Autoencoders

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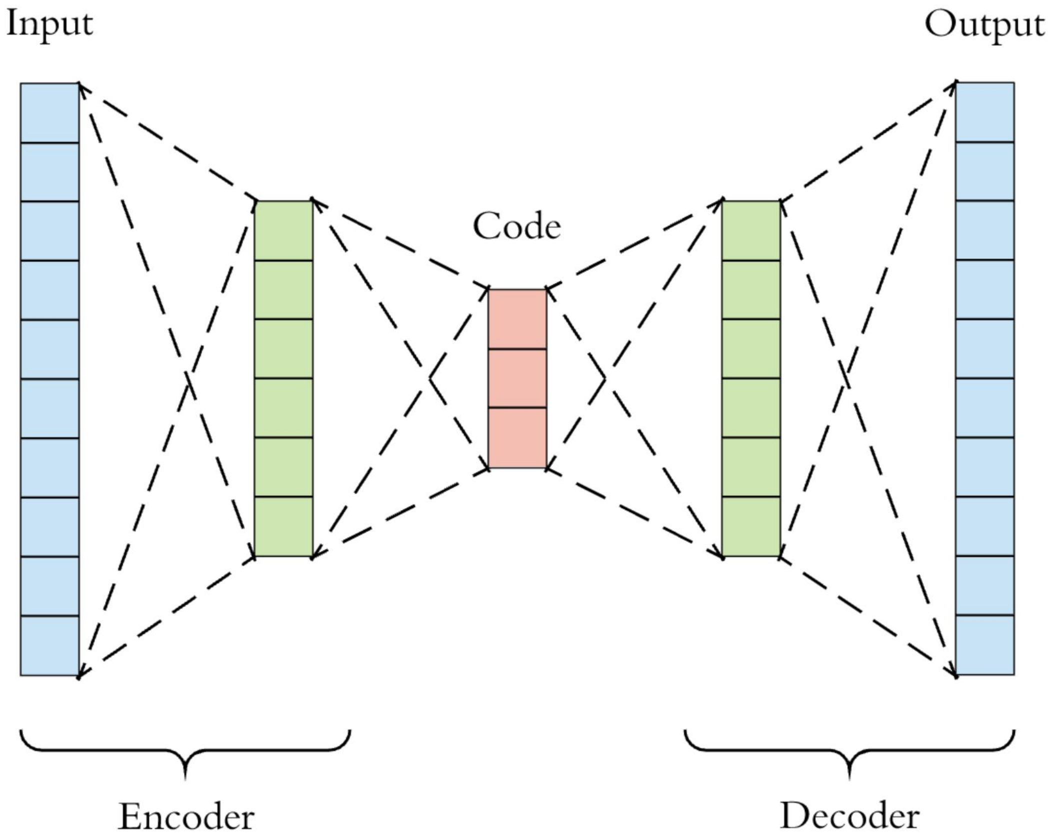
Autoencoders



Autoencoders

- Unsupervised learning: there is no separate “desired output” from the network
  - Data can be a lot easier to come by
- Central layer is the compressed representation of the input
  - Must preserve the information content of the input, but with fewer dimensions
  - “Latent representation”

Latent Representations

Can be used as:

- Inputs to other networks
  - Transfer learning: further training with a labeled data set
  - Tend to have less noise than the original input, so less prone to overfitting
- Visualization of the high-dimensional input
  - Often need further compression to do this: PCA, ISOmap, tSNE

Latent Representations

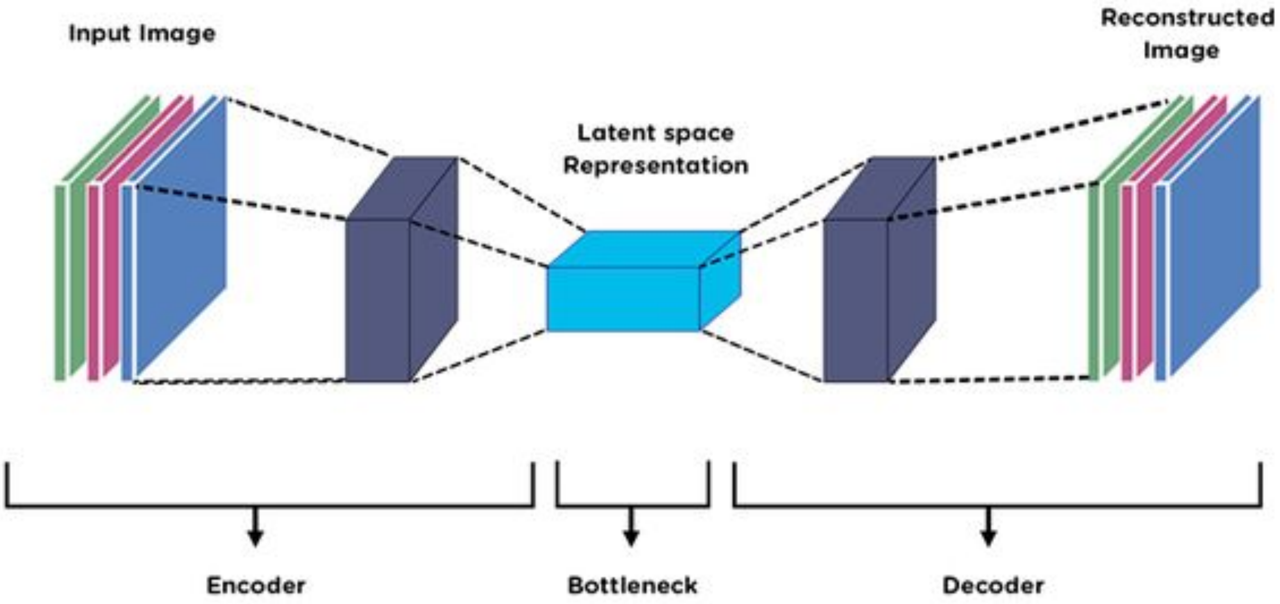
Can be grown incrementally:

- Start with training a shallow network
- Keep the encoder, but then add:
  - A more compressed encoder
  - A full decoder
- Train again
- Repeat

Convolutional Autoencoders

- Input / output are images
- Encoder: reduce the spatial resolution at each step
- Decoder: increase resolution

Convolutional Autoencoders



medium.com/@birla.deepak26

Convolutional Autoencoders

Encoder:

- Spatial resolution generally reduces at each step (Convolution + striding)
- Number of channels increases
- So: trading spatial resolution for resolution in the channels
- But: (r x c) / ch still will generally drop with each step

Convolutional Autoencoders

Decoder: increase resolution at some steps

- Conv 2D Transpose: kernel maps one pixel in the input to k x k pixels in the output
- Upsample: Copy one pixel in the input to k x k pixels in the output

Because the former can lead to strange artifacts, the latter is preferred practice today

Convolutional Autoencoders: Practice

Can be hard to end up with the same dimensions on the input and output sides of the autoencoder

- Keep kernel size and stride the same
- Only choose kernel sizes to be integer factors of the image size
- Middle-most layer: can bring to a 1x1 image
    - Vector summarizes the image a non-spatial manner
    - Latent representation of the input

Autoencoders: Dealing with Training Set Size

- When training set size is small, we run the risk of capturing the noise in the image, as well as the real structure
- One approach: data augmentation
  - Augment training set with additional training samples derived from the original training set

Data Augmentation

A cat is still a cat if:

- Shifted laterally or vertically
- Rotated
- Scaled
- :

Keras ImageDataGenerator class will augment an image set on the fly

    ○

Data Augmentation and Autoencoders

- Want our autoencoder to capture the ‘real’ aspects of the image and not the noise
- Denoising autoencoder:
  - Select training image
  - Add pixel-level noise (typically Gaussian-distributed)
  - Input: noisy image
  - Desired output: original image

Developing Sparse Representations

Goal: want very different input images to have very different latent representations (best case: vectors are orthogonal)

- Can add a regularization term that punishes similar representations
- Activity regularization
- Kullback-Leibler divergence
  - Measure of the difference between two distributions

KL math

KL vs MSE

Variational Autoencoder

- Encoder output:
  - Mean and standard deviation in the latent space
- Latent representation: sampled from this Gaussian distribution
- Decoder output:
  - Desire is to recover the original image

Variational Autoencoder

- Reconstruction loss: difference between input and output images
- But: this alone will generally force the standard deviation to zero
- Add a regularization term:
  - Expected distribution in latent space is N(0,1)
  - Measure KL divergence between N(0,1) and N(mu, sigma)

VAE math

Variational Autoencoder

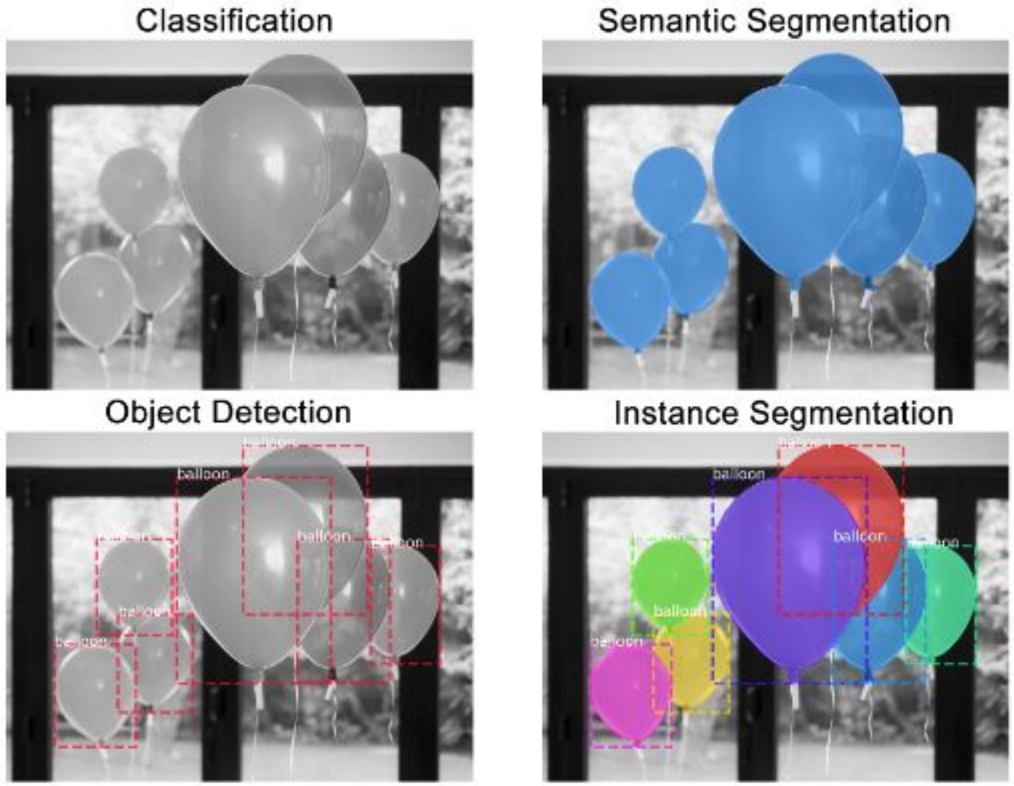
Regularization implications

- The training samples in the latent space must be N(0,1)
- Nice property: the weighted average between any two samples is still covered by the distribution
  - Can often result in a decoded mean being meaningful
- But: strange that samples from very different classes should still fall as one N(0,1)
  - Really expect non-overlapping clusters

Image to Image Translation

- If we have the labeled data set, we don't have to reconstruct the same image
- Instead, could reconstruct different images
  - Remove noise
  - Make some semantic change to the image (e.g., changing seasons)
  - Label pixels by their semantic role in the image

Forms of Segmentation



towardsdatascience.com/semantic-segmentation-popular-architectures-dff0a75f39d0

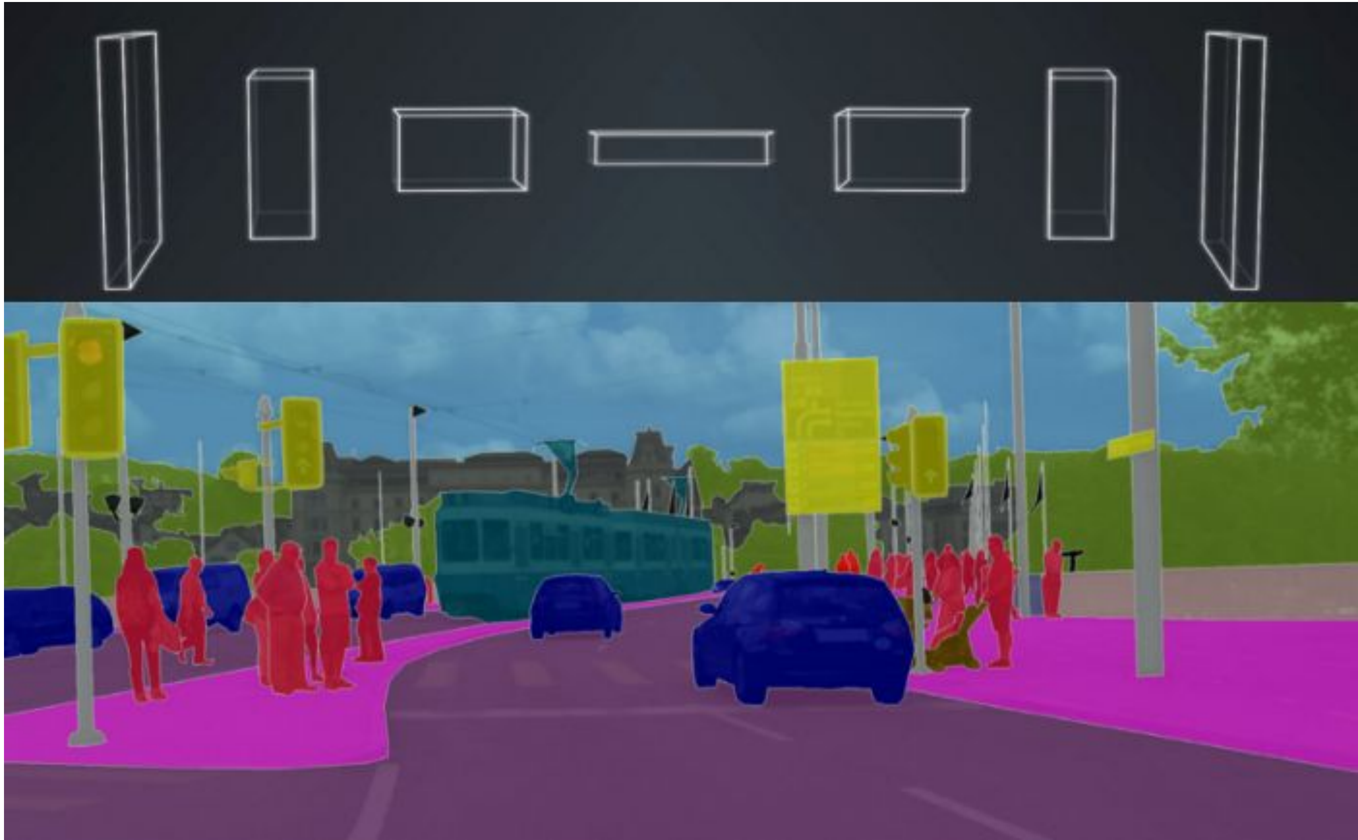
Semantic Segmentation

- What kind of an object are we looking at?
- What type of a role does the object play in the image?

Both: what is the class of each pixel?

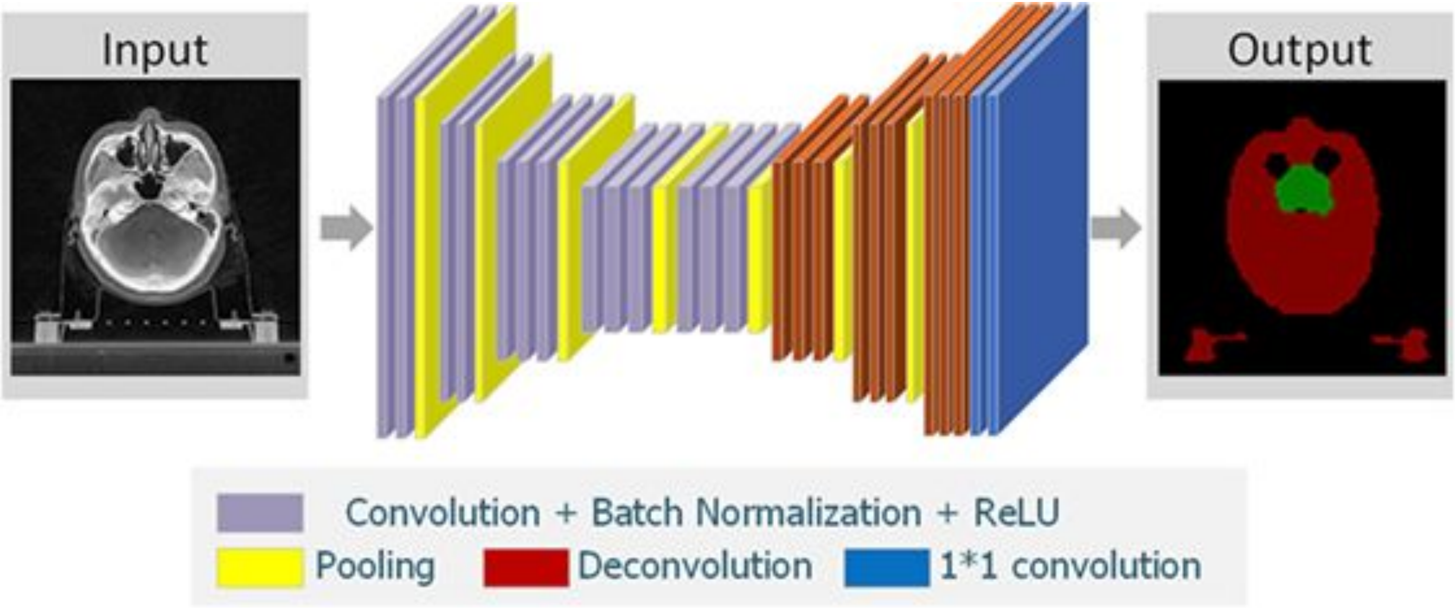
Challenge: need images labeled at the pixel level

Encoder/Decoder for Segmentation



ckyrkou.medium.com/udacity-sdce-nanodegree-term-3-project-2-advanced-deep-learning-and-semantic-segmentation-9ce5fcb46969

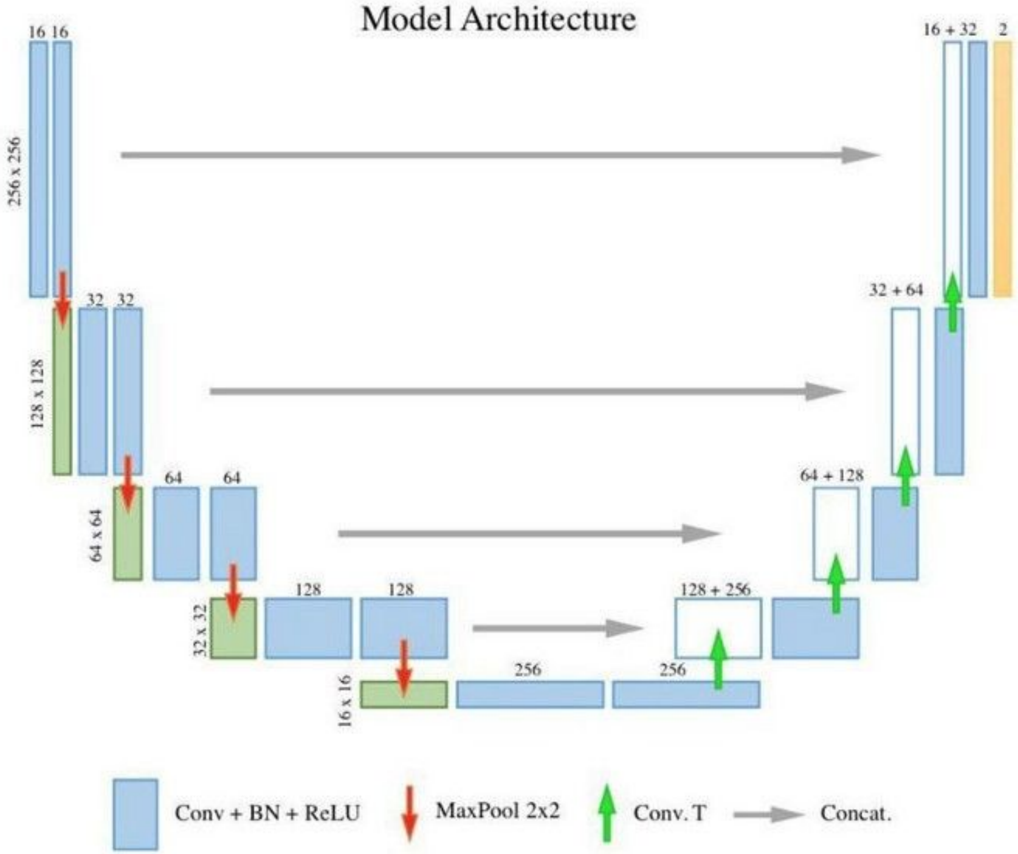
Encoder/Decoder for Segmentation



www.frontiersin.org/articles/10.3389/fonc.2017.00315/full

U-Net Architecture

- U: compressed representation
  - More abstraction
- Skip connections
  - Less abstraction
  - Shallower pathway for learning

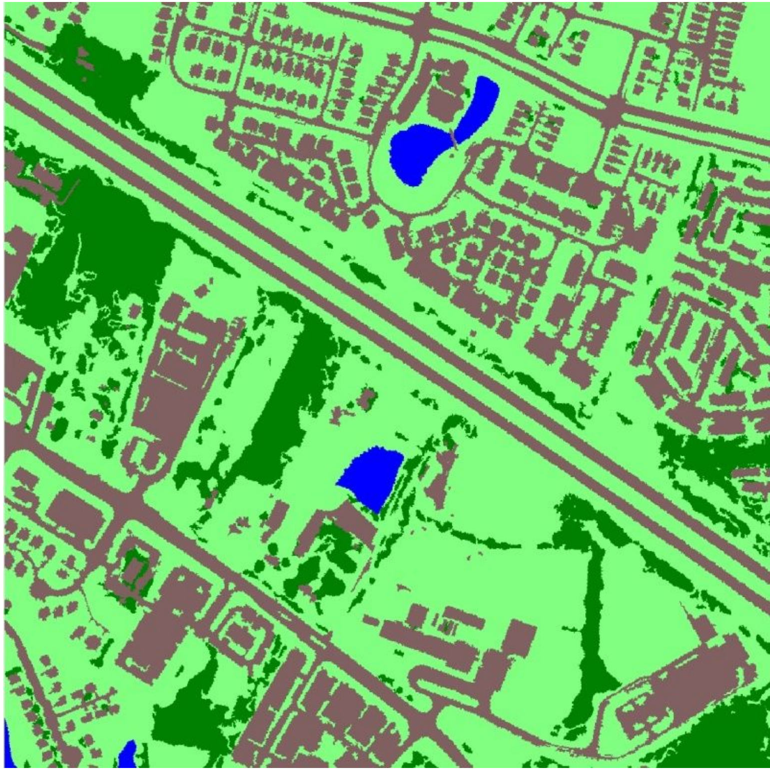


towardsdatascience.com/semantic-segmentation-popular-architectures-dff0a75f39d0

Homework 7

Chesapeake Watershed Land Cover data set

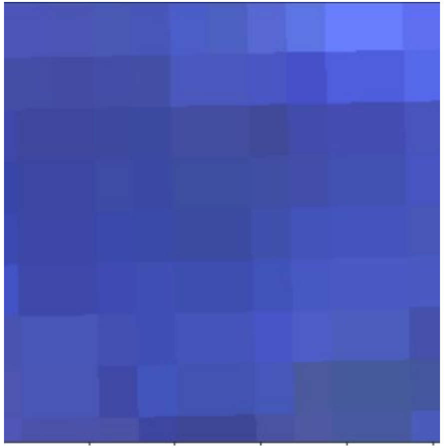
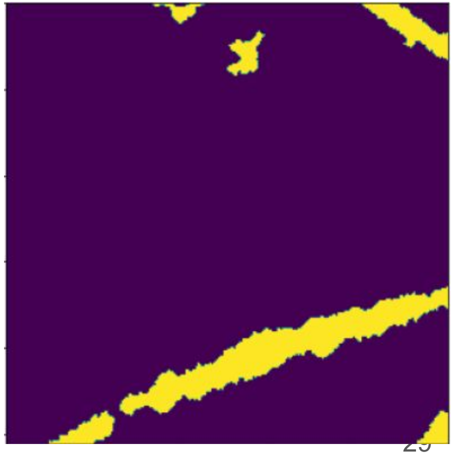
- https://www.radiant.earth/mlhub/
- "Patches" data set
- 1 pixel =~ 1 foot^2
- Data for each pixel: various imaging sensors + label



Chesapeake Watershed Land Cover

- Images: (R, G, B, NIR) x 2
- Leaf on: Landsat 8 surface reflectance (9 bands)
- Leaf off: Landsat 8 surface reflectance (9 bands)



Data Details

- Input: 256 x 256 x N
  - N = 24 (?)
- Output: 256 x 256 x K
  - 1 = water
  - 2 = tree canopy / forest
  - 3 = low vegetation / field
  - 4 = barren land
  - 5 = impervious (other)
  - 6 = impervious (road)
  - 15 = no data

Data Details

- We are only focused on the Pennsylvania portion of the data set
- 50,000 examples for training
  - Compressed images: ~20GB
- Will provide:
  - Data on OSCER
  - Data loader
  - Probably a generator that dynamically loads from the disk

Network Architecture

- Input: images
- Output: probability distribution over classes (for each pixel!)
- In between:
    - Start simple
    - Grow the network, as needed