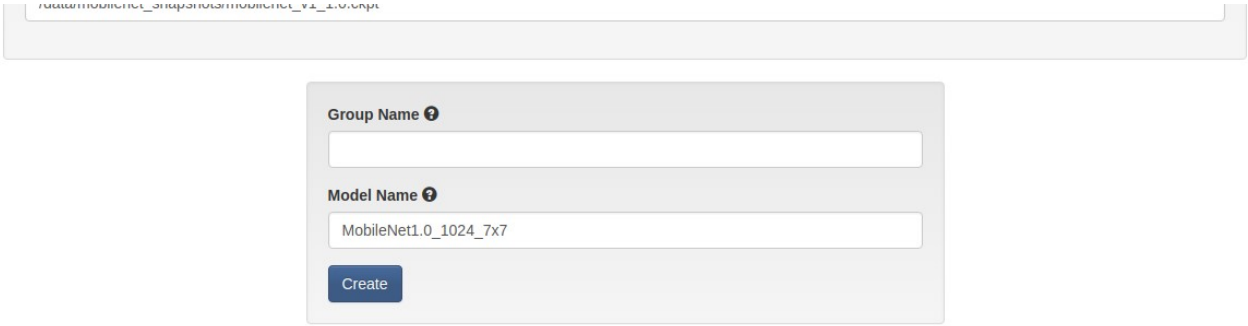
Per epoch, we will perform a forward pass for 1000 images (training + validation set combined), and perform a backward pass for the 900 training images. To save time, you could use several GPUs for distributed training. Let's first check how many GPUs we have at our exposure by running the following snippet (we could also look at `nvidia-smi`):

In [29]:
```
from tensorflow.python.client import device_lib
local_devices = device_lib.list_local_devices()
available_gpus =  sum(1 if x.device_type == 'GPU' else 0 for x in local_devices)
```

```
Number of GPUs available for training: 1
```

With the following setting, you can distribute the training workload over your available GPUs:

We are finally there! Give your model a meaningful name and click on `Create` to start the training process. For 15 epochs running on a single GPU, this can easily take around 10 minutes (or even more):



Question 7.2.1

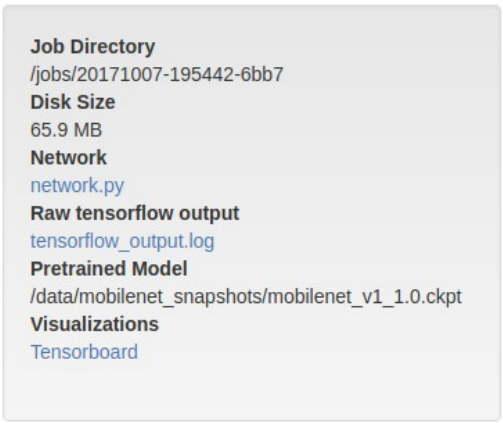
How is accuracy (in training or validation) defined (as shown in your tensorflow board)? Why is accuracy of your net on this dataset much higher than the IoU? Type your answers within this Markdown cell.

At epoch 15, Accuracy (train) is 88.286 and accuracy (val) is 86.86. The accuracy for IOU (train) is 59.98 and for IOU (val) 55.95. Accuracy is defined as pixel-wise accuracy and thus, the IoU is lower because it is averaged over all classes. Cross-entropy loss is also shown. The accuracy is plotted over each epoch.

7.3 Performance evaluation

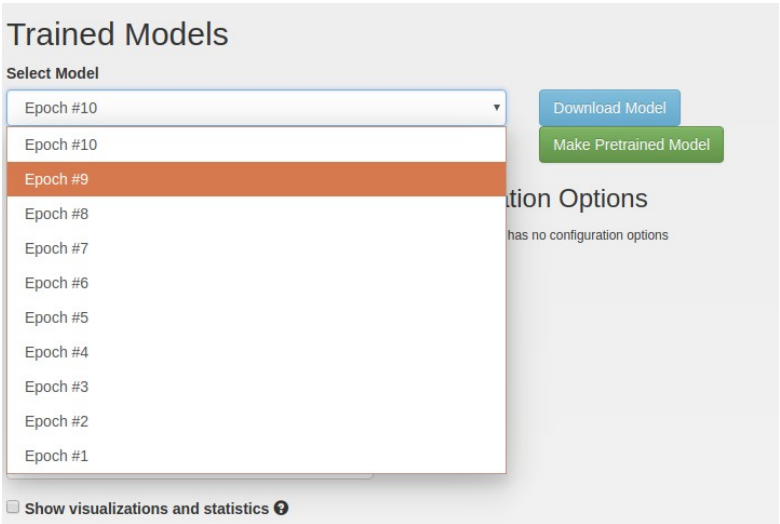
If you feel comfortable with your training results, the time for our final assessment has come: Let's visualize the trained MobileNet-FCN's inference on the Cityscapes test set in a video sequence and let's also find the Intersection over Union metric during that run.

To do so, you will need to provide the job ID of your DIGITS training task. This is shown in the top left box of the model menu:



Copy the job ID into your clipboard and paste it into the code block below. We gave you an example of the format below (to prevent that you confuse it with your own, the prefix dates our training period to the year 1900).

In addition to the job ID, you can select the most promising snapshot epoch – typically the one scoring best for the validation score – and also fill that number into the code snippet below. To make sure that the target snapshot is really present (you could have specified earlier that you do not want to take a snapshot after every epoch), check the drop-down menu in the model menu, directly under your graphs:



At last, execute the cell. Look at the inference results, and write down the IoU score of your model.

In [31]:
```
from run_inference_test import run_inference, get_labeled_pairs

%matplotlib inline
%pylab inline

# Fill in the training job ID, together with the snapshot epoch that you would like to have as
######################################################################
JOB_ID='20190202-050726-926d'
SNAPSHOT_EPOCH = 15
######################################################################


# Here we parse the test image folder and associate the correct label with each feature image.
base_path = '/data/Cityscapes_preprocessed/'
image_folder = base_path + 'test'
label_folder = base_path + 'testannot'
filename_pairs = get_labeled_pairs(image_folder,label_folder)

color_map = [
    (70, 130, 180), # 0: Sky - light blue
    (255, 255, 0), # 1: Infrastructure - yellow
    (0, 255, 0), # 2: Road - green
    (244, 35, 232), # 3: Sidewalk - purple
    (0, 0, 255), # 4: Vehicles - dark blue
    (255, 0, 0), # 5: VRU (Vulnerable Road Users) - red
    (0, 0, 0) # 6: Void - transparent
]

job_path = '/jobs/' + JOB_ID
run_inference(job_path, SNAPSHOT_EPOCH, filename_pairs, color_map)
```

```
SUCCESS! All images have been evaluated. You can submit your score.
IoU score for 59/59 images: 36.3
```

Question 7.3.1

According to latest research, what change in the architecture of the stem of your network could provide an additional boost in IoU? Type your answers within this Markdown cell. Hint: recall our discussion of latest papers in segmentation in class and think about an architecture that would feed both details and context for details into the FCN head.

According to Rahman and Wang, instead of computing softmax loss, one can pass the pixel probabilities out of the sigmoid layer to a loss layer that computes the IoU loss from the pixel probabilities and then train the whole FCN based on this loss

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In [ ]: