DATA SCIENCE

An overview of semantic image segmentation.

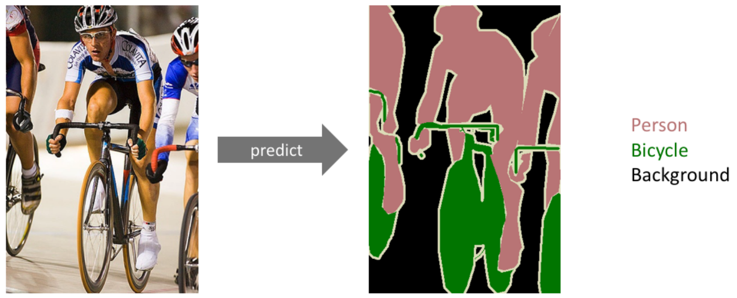
JEREMY JORDAN
21 MAY 2018 • 12 MIN READ

In this post, I'll discuss how to use convolutional neural networks for the task of **semantic image segmentation**. Image segmentation is a computer vision task in which we label specific regions of an image according to what's being shown.

> *"What's in this image, and where in the image is it located?"*

Jump to:

More specifically, the goal of semantic image segmentation is to label *each pixel* of an image with a corresponding ***class*** of what is being represented. Because we're predicting for every pixel in the image, this task is commonly referred to as **dense prediction**.



An example of semantic segmentation, where the goal is to predict class labels for each pixel in the image. (Source)

One important thing to note is that we're not separating *instances* of the same class; we only care about the category of each pixel. In other words, if you have two objects of the same category in your input image, the segmentation map does not inherently distinguish these as separate objects. There exists a different class of models, known as *instance segmentation* models, which *do* distinguish between separate objects of the same class.

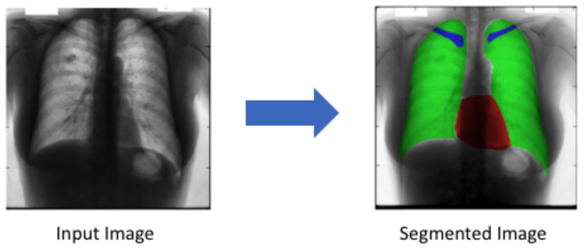
Segmentation models are useful for a variety of tasks, including:

- **Autonomous vehicles**
  We need to equip cars with the necessary perception to

DeepLab V3 xception_cityscapes_trainfine (GTX980M) INPUT_SIZE=1539
Prediction time: 403ms (2.5 fps) AVG: 356ms (2.8 fps)

A real-time segmented road scene for autonomous driving. (Source)

- **Medical image diagnostics**
  Machines can augment analysis performed by radiologists, greatly reducing the time required to run diagnositic tests.

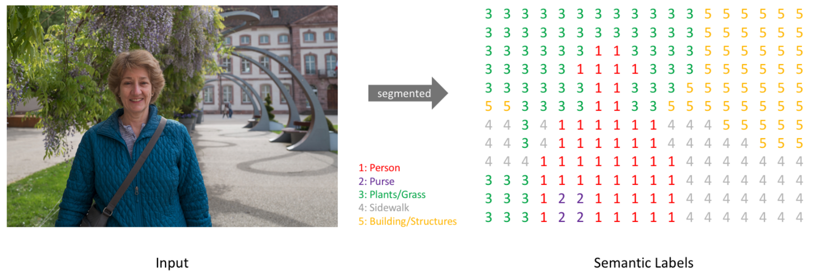


A chest x-ray with the heart (red), lungs (green), and clavicles (blue) are segmented. (Source)

Representing the task

Simply, our goal is to take either a RGB color image (

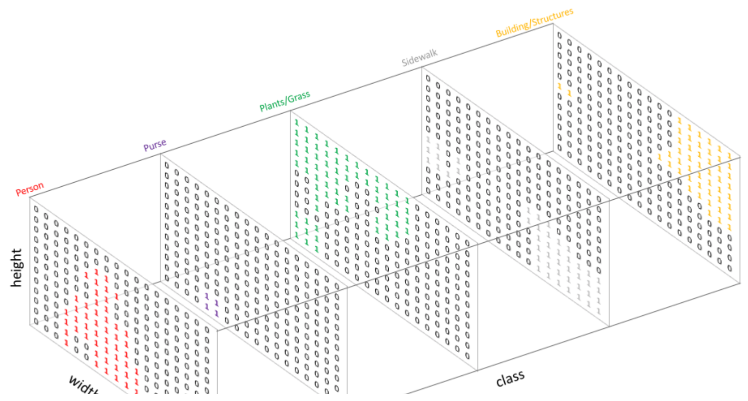
output a segmentation map where each pixel contains a class label represented as an integer ($height \times width \times 1$).



3	3	3	3	3	3	3	3	3	3	3	3	5	5	5	5	5	5
3	3	3	3	3	3	3	3	3	3	3	3	5	5	5	5	5	5
3	3	3	3	3	3	1	1	3	3	3	3	5	5	5	5	5	5
3	3	3	3	3	1	1	1	1	3	3	3	5	5	5	5	5	5
3	3	3	3	3	3	1	1	3	3	3	5	5	5	5	5	5	5
5	5	3	3	3	3	1	1	3	3	5	5	5	5	5	5	5	5
4	4	3	4	1	1	1	1	1	1	4	4	4	5	5	5	5	5
4	4	3	4	1	1	1	1	1	1	4	4	4	4	4	5	5	5
4	4	4	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4
3	3	3	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4
3	3	3	1	2	2	1	1	1	1	1	4	4	4	4	4	4	4
3	3	3	1	2	2	1	1	1	1	1	4	4	4	4	4	4	4

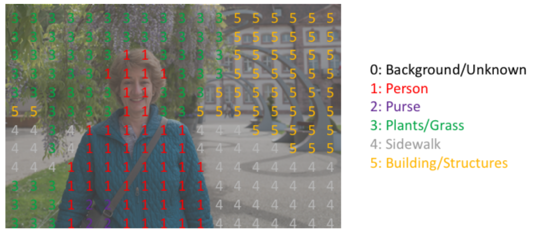
Note: For visual clarity, I've labeled a low-resolution prediction map. In reality, the segmentation label resolution should match the original input's resolution.

Similar to how we treat standard categorical values, we'll create our **target** by one-hot encoding the class labels - essentially creating an output channel for each of the possible classes.



A prediction can be collapsed into a segmentation map (as shown in the

We can easily inspect a target by overlaying it onto the observation.



When we overlay a *single channel* of our target (or prediction), we refer to this as a **mask** which illuminates the regions of an image where a specific class is present.

Constructing an architecture

A naive approach towards constructing a neural network architecture for this task is to simply stack a number of convolutional layers (with `same` padding to preserve dimensions) and output a final segmentation map. This directly learns a mapping from the input image to its corresponding segmentation through the successive transformation of feature mappings; however, it's quite computationally expensive to preserve the full resolution throughout the network.

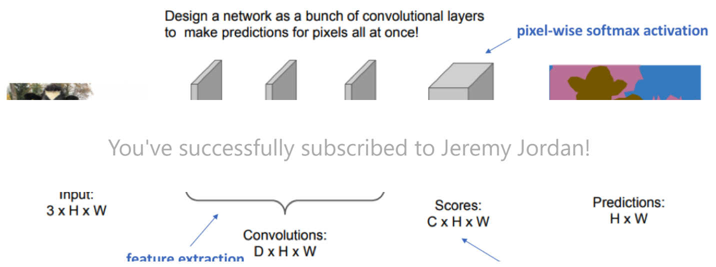

Design a network as a bunch of convolutional layers to make predictions for pixels all at once!
pixel-wise softmax activation
Input: 3 x H x W
Convolutions: D x H x W
feature extraction
Scores: C x H x W
Predictions: H x W

Image credit

Recall that for deep convolutional networks, earlier layers tend to learn low-level concepts while later layers develop more high-level (and specialized) feature mappings. **In order to maintain expressiveness, we typically need to increase the number of feature maps (channels) as we get deeper in the network.**

This didn't necessarily pose a problem for the task of image classification, because for that task we only care about *what* the image contains (and not where it is located). Thus, we could alleviate computational burden by periodically downsampling our feature maps through pooling or strided convolutions (ie. compressing the spatial resolution) without concern. However, for image segmentation, we would like our model to produce a *full-resolution* semantic prediction.

One popular approach for image segmentation models is to follow an **encoder/decoder structure** where we *downsample* the spatial resolution of the input, developing lower-resolution feature mappings which are learned to be highly efficient at discriminating between classes, and the *upsample* the feature representations into a full-resolution segmentation map.

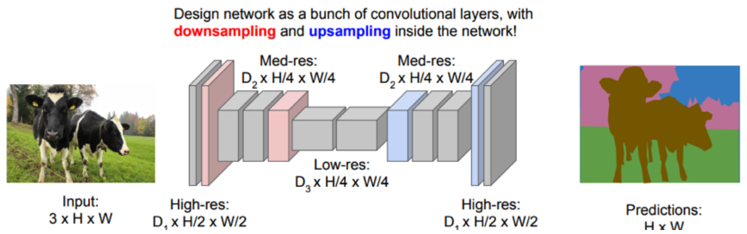

Design network as a bunch of convolutional layers, with downsampling and upsampling inside the network!
Med-res: D_2 x H/4 x W/4
Med-res: D_2 x H/4 x W/4
Low-res: D_3 x H/4 x W/4
Input: 3 x H x W
High-res: D_1 x H/2 x W/2
High-res: D_1 x H/2 x W/2
Predictions: H x W

Image credit

Methods for upsampling

There are a few different approaches that we can use to *upsample* the resolution of a feature map. Whereas pooling operations downsample the resolution by summarizing a local area with a single value (ie. average or max pooling), "unpooling" operations upsample the resolution by distributing a single value into a higher resolution.

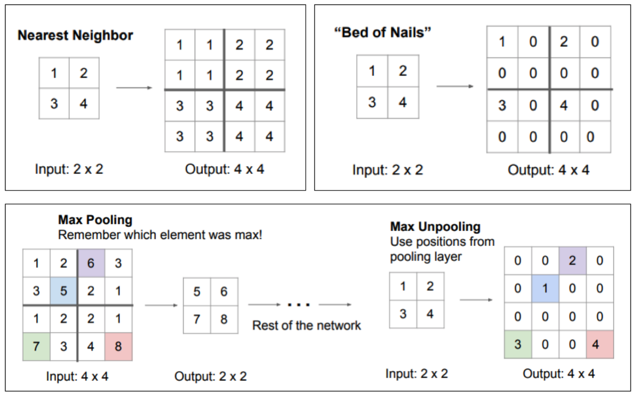
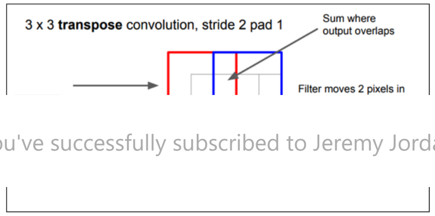
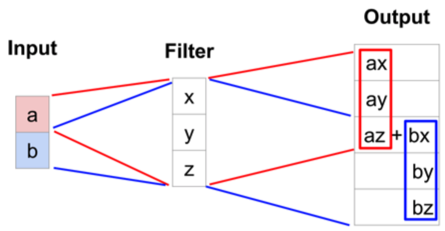


Image credit

However, **transpose convolutions** are by far the most popular approach as they allow for us to develop a *learned upsampling*.

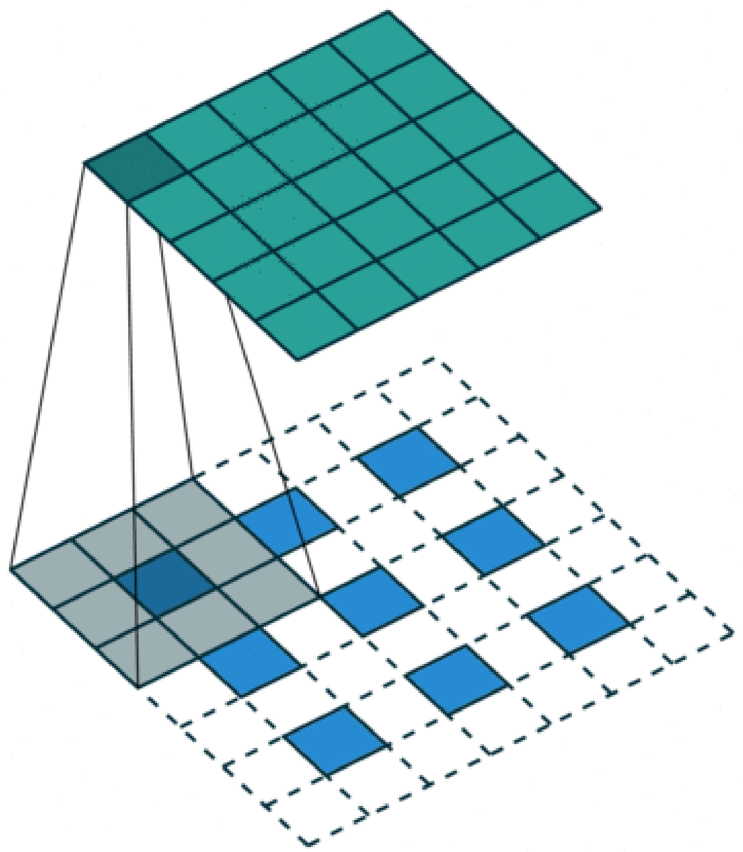

3 x 3 **transpose** convolution, stride 2 pad 1
Sum where output overlaps
Filter moves 2 pixels in

Whereas a typical convolution operation will take the dot product of the values currently in the filter's view and produce a single value for the corresponding output position, a transpose convolution essentially does the opposite. For a transpose convolution, we take a single value from the low-resolution feature map and multiply all of the weights in our filter by this value, projecting those weighted values into the output feature map.



A simplified 1D example of upsampling through a transpose operation. (Source)

For filter sizes which produce an overlap in the output feature map (eg. 3x3 filter with stride 2 - as shown in the below example), the overlapping values are simply added together. Unfortunately, this tends to produce a checkerboard artifact in the output and is undesirable, so it's best to ensure that your filter size does not produce an overlap.



Input in blue, output in green. (Source)

Fully convolutional networks

The approach of using a "fully convolutional" network trained end-to-end, pixels-to-pixels for the task of image segmentation was introduced by Long et al. in late 2014. The paper's authors propose adapting existing, well-studied *image classification* networks (eg. AlexNet) to serve as the encoder module of the network, appending a decoder module with transpose convolutional layers to upsample the coarse feature maps into a full-resolution segmentation map.

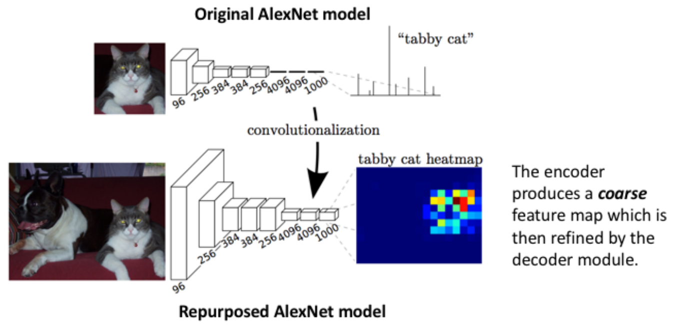
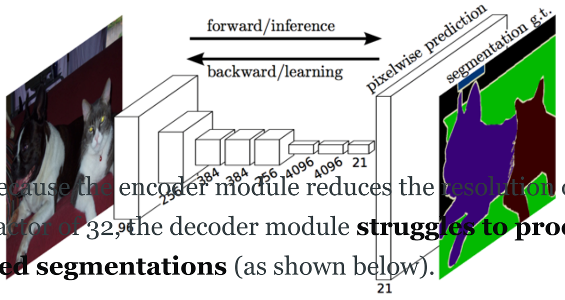
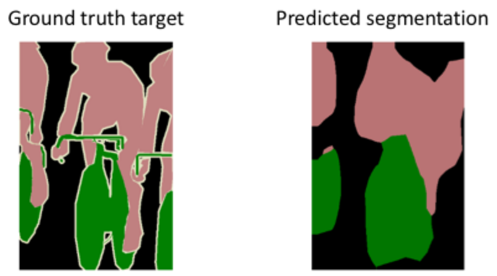


Image credit (with modification)

The full network, as shown below, is trained according to a pixel-wise cross entropy loss.



However, because the encoder module reduces the resolution of the input by a factor of 32, the decoder module **struggles to produce fine-grained segmentations** (as shown below).



The paper's authors comment eloquently on this struggle:

> *Semantic segmentation faces an inherent tension between semantics and location: global information resolves **what** while local information resolves **where**... Combining fine layers and coarse layers lets the model make local predictions that respect global structure.* – *Long et al.*

Adding skip connections

and summing these two feature maps.

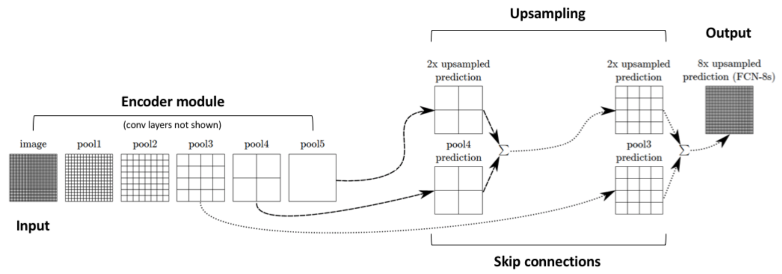
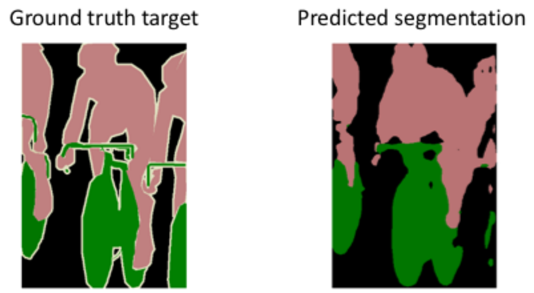


Image credit (with modification)

These skip connections from earlier layers in the network (prior to a downsampling operation) should provide the necessary detail in order to reconstruct accurate shapes for segmentation boundaries. Indeed, we can recover more fine-grain detail with the addition of these skip connections.



Ronneberger et al. improve upon the "fully convolutional" architecture primarily through ***expanding the capacity of the decoder*** module of the network. More concretely, they propose the **U-Net architecture**

simpler architecture has grown to be very popular and has been adapted for a variety of segmentation problems.

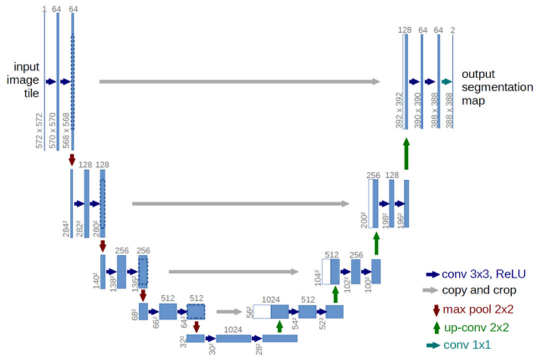


Image credit

Note: The original architecture introduces a decrease in resolution due to the use of `valid` *padding. However, some practitioners opt to use* `same` *padding where the padding values are obtained by image reflection at the border.*

Whereas Long et al. (FCN paper) reported that data augmentation ("randomly mirroring and "jittering" the images by translating them up to 32 pixels") did not result in a noticeable improvement in performance, Ronneberger et al. (U-Net paper) credit data augmentations ("random elastic deformations of the training samples") as a key concept for learning. It appears as if **the usefulness (and type) of data augmentation depends on the problem domain**.

Advanced U-Net variants

The standard U-Net model consists of a series of convolution operations for each "block" in the architecture. As I discussed in my post on common convolutional network architectures, there exist a number of

Drozdzal et al. swap out the basic stacked convolution blocks in favor of

the corresponding feature maps of encoder and decoder modules) found in the standard U-Net structure. They report that the short skip connections allow for faster convergence when training and allow for deeper models to be trained.

Expanding on this, Jegou et al. proposed the use of **dense blocks**, still following a U-Net structure, arguing that the "characteristics of DenseNets make them a very good fit for semantic segmentation as they *naturally induce skip connections and multi-scale supervision*." These dense blocks are useful as they carry low level features from previous layers directly alongside higher level features from more recent layers, allowing for highly efficient feature reuse.

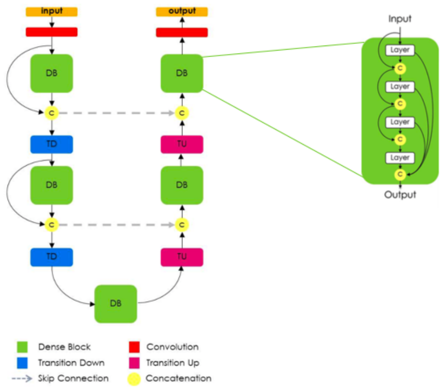


Image credit (with modification)

One very important aspect of this architecture is the fact that the upsampling path *does not* have a skip connection between the input and output of a dense block. The authors note that because the "upsampling path *increases* the feature maps spatial resolution, the linear growth in

The FC-DenseNet103 model acheives state of the art results (Oct 2017) on the CamVid dataset.

Dilated/atrous convolutions

One benefit of downsampling a feature map is that it *broadens the receptive field* (with respect to the input) for the following filter, given a constant filter size. Recall that this approach is more desirable than increasing the filter size due to the parameter inefficiency of large filters (discussed here in Section 3.1). However, this broader context comes at the cost of reduced spatial resolution.

Dilated convolutions provide alternative approach towards gaining a wide field of view while preserving the full spatial dimension. As shown in the figure below, the values used for a dilated convolution are spaced apart according to some specified *dilation rate*.

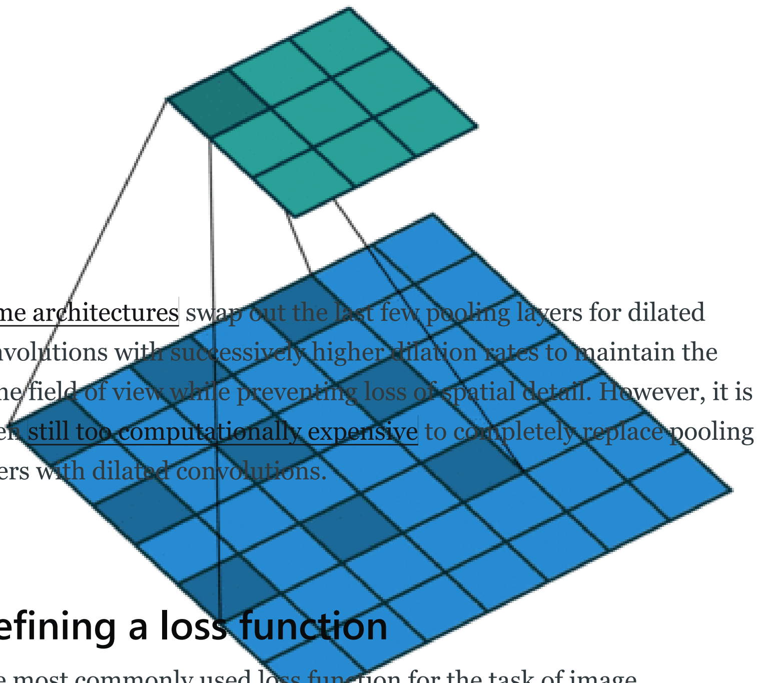
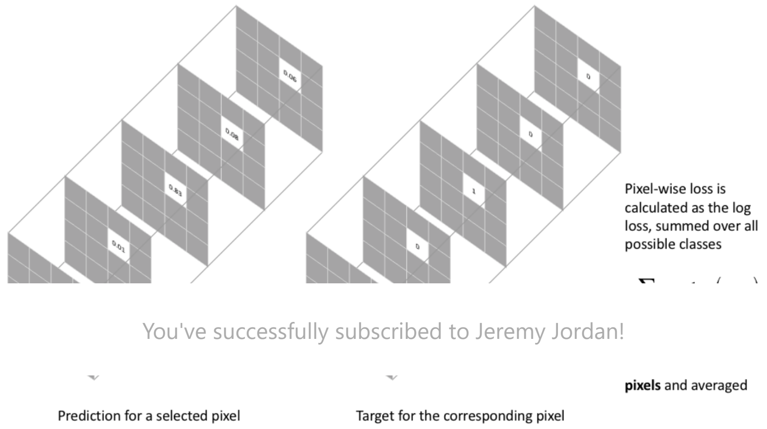


Image credit

Some architectures swap out the last few pooling layers for dilated convolutions with successively higher dilation rates to maintain the same field of view while preventing loss of spatial detail. However, it is often still too computationally expensive to completely replace pooling layers with dilated convolutions.

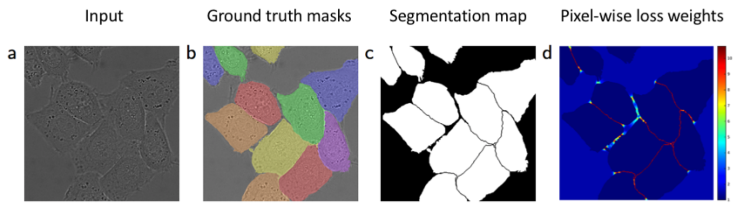
Defining a loss function

The most commonly used loss function for the task of image segmentation is a **pixel-wise cross entropy loss**. This loss examines *each pixel individually*, comparing the class predictions (depth-wise pixel vector) to our one-hot encoded target vector.


Pixel-wise loss is calculated as the log loss, summed over all possible classes
pixels and averaged
Prediction for a selected pixel
Target for the corresponding pixel

Because the cross entropy loss evaluates the class predictions for each pixel vector individually and then averages over all pixels, we're essentially asserting equal learning to each pixel in the image. This can be a problem if your various classes have unbalanced representation in the image, as training can be dominated by the most prevalent class. Long et al. (FCN paper) discuss weighting this loss for each **output channel** in order to counteract a class imbalance present in the dataset.

Meanwhile, Ronneberger et al. (U-Net paper) discuss a loss weighting scheme for each **pixel** such that there is a higher weight at the border of segmented objects. This loss weighting scheme helped their U-Net model segment cells in biomedical images in a *discontinuous* fashion such that individual cells may be easily identified within the binary segmentation map.



Notice how the binary segmentation map produces clear borders around the cells. (Source)

Another popular loss function for image segmentation tasks is based on

of 1 denotes perfect and complete overlap. The Dice coefficient was originally developed for binary data, and can be calculated as:

$$Dice = \frac{2\,|A \cap B|}{|A| + |B|}$$

where $|A \cap B|$ represents the common elements between sets A and B, and $|A|$ represents the number of elements in set A (and likewise for set B).

For the case of evaluating a Dice coefficient on predicted segmentation masks, we can approximate $|A \cap B|$ as the element-wise multiplication between the prediction and target mask, and then sum the resulting matrix.

$$|A \cap B| = \underbrace{\begin{bmatrix} 0.01 & 0.03 & 0.02 & 0.02 \\ 0.05 & 0.12 & 0.09 & 0.07 \\ 0.89 & 0.85 & 0.88 & 0.91 \\ 0.99 & 0.97 & 0.95 & 0.97 \end{bmatrix}}_{\text{prediction}} * \underbrace{\begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix}}_{\text{target}} \xrightarrow{\text{element-wise multiply}} \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0.89 & 0.85 & 0.88 & 0.91 \\ 0.99 & 0.97 & 0.95 & 0.97 \end{bmatrix} \xrightarrow{\text{sum}} 7.41$$

Because our target mask is binary, we effectively zero-out any pixels from our prediction which are not "activated" in the target mask. For the remaining pixels, we are essentially penalizing low-confidence predictions; a higher value for this expression, which is in the numerator, leads to a better Dice coefficient.

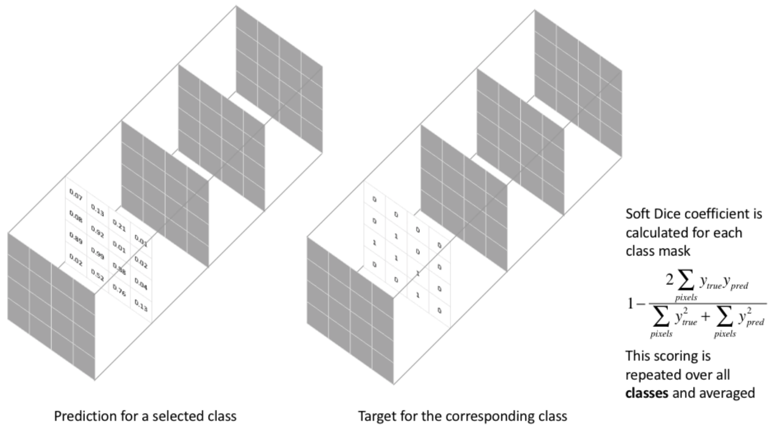
In order to quantify $|A|$ and $|B|$, some researchers use the simple sum whereas other researchers prefer to use the squared sum for this calculation. I don't have the practical experience to know which performs better empirically over a wide range of tasks, so I'll leave you to try them both and see which works better.

$$\Big[\quad \Big]^{2\ (optional)}$$

$$|B| = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}^{2\ (optional)} \xrightarrow{\text{sum}} 8$$

In case you were wondering, there's a 2 in the numerator in calculating the Dice coefficient because our denominator "double counts" the common elements between the two sets. In order to formulate a loss function which can be minimized, we'll simply use $1 - Dice$. This loss function is known as the **soft Dice loss** because we directly use the predicted probabilities instead of thresholding and converting them into a binary mask.

With respect to the neural network output, the numerator is concerned with the *common activations* between our prediction and target mask, where as the denominator is concerned with the quantity of activations in each mask *separately*. This has the effect of normalizing our loss according to the size of the target mask such that the soft Dice loss does not struggle learning from classes with lesser spatial representation in an image.


Soft Dice coefficient is calculated for each class mask
$1 - \frac{2\sum_{pixels} y_{true} y_{pred}}{\sum_{pixels} y_{true}^2 + \sum_{pixels} y_{pred}^2}$
This scoring is repeated over all **classes** and averaged
Prediction for a selected class
Target for the corresponding class

```
def soft_dice_loss(y_true, y_pred, epsilon=1e-6):
    '''
    Soft dice loss calculation for arbitrary batch size, number of classes, and number of spatial dimen
    Assumes the `channels_last` format.

    # Arguments
        y_true: b x X x Y( x Z...) x c One hot encoding of ground truth
        y_pred: b x X x Y( x Z...) x c Network output, must sum to 1 over c channel (such as after soft
        epsilon: Used for numerical stability to avoid divide by zero errors

    # References
        V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation
        https://arxiv.org/abs/1606.04797
        More details on Dice loss formulation
        https://mediatum.ub.tum.de/doc/1395260/1395260.pdf (page 72)

        Adapted from https://github.com/Lasagne/Recipes/issues/99#issuecomment-347775022
    '''

    # skip the batch and class axis for calculating Dice score
    axes = tuple(range(1, len(y_pred.shape)-1))
    numerator = 2. * np.sum(y_pred * y_true, axes)
    denominator = np.sum(np.square(y_pred) + np.square(y_true), axes)

    return 1 - np.mean((numerator + epsilon) / (denominator + epsilon)) # average over classes and batc
    # thanks @mfernezir for catching a bug in an earlier version of this implementation!
```

_dice_loss.py hosted with ♡ by GitHub v

Common datasets and segmentation competitions

Below, I've listed a number of common datasets that researchers use to train new models and benchmark against the state of the art. You can also explore previous Kaggle competitions and read about how winning solutions implemented segmentation models for their given task.

Datasets

- COCO 2018 Stuff Segmentation Task
- BDD100K: A Large-scale Diverse Driving Video Database

- Cityscapes Dataset
- Mapillary Vistas Dataset
- ApolloScape Scene Parsing

Past Kaggle Competitions

- 2018 Data Science Bowl
  - Read about the first place solution.
- Carvana Image Masking Challenge
  - Read about the first place solution.
- Dstl Satellite Imagery Feature Detection
  - Read about the third place solution.

Further Reading

Papers

- Fully Convolutional Networks for Semantic Segmentation
- U-Net: Convolutional Networks for Biomedical Image Segmentation
- The Importance of Skip Connections in Biomedical Image Segmentation
- The One Hundred Layers Tiramisu: Fully Convolutional DenseNets for Semantic Segmentation
- Multi-Scale Context Aggregation by Dilated Convolutions

CRFs

- Evaluation of Deep Learning Strategies for Nucleus Segmentation in Fluorescence Images

Lectures

- Stanford CS231n: Detection and Segmentation
  - Lecture Slides

Blog posts

- Mat Kelcey's (Twitter Famous) Bee Detector
- Semantic Image Segmentation with DeepLab in TensorFlow
- Going beyond the bounding box with semantic segmentation
- U-Net Case Study: Data Science Bowl 2018
- Lyft Perception Challenge: 4th place solution

Image labeling tools

- labelme: Image Polygonal Annotation with Python

Useful Github repos

- Pytorch implementations

ALSO ON JEREMYJORDAN

4 years ago
Gradient descent.

4 years ago • 3 comments
Neural networks: activation

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OR SIGN UP WITH DISQUS ?

Name

Ecem sogancıoglu • 2 years ago
this is just the best!!!!! thanks a lot
1 ^ | v • Reply • Share ›

MadCircus • 2 days ago • edited
Hi Jeremy, this blog is very helpful for understanding semantic segmentation, especially your great visualizations! I would love to know how you created the images that show the mapping to one-hot-encoding and back to the classified image! Any chance you might publish those "source files"?
^ | v • Reply • Share ›

Neo • 4 months ago • edited
Hi, thanks for this amazing piece of explanation. One query, the link for common conv architectures is not working: https://www.jeremyjordan.me...
^ | v • Reply • Share ›

Thanks for letting me know, it should be fixed now!
^ | v • Reply • Share ›

prediction is 0 and the loss doesn't converge during training. If I change the loss to cross entropy, everything goes well for me. I don't know why the loss keeps unvaried when I use dice loss. Can you give me some advice? Thanks a lot.
^ | v • Reply • Share ›

Jeremy Jordan Mod ➦ Sophie Cong • 2 years ago
Could you share how you're calculating the dice loss? Are there differences between your implementation and the one I provided in this post?
^ | v • Reply • Share ›

Sophie Cong ➦ Jeremy Jordan • 2 years ago
Thanks a lot for your kind reply. I used another one like below before.
def dice_coef(y_true, y_pred, smooth=1):
y_true_f = K.flatten(y_true)
y_pred_f = K.flatten(y_pred)
intersection = K.sum(y_true_f * y_pred_f)
return (2. * intersection + smooth) / (K.sum(y_true_f) + K.sum(y_pred_f) + smooth)
def dice_coef_loss(y_true, y_pred):
return 1 -dice_coef(y_true, y_pred)
Now I have changed the original one to your version. Then it works. Thanks a lot.
^ | v • Reply • Share ›

Preet Khaturia • 2 years ago
Hi @Jeremy Jordan , thankyou for the post. I am applying soft dice loss for multiclass classification (having 14 class) using Unet model. The problem I am facing is that my model predicts 0 class for the complete image. Can you help me to find where I am being wrong?
^ | v • Reply • Share ›

Sophie Cong ➦ Preet Khaturia • 2 years ago
Hi, I am applying soft dice loss for semantic segmentation using u-net model. I also encounter

Thanks.
^ | v • Reply • Share ›

There could be many reasons for this. Did you follow the steps for building a model that I outline here? This can be very helpful to catch/prevent bugs from entering your model code.

Reply • Share ›

shing • 2 years ago

this post is easy to understand! thanks!

Reply • Share ›

reggie09 • 2 years ago

Great post! Very clear exposition. Thanks for linking to the various resources as well.

Reply • Share ›

Jae Duk Seo • 3 years ago

very good post!

Reply • Share ›

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