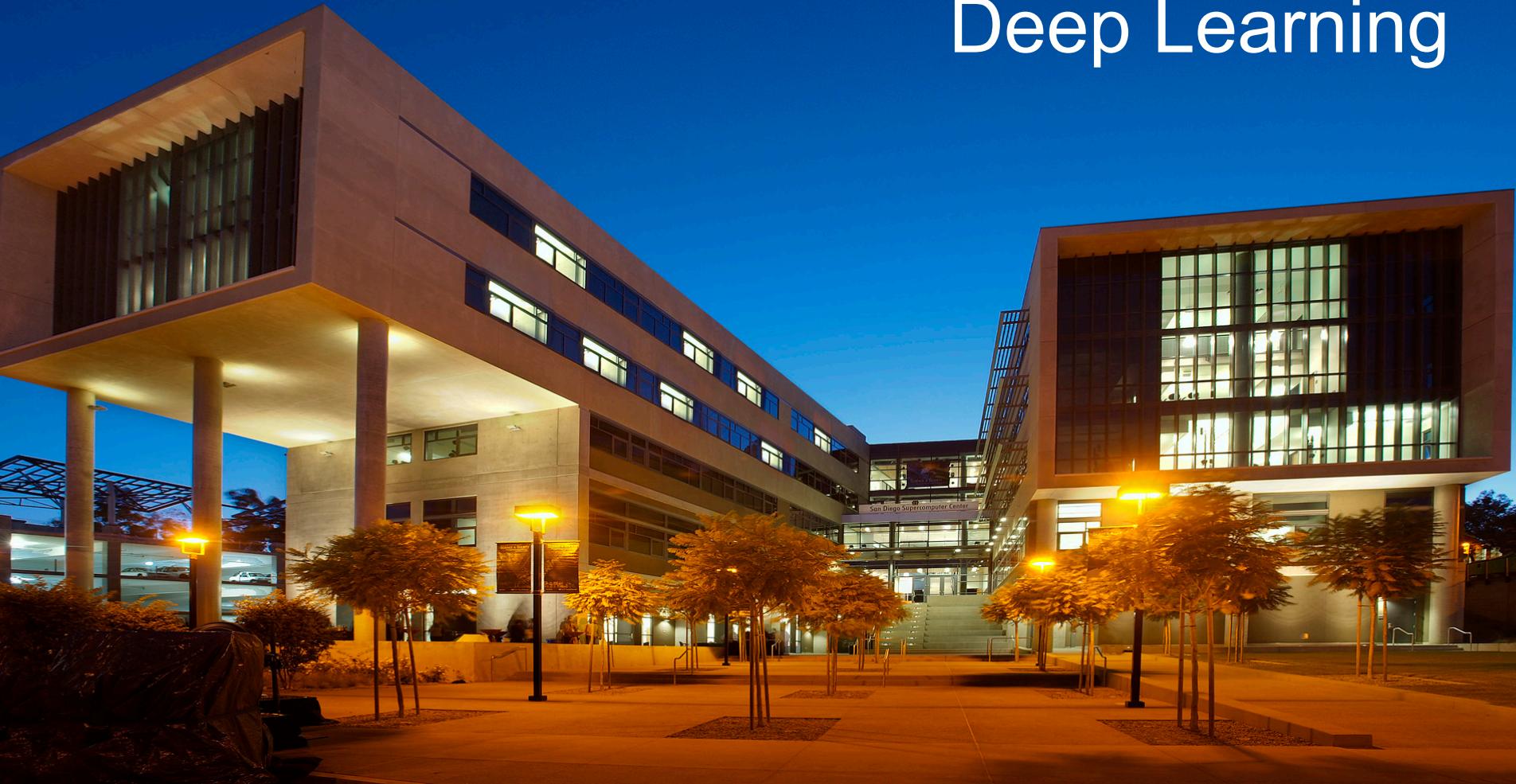


2018 Summer Institute Deep Learning



U-Net and LSTM

Mai H. Nguyen, Ph.D.

U-Net

Image Segmentation

- Dividing image into multiple salient image regions
 - Assign label to every pixel in image
 - Pixels with same label are similar

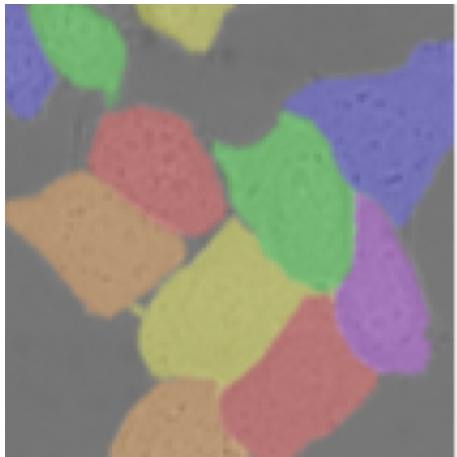


<https://medium.com/@keremturgutlu/semantic-segmentation-u-net-part-1-d8d6f6005066>

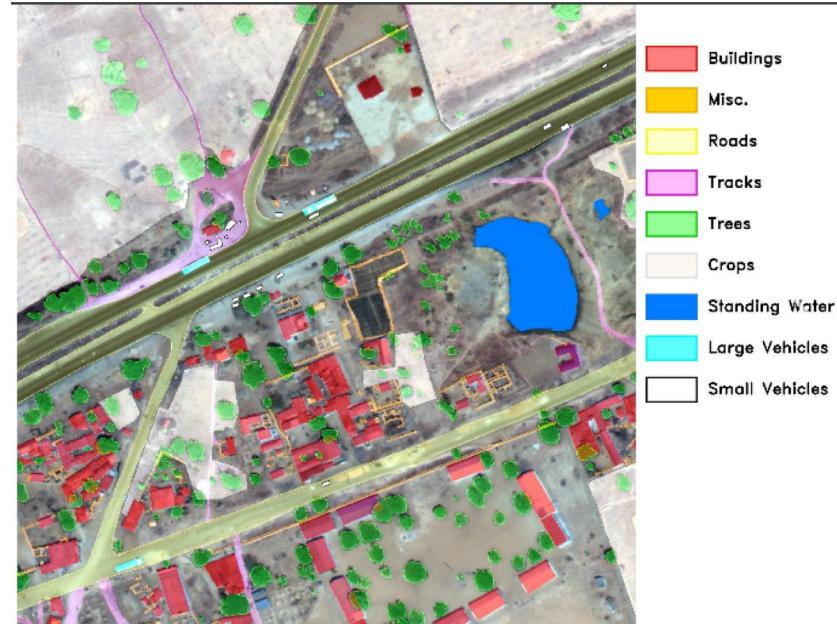
U-Net

- **Used for image segmentation**
- **Architecture**
 - Encoder-decoder network
 - Contracting part of network performs feature extraction
 - Encoding path
 - Expansion part of network performs segmentation
 - Decoding path

U-Net Applications



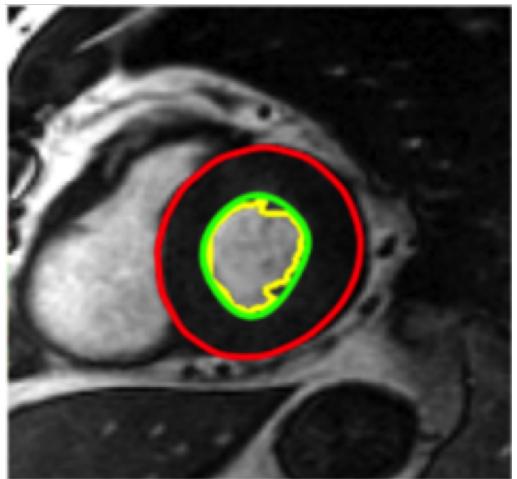
Biomedical Segmentation



Satellite Image Processing

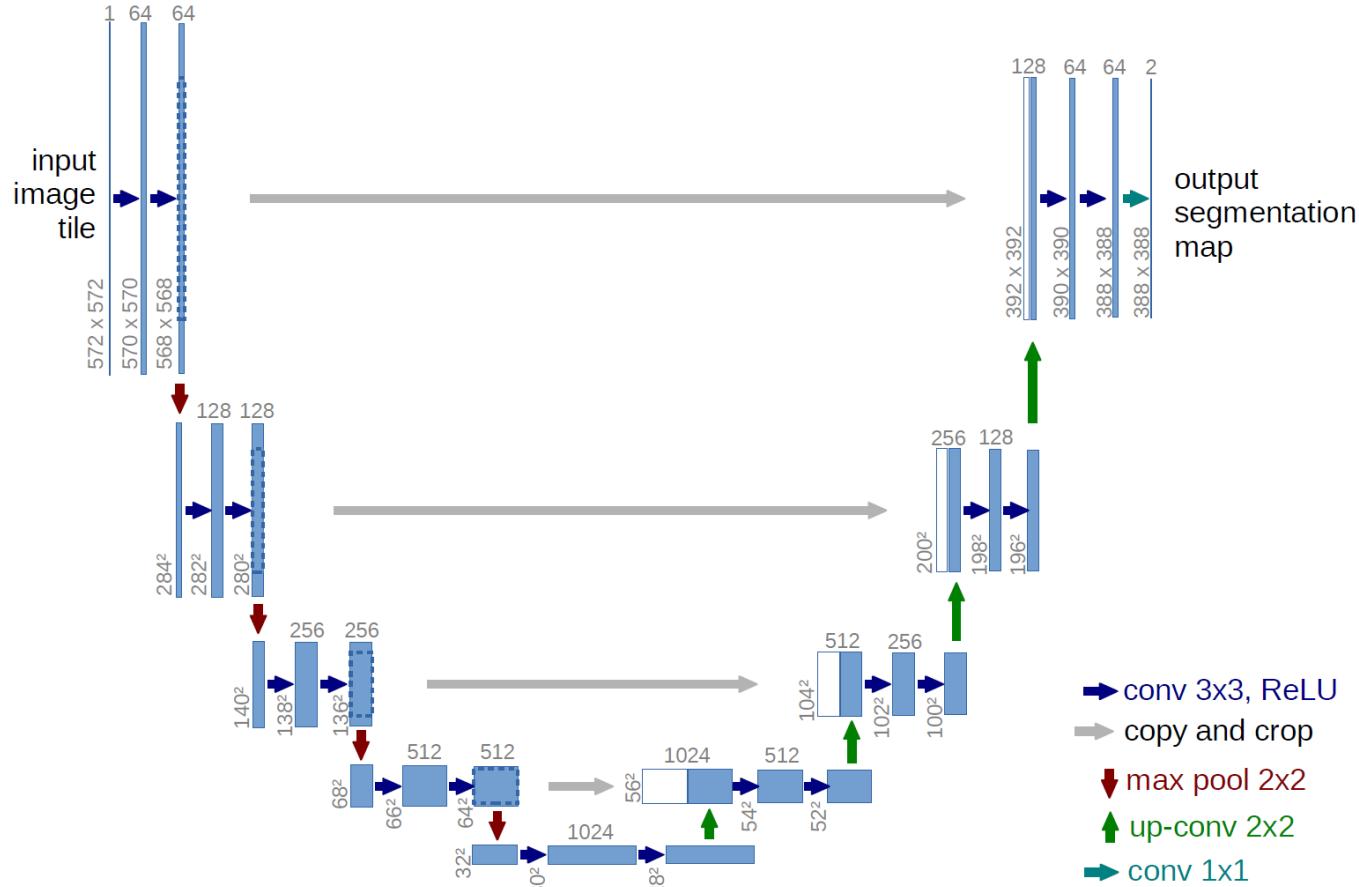


Object Detection



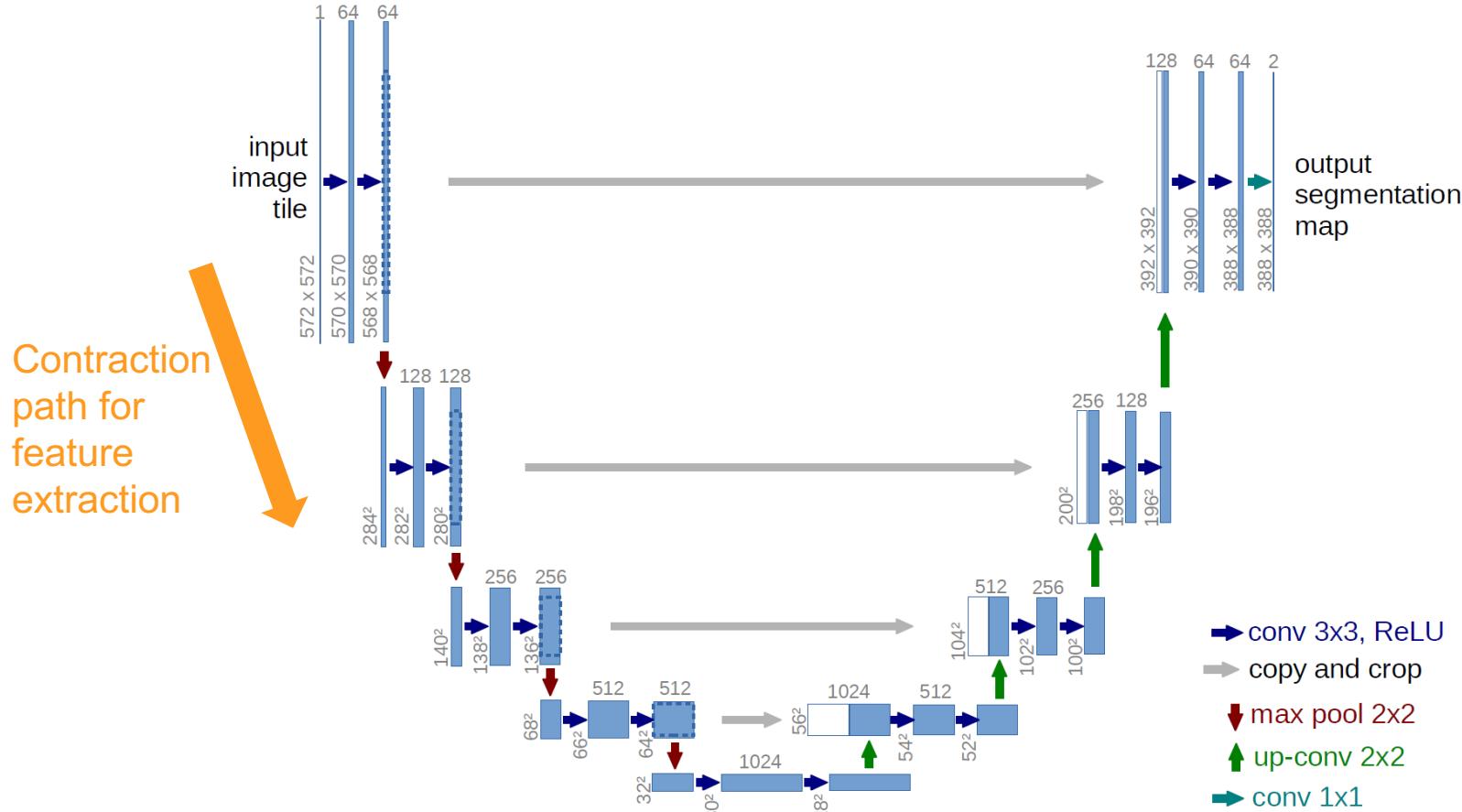
Medical Image Analysis

U-Net Architecture



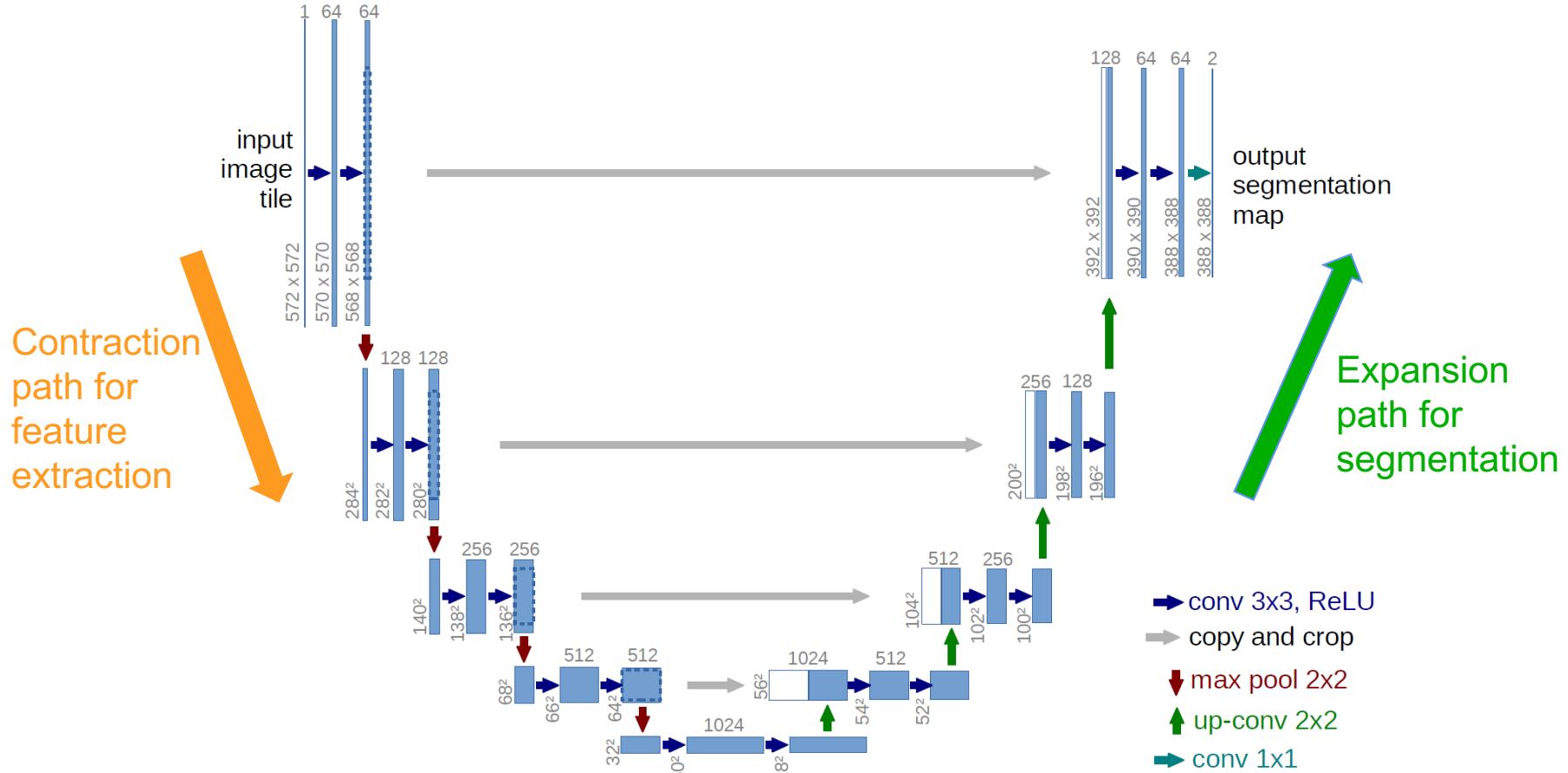
<https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/>

U-Net Architecture



<https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/>

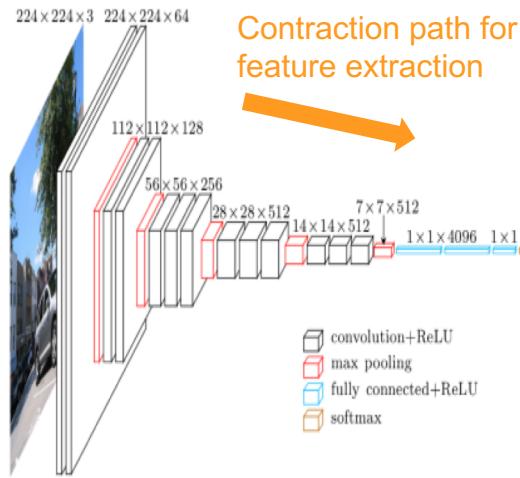
U-Net Architecture



<https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/>

U-Net Architecture

VGG16 CNN Architecture

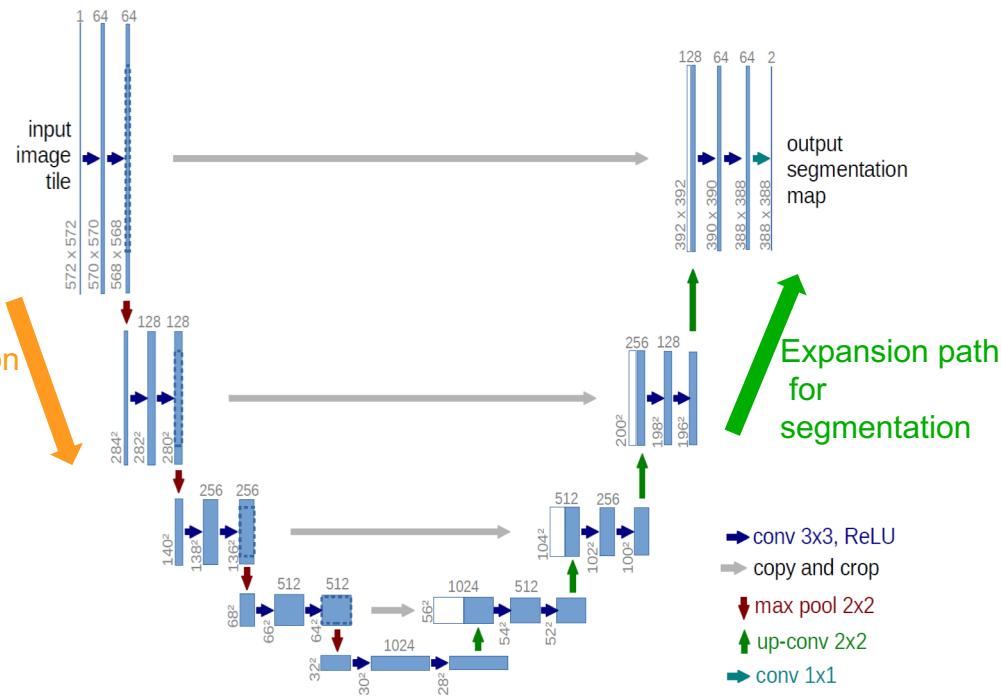


Contraction path for feature extraction

Classification

Contraction path for feature extraction

U-Net Architecture



output segmentation map

Expansion path for segmentation

- conv 3x3, ReLU
- copy and crop
- ↓ max pool 2x2
- ↑ up-conv 2x2
- conv 1x1

<https://spark-in.me/post/unet-adventures-part-one-getting-acquainted-with-unet>.

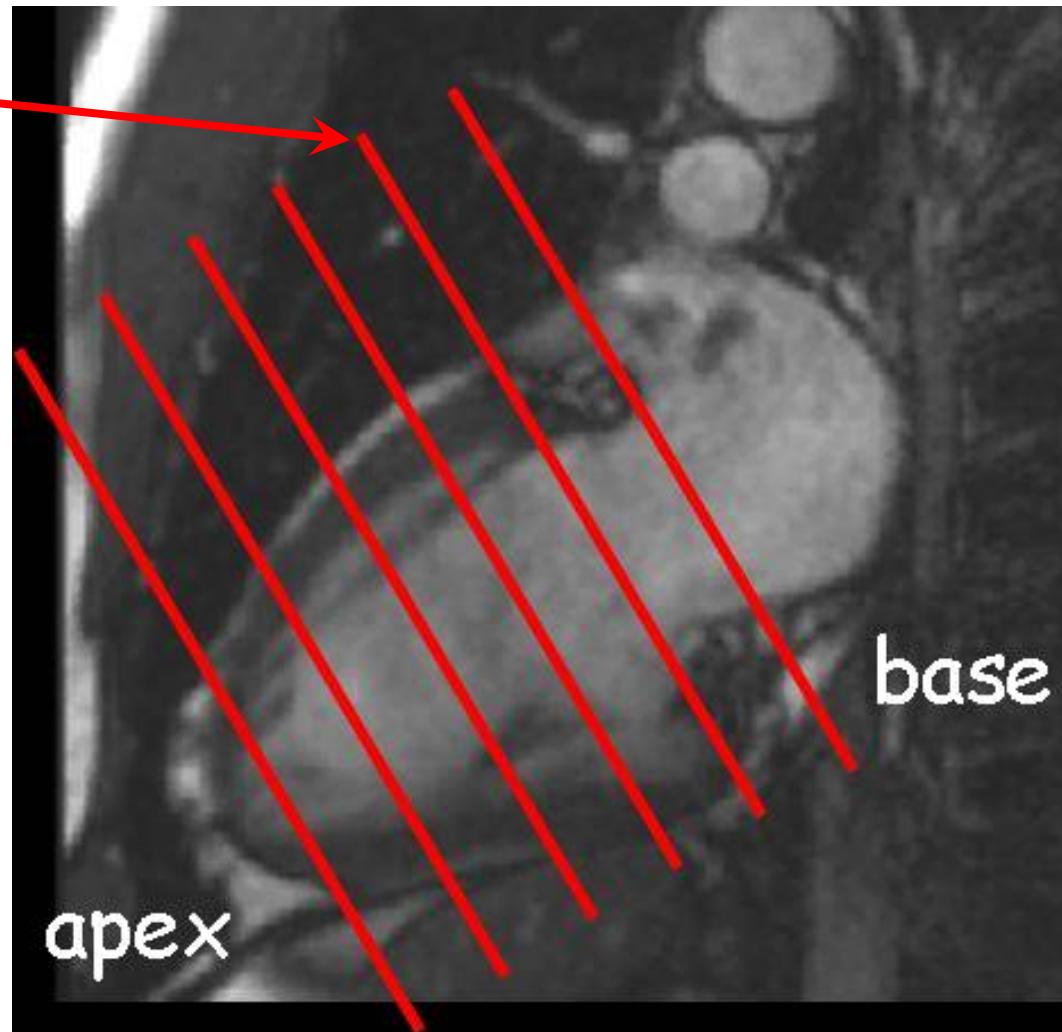
<https://imb.informatik.uni-freiburg.de/people/ronneber/u-net/>

U-Net Case Study

- **Cardiac image analysis**
- **Goal**
 - Aid in non-invasive detection of cardiac disease
- **Motivation**
 - Cardiac imaging allows visualization of heart structure and functionality non-invasively
 - But process of analyzing cardiac images is time-consuming and labor-intensive
- **Approach**
 - Apply deep/machine learning to provide faster and more consistent analysis results

Cardiac Images

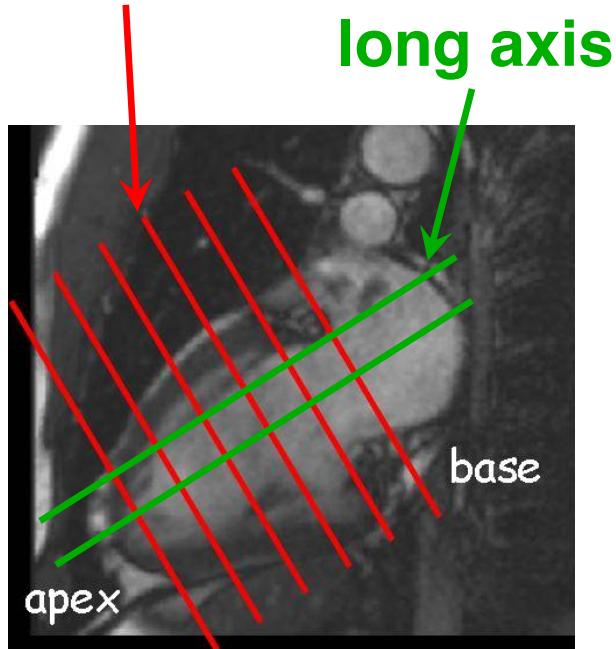
- **Slices**
 - At different locations to cover heart
 - Each slice acquired on single breath hold
- **Frames**
 - 2D images of heart during heartbeat
 - MRI: 10-30 frames per slice



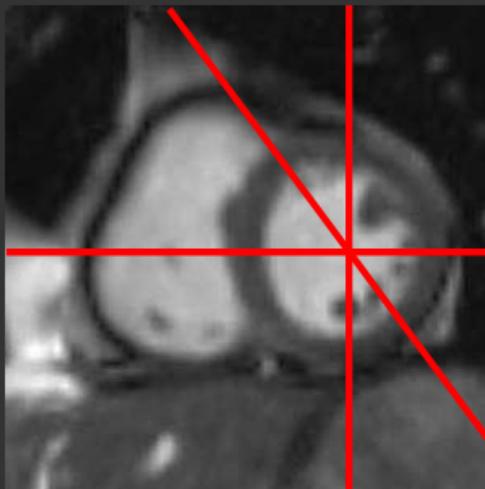
<http://radiology.cornfeld.org/CMR/planes.php>

Different Views of Heart

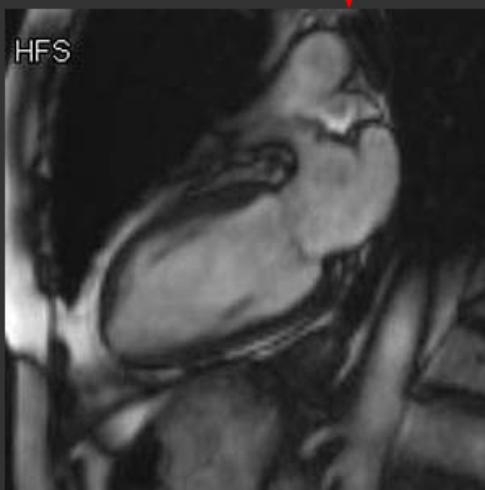
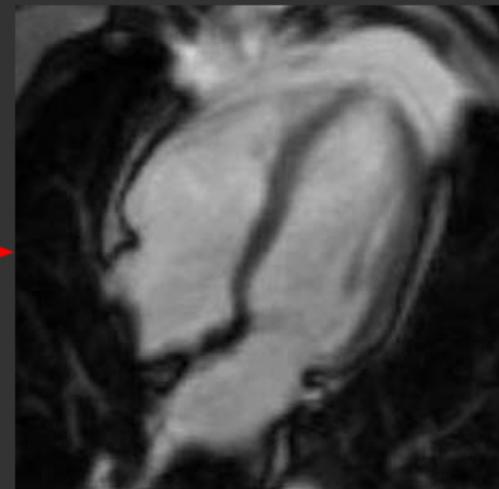
short axis



Short axis



4 chamber view



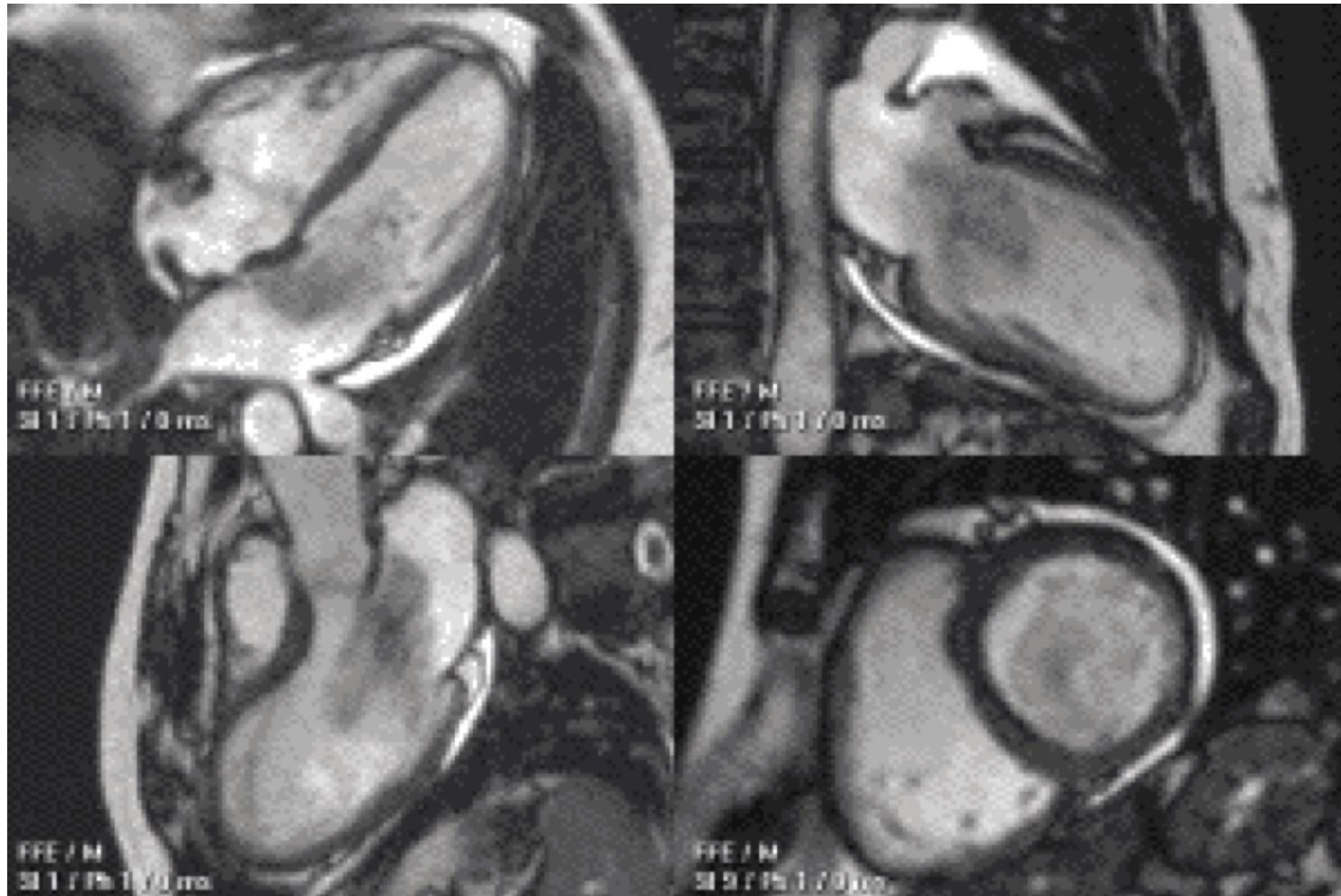
Vertical long axis



3 chamber view

<https://www.med-ed.virginia.edu/courses/rad/cardiacmr/Anatomy/Views.html>

Cardiac Cine

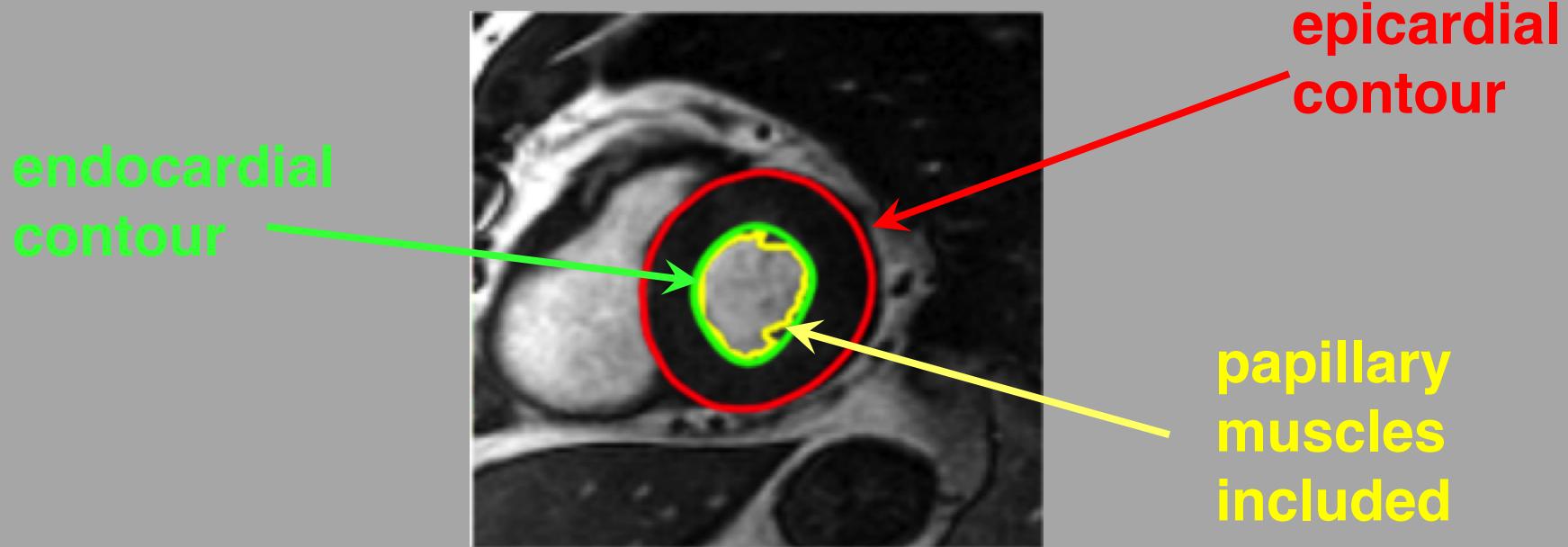


https://en.wikipedia.org/wiki/Cardiac_magnetic_resonance_imaging

LV Segmentation

- LV contours

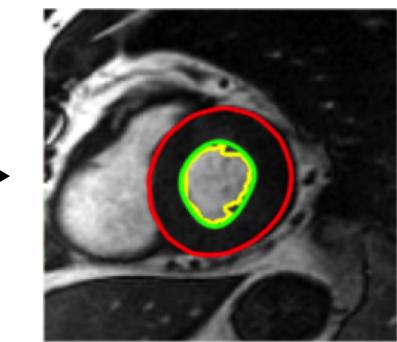
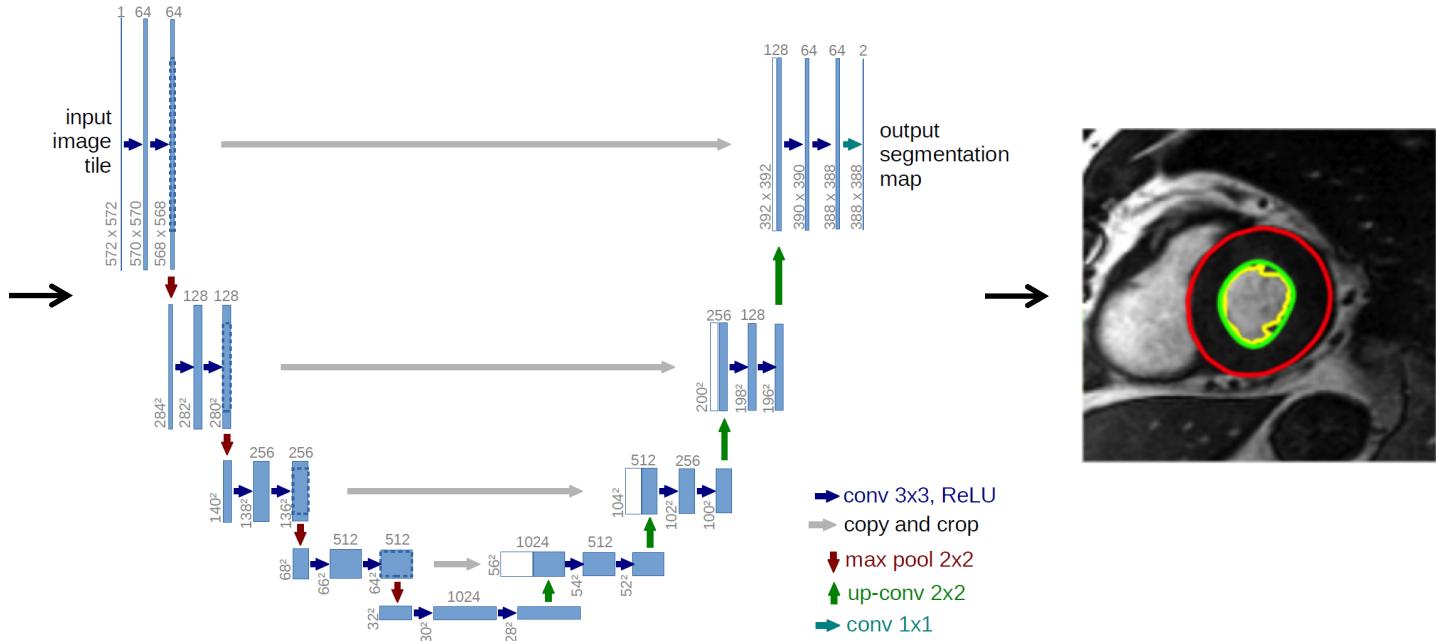
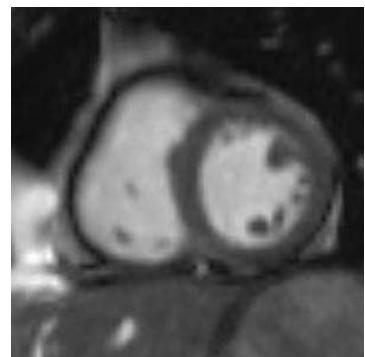
http://smial.sri.utoronto.ca/LV_Challenge/Home.html



- Current approach:
 - Predict endocardial contour

Medical Image Analysis

- Segmentation

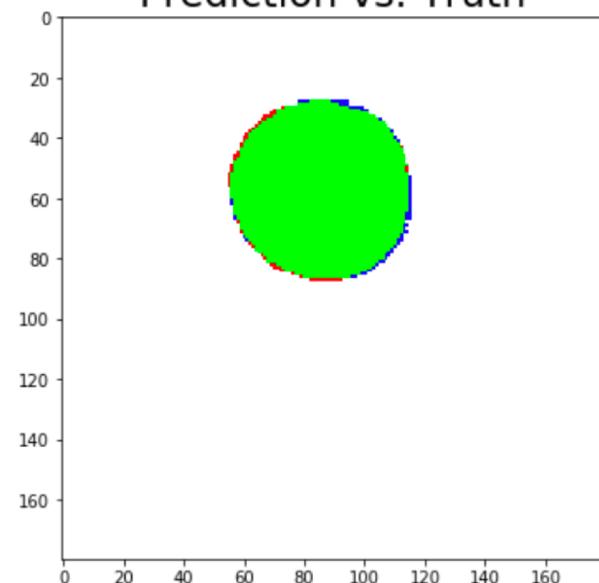


LV Segmentation on Test Image

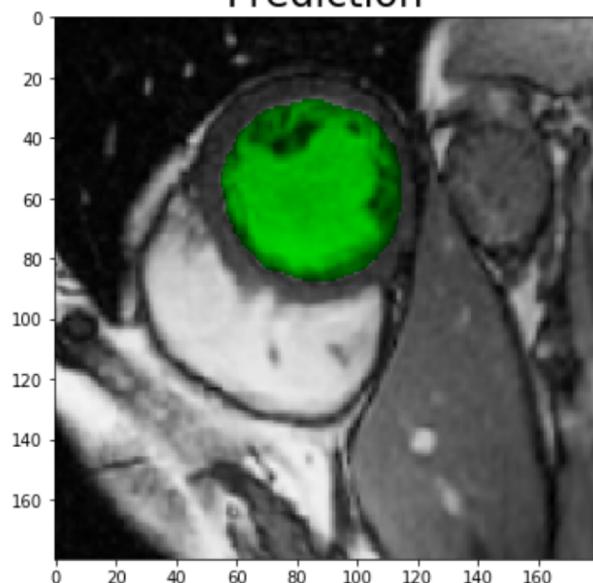
PatientName: ^SC-N-9 SeriesNumber: 302 InstanceNumber 80

dice coefficient: 97.6047904192

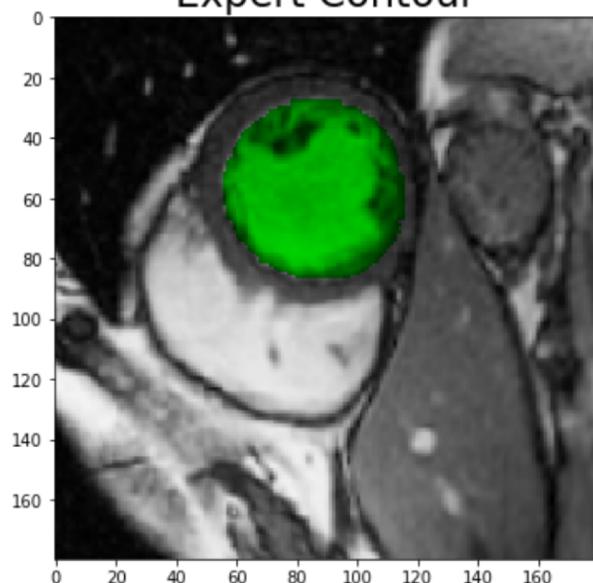
Prediction vs. Truth



Prediction



Expert Contour



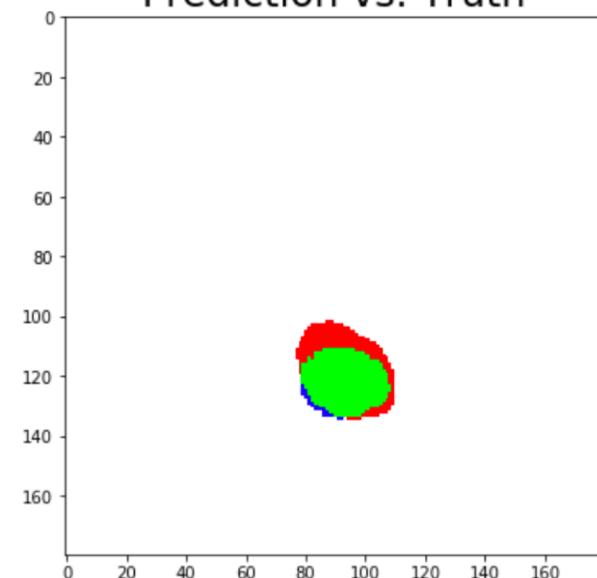
True Positive : green
False Positive: red

True Negative: white
False Negative: blue

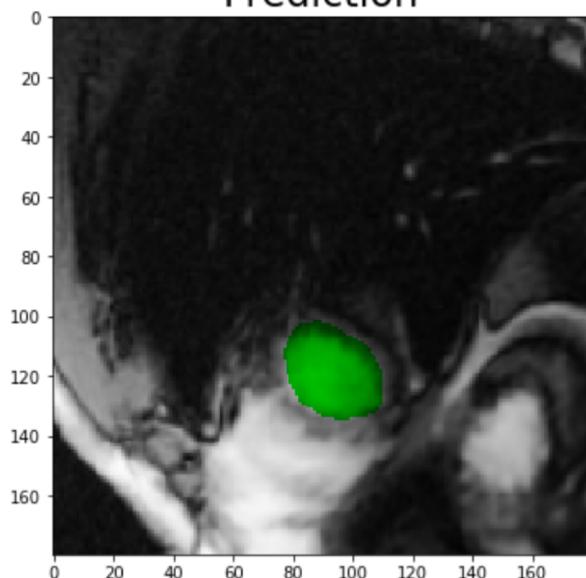
LV Segmentation on Test Image

PatientName: ^SC-HF-NI-14 SeriesNumber: 303 InstanceNumber 216
dice coefficient: 77.4945375091

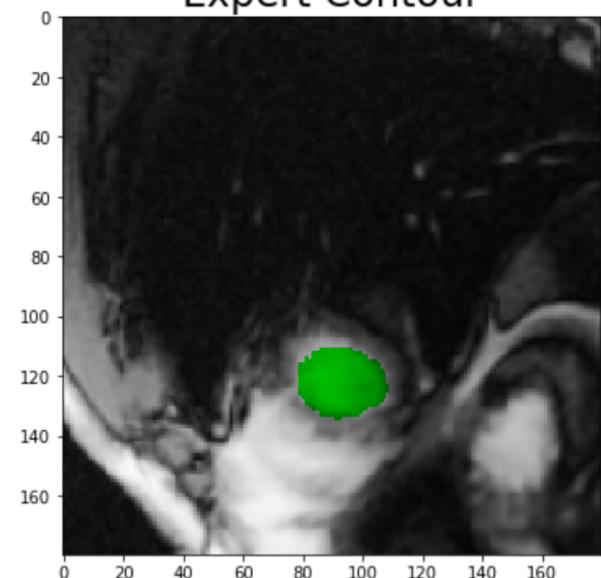
Prediction vs. Truth



Prediction



Expert Contour



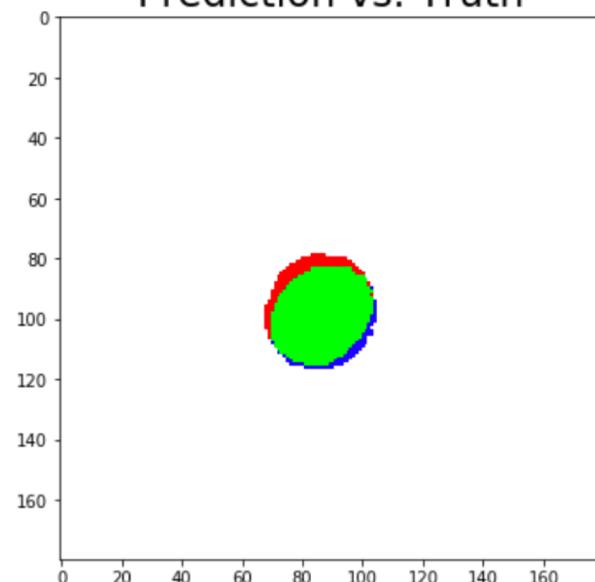
True Positive : green
False Positive: red

True Negative: white
False Negative: blue

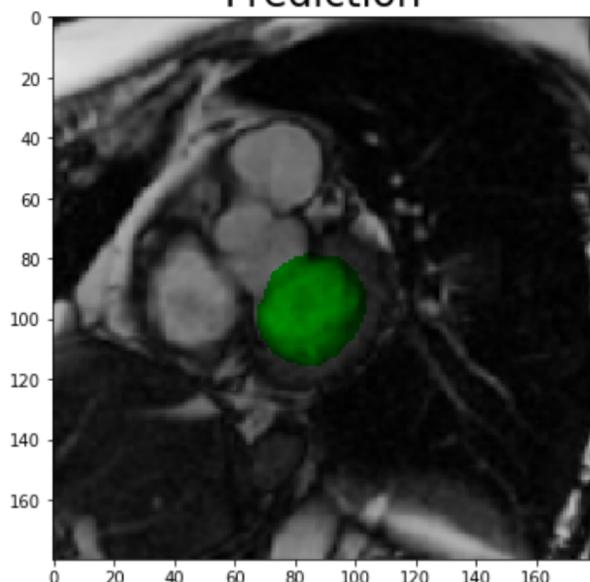
LV Segmentation on Test Image

PatientName: ^SC-HYP-11 SeriesNumber: 300 InstanceNumber 80
dice coefficient: 87.8665318504

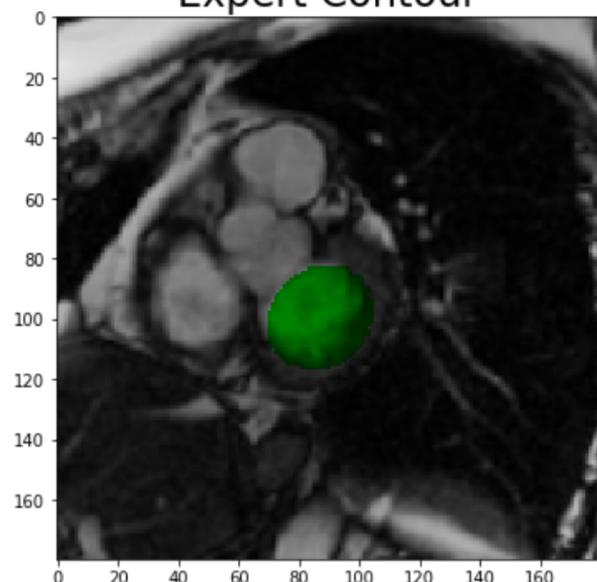
Prediction vs. Truth



Prediction



Expert Contour



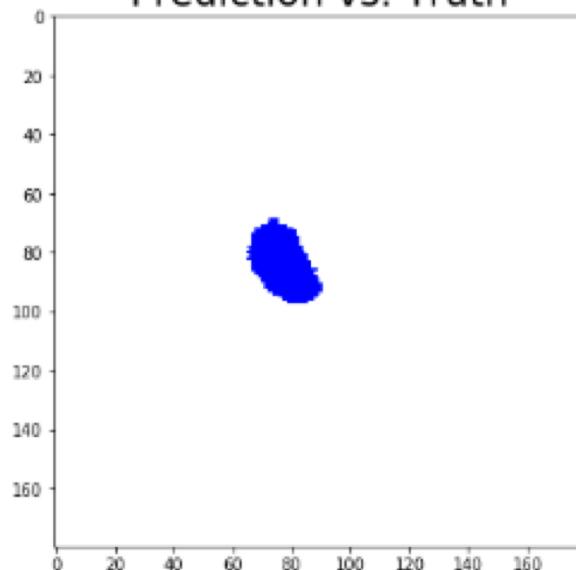
True Positive : green
False Positive: red

True Negative: white
False Negative: blue

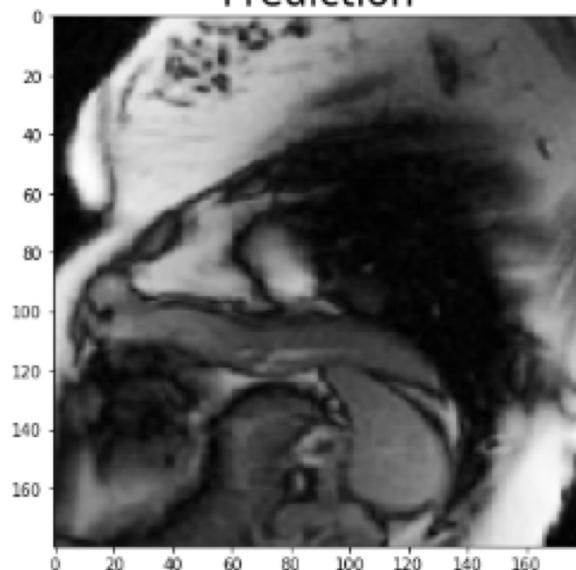
LV Segmentation on Test Image

PatientsName: ^SC-HF-NI-13 SeriesNumber: 400 InstanceNumber 208
dice coefficient: 0.0

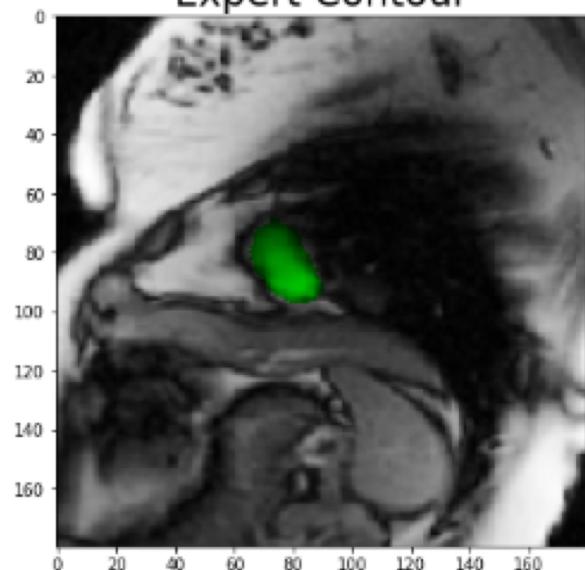
Prediction vs. Truth



Prediction



Expert Contour



True Positive : green
False Positive: red

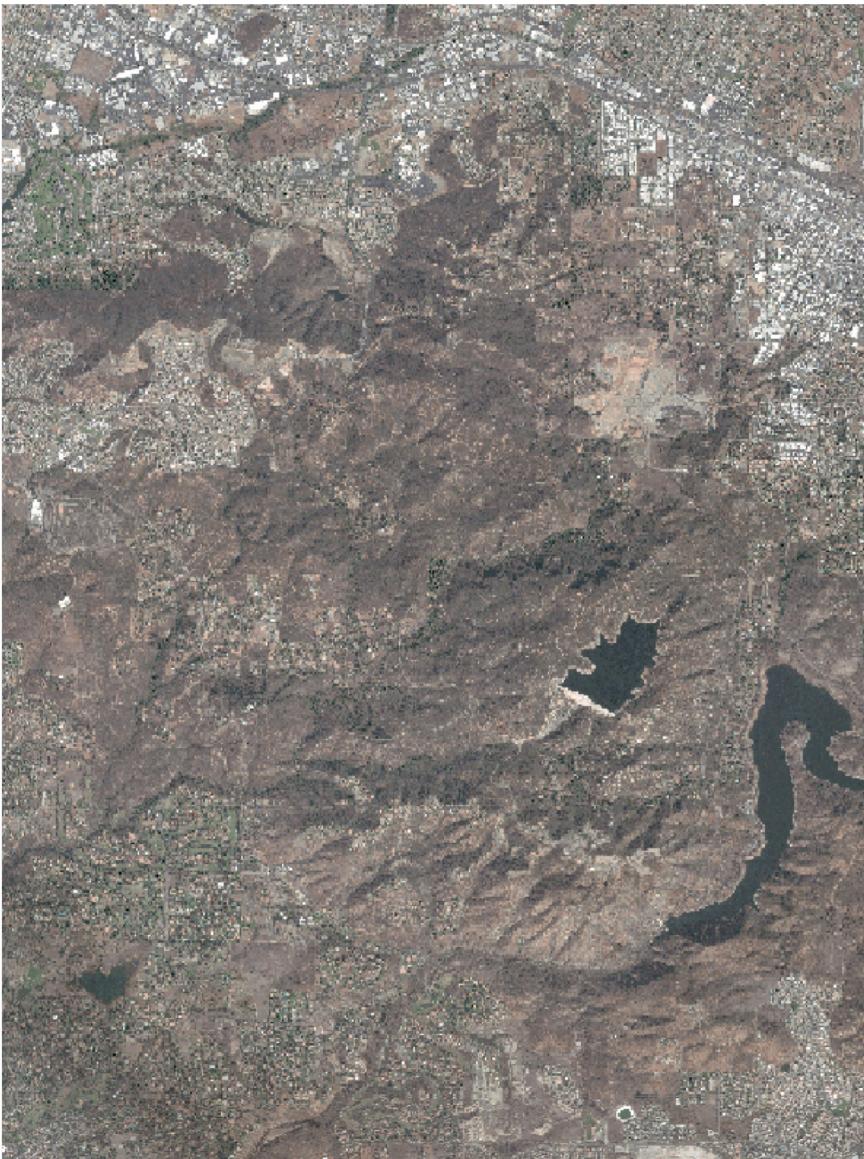
True Negative: white
False Negative: blue

Another U-Net Use Case

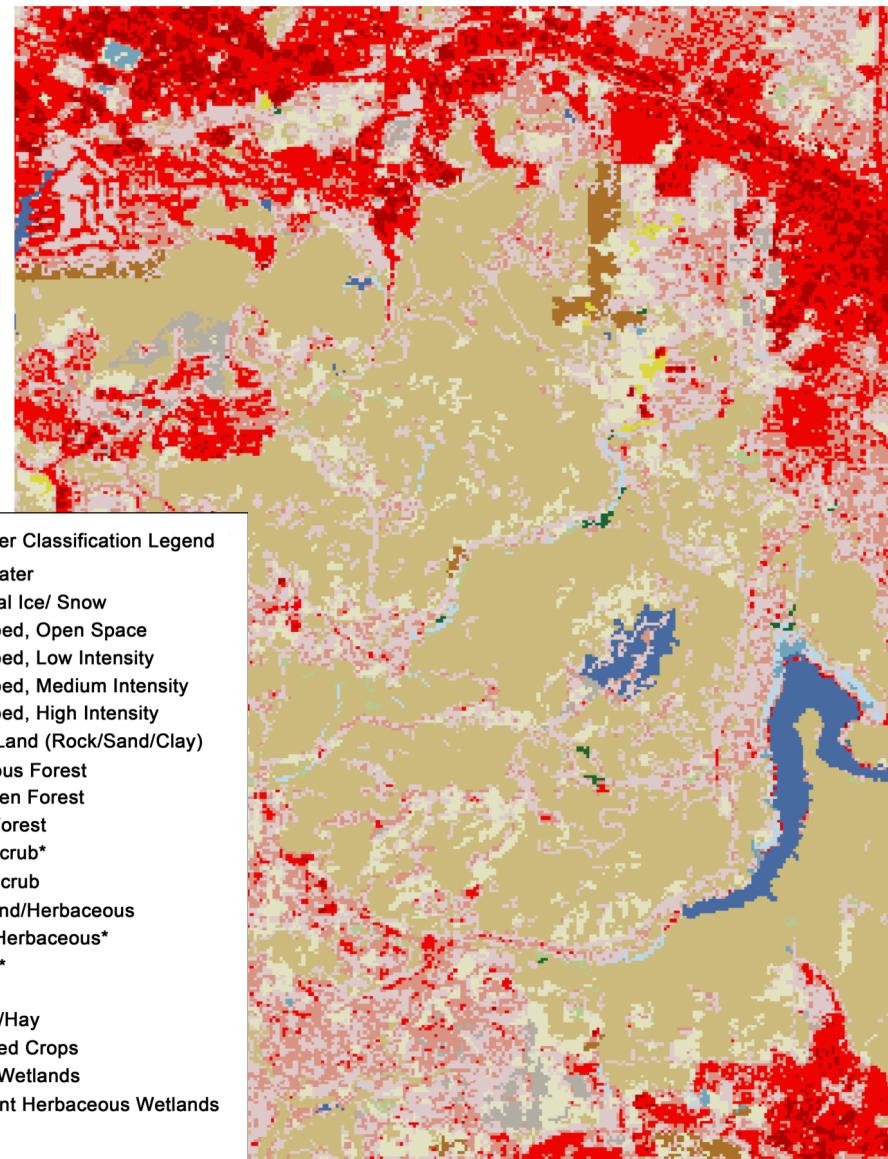
Satellite Image Analysis

- **Goal**
 - Generate land cover maps from satellite imagery
- **Motivation**
 - Land data products are critical for many applications
 - Current land data products are released every few years
 - Want to generate land data products at scale, as needed, and based on up-to-date data
- **Approach**
 - Use deep/machine learning techniques to extract and analyze features from satellite imagery

Land Cover Map Example

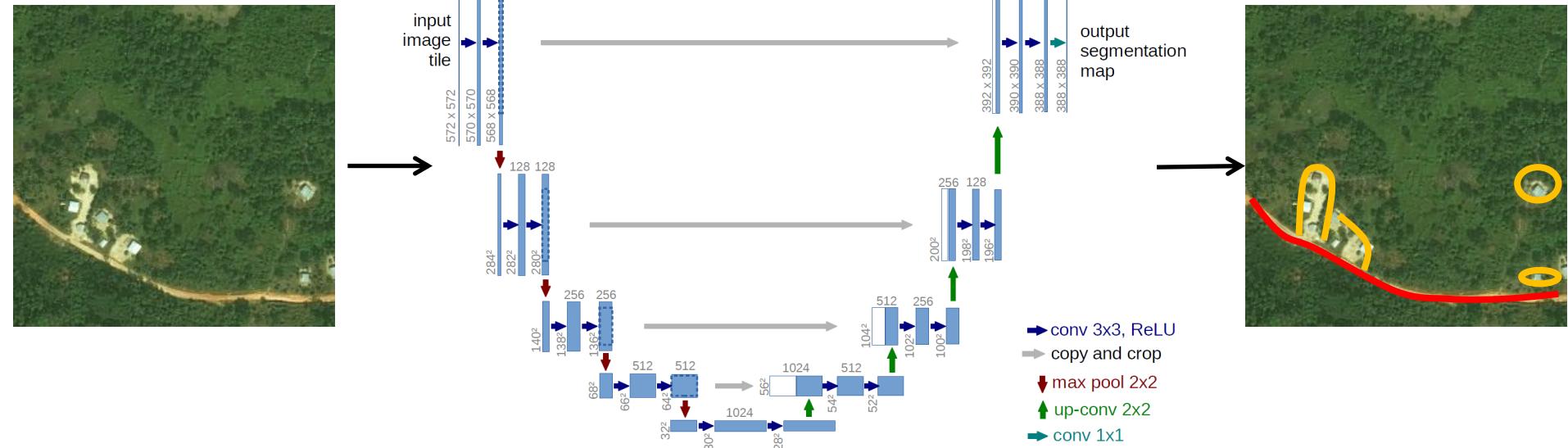


NLCD Land Cover Classification Legend	
11	Open Water
12	Perennial Ice/ Snow
21	Developed, Open Space
22	Developed, Low Intensity
23	Developed, Medium Intensity
24	Developed, High Intensity
31	Barren Land (Rock/Sand/Clay)
41	Deciduous Forest
42	Evergreen Forest
43	Mixed Forest
51	Dwarf Scrub*
52	Shrub/Scrub
71	Grassland/Herbaceous
72	Sedge/Herbaceous*
73	Lichens*
74	Moss*
81	Pasture/Hay
82	Cultivated Crops
90	Woody Wetlands
95	Emergent Herbaceous Wetlands
* Alaska only	



Deep Learning

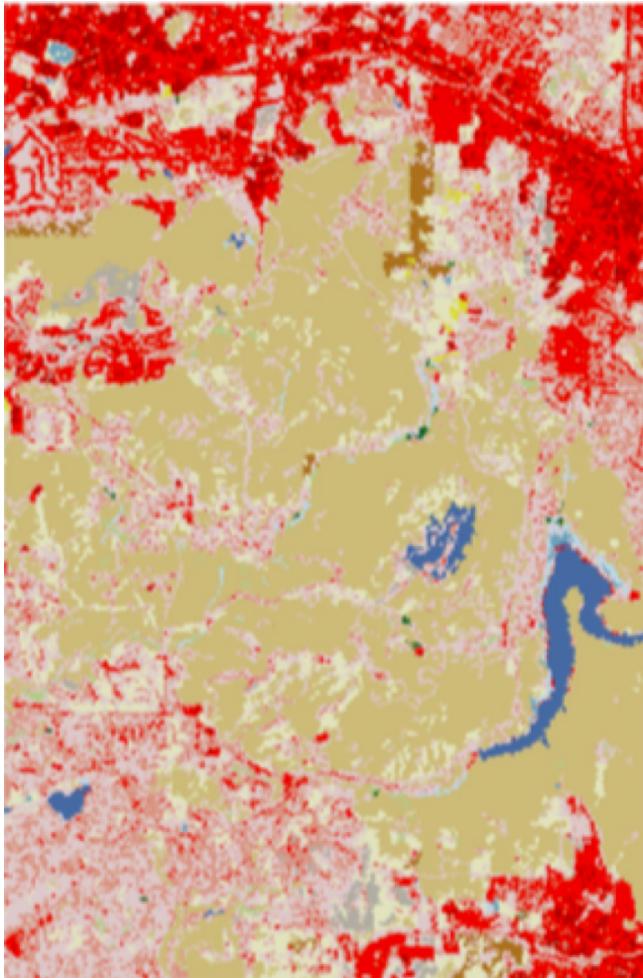
U-Net



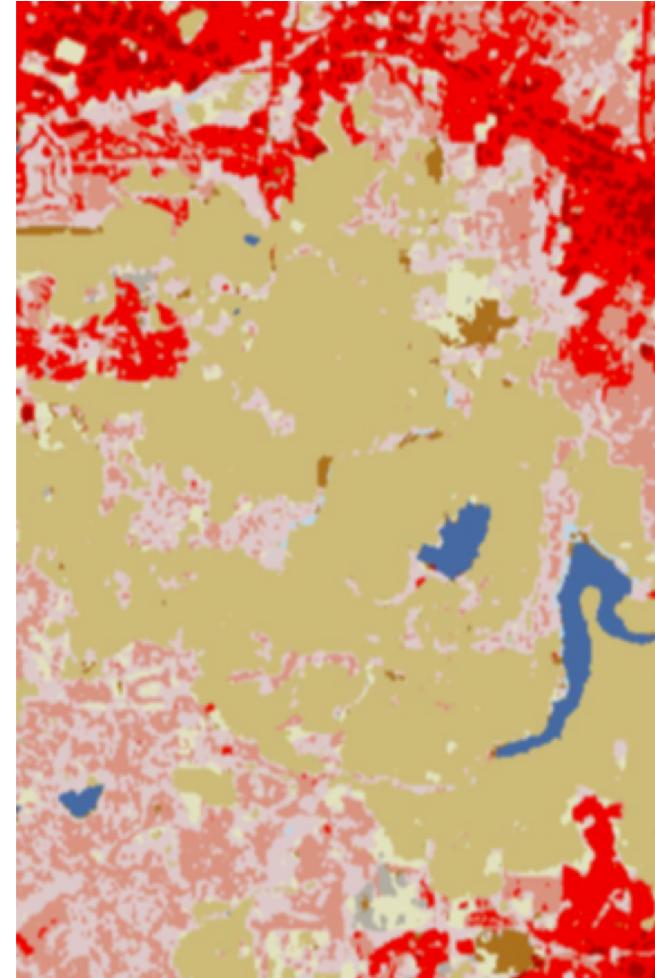
<https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/>

Land Cover Predictions

Original Labels



U-Net Predicted Labels



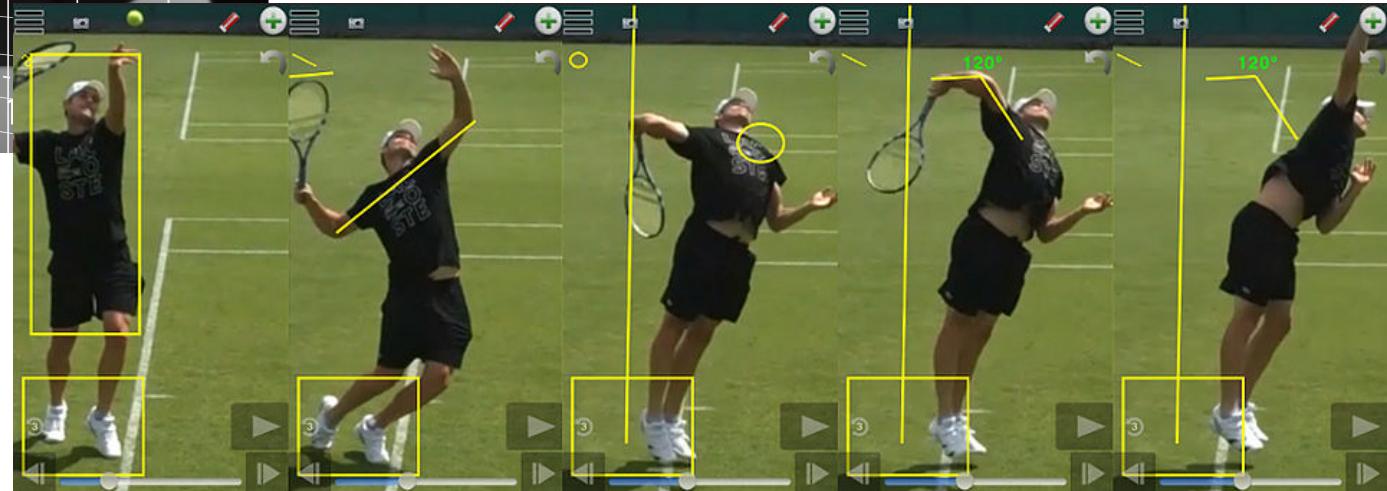
LSTM

Sequence Learning

- Problem description
 - Learning a signal with an ordering or time component

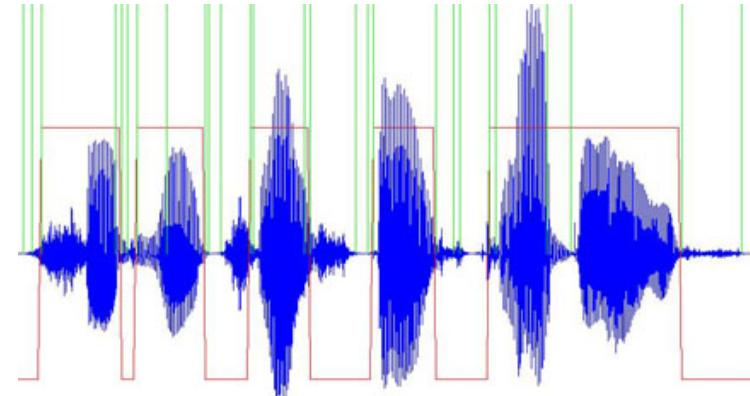


Stock Price



Video

Speech



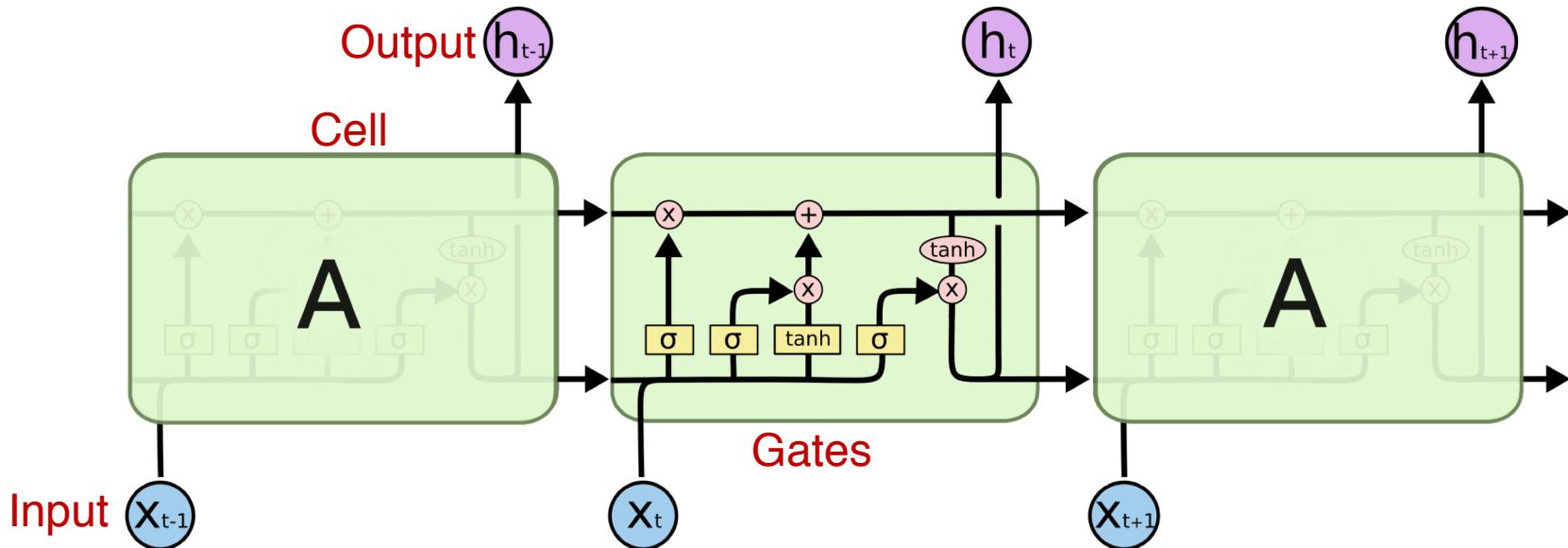
Long Short-Term Memory (LSTM)

- **Recurrent neural network (RNN)**
 - RNNs can model sequences and time-dependent signals
 - RNN architectures have cyclic connections that feed network activations from a previous time step as part of input back to network
 - Allows for temporal contextual information to be stored
 - Predictions at current time step depend on current input and previous predictions
 - Context required must be learned
- **LSTM**
 - Type of RNN
 - Addresses important issues with conventional RNN training

LSTM Applications

- Speech recognition
- Machine translation
- Language modeling
- Speech synthesis
- Handwriting recognition
- Text generation
- Video analysis
- Protein structure prediction
- Stock price prediction

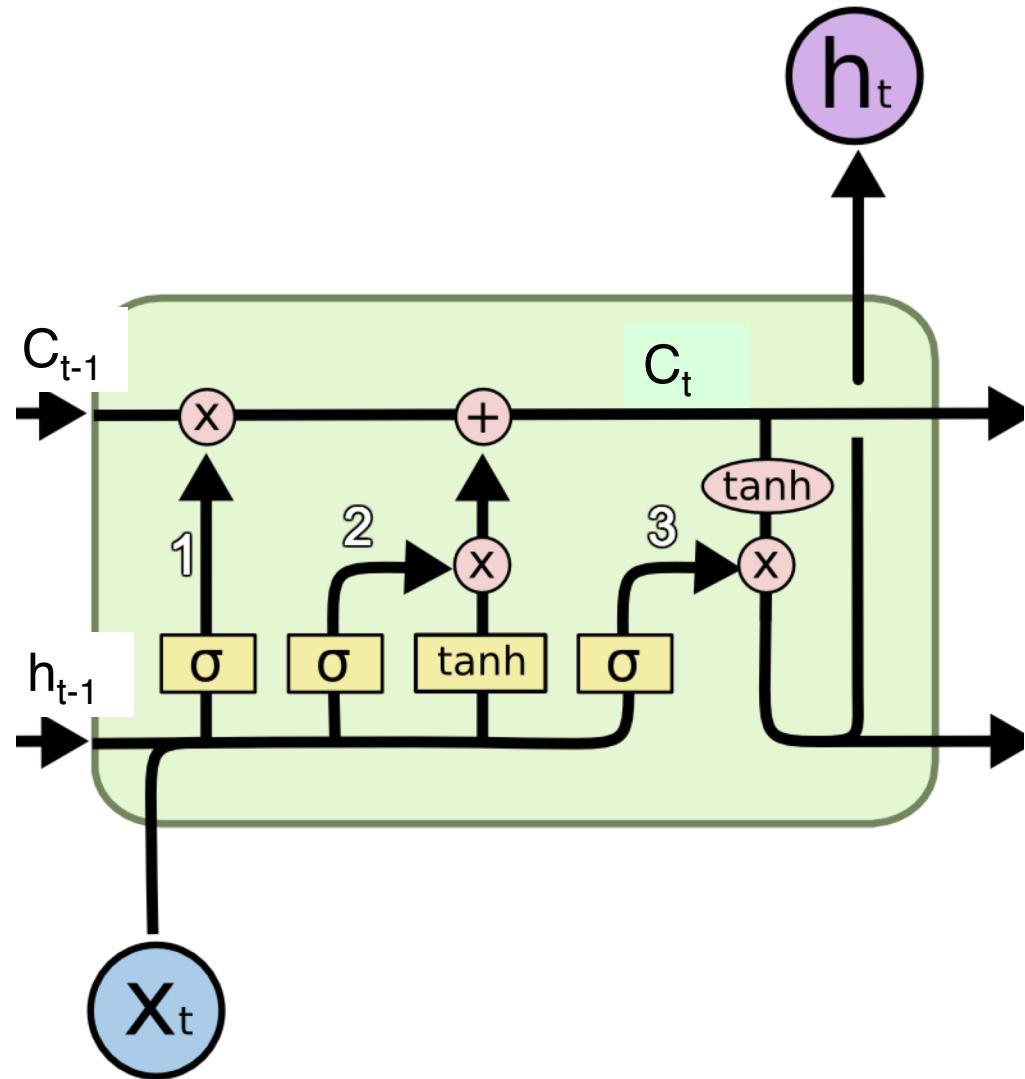
LSTM Architecture



<http://colah.github.io/posts/2015-08-Understanding-LSTMs/>

- Info flows through memory blocks called ‘cells’
- Structure of cell allows LSTM to selectively remember/forget pieces of information
- Each cell manipulates memory through ‘gates’

LSTM Cell



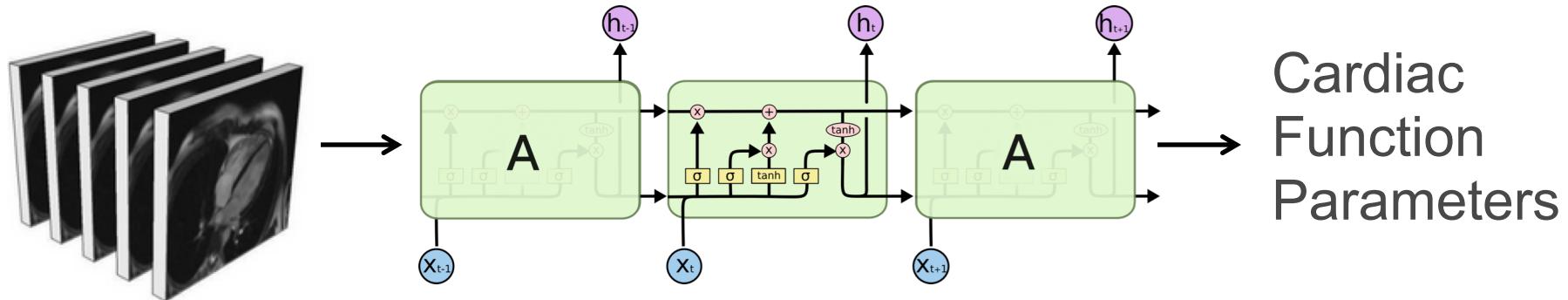
- X_t
 - Current input
- C_{t-1}
 - Memory from last cell
- h_{t-1}
 - Output from last cell
- h_t
 - Current output
- **1: forget gate**
 - Removes info
- **2: input gate**
 - Adds info
- **3: output gate**
 - Selects useful info as output

LSTM Use Case

- **Predicting job status of computer processes**
 - For experiments related to particle physics

LSTM Use Case

Cardiac Image Analysis



References

- **U-Net**
 - Original paper:
 - <https://arxiv.org/abs/1505.04597>
 - Short description and video:
 - <https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/>
 - U-Net & Keras
 - <https://spark-in.me/post/unet-adventures-part-one-getting-acquainted-with-unet>
 - U-Net for medical image segmentation
 - <https://towardsdatascience.com/medical-image-segmentation-part-1-unet-convolutional-networks-with-interactive-code-70f0f17f46c6>
 - U-Net for satellite analysis
 - <https://medium.com/vooban-ai/satellite-image-segmentation-a-workflow-with-u-net-7ff992b2a56e>

References

- **LSTM**
 - Original paper
 - <https://www.mitpressjournals.org/doi/abs/10.1162/neco.1997.9.8.1735>
 - Understanding LSTM Networks
 - <http://colah.github.io/posts/2015-08-Understanding-LSTMs/>
 - Introduction to LSTM
 - <https://www.analyticsvidhya.com/blog/2017/12/fundamentals-of-deep-learning-introduction-to-lstm/>

Deep Learning Topics

- Deep Learning Overview
 - Neural network & deep learning overview
 - MNIST tutorial
- CNN Transfer Learning with Keras
 - Pre-trained CNN to speed up CNN training
 - Feature extraction & fine tuning
- FasterCNN
 - Object detection
- Unet
 - Segmentation
- LSTM
 - Sequence & temporal learning

Questions?

