These slides have not yet been updated for the Spring 2019 semester

Vision

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Outline

- Motivation
- Images
- Classification
- Pixel segmentation
- Multiple object detection
- Object based segmentation
- Depth estimation
- Motion estimation
- References

Motivation

A Brief History Of Classical Vision

- Pre processing
- Feature extraction
  - Hand engineered for region candidates
  - Hand engineered for objects
  - Hand engineered for depth
  - Hand engineered for motion
- Prediction
  - Trainable classifier
- Post processing

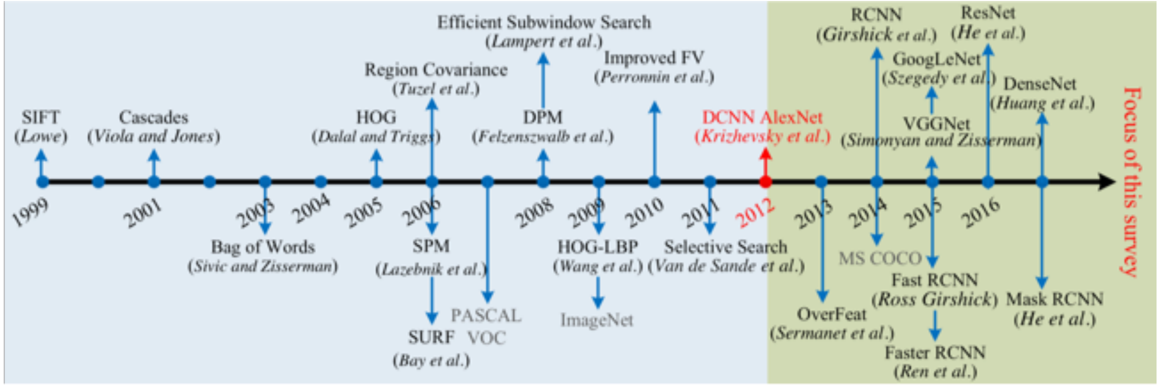


Figure from https://arxiv.org/abs/1809.02165

Image Understanding Is A Classification Problem

Multiple object detection

- Input: Image
- Box each object
- Classify the object in each box

Pixel segmentation

- Input: Image
- Classify each pixel

Figures from Pascal VOC (http://host.robots.ox.ac.uk:8080/pascal/VOC/) and Microsoft COCO (http://mscoco.org); note example on right is actually instance segmentation

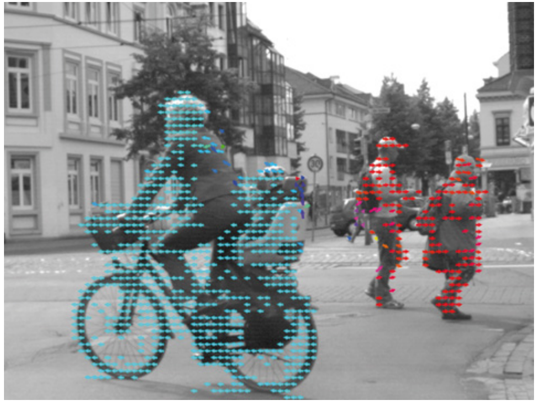
Structure Estimation Is A Classification Problem

Depth estimation

- Input: 2+ images with spatial separation
- Preprocessing (rectification)
- Cost (find the same point in 2+ images = classification)
- Depth estimation (smoothing, SGM, ...)

Motion estimation

- Input: 2+ images at separate time instants
- Preprocessing (rectification)
- Cost (find the same point in 2+ images = classification)
- Motion estimation (refinement, ...)



Figures https://ieeexplore.ieee.org/document/6327192 and https://www.commonvisionblox.com/en/products/series/cvb-optical-flow/

The Strategy Described Here

- Replace hand engineered feature extraction and prediction with xNN based methods
  - xNNs are universal approximators
  - Most vision problems can be cast as approximating a mapping from pixels to classes
  - Typically use CNNs to take advantage of spatial invariance to reduce compute
  - Train end to end
- Network design and training
  - Frequently start from a base classification network trained on ImageNet
  - Remove the classification head, add a head appropriate for the problem, restart training

Disclaimer

- There's a lot of vision related stuff not included here
    - Different methods within the categories of problems included here
    - Problems that are not included here
- Possibly some of this will be addressed in future versions of the slides
- Regardless of whether it is or not, hopefully these slides provide enough of a base from which to branch off and learn more on your own

Images

Understand The Data Available For Processing

- Understanding how images are captured is helpful for understanding vision
  - It's the data the vision algorithm has to work with
  - Apertures, lens, sensors, image signal processing pipelines, ...

- But the realities of a 1 semester course, the content we've covered so far and the content we have left to cover makes it impractical to spend a lot of time on this

- So the following are a few of many excellent links for more information on the image capture process
  - Brown CSCI 1290: computational photography and image manipulation
    - http://cs.brown.edu/courses/csci1290/
  - Digital photography
    - YouTube links: https://sites.google.com/site/marclevoylectures/
    - PDFs: https://sites.google.com/site/marclevoylectures/schedule
    - Lenses and optics: https://drive.google.com/file/d/0B6w2XfPHEcZYT0dwaFF4emd6Vzg/view https://drive.google.com/file/d/0B6w2XfPHEcZYTnZIR2VpWThHM0U/view
    - Post processing: https://drive.google.com/file/d/0B6w2XfPHEcZYeTFKZWhndVBOYTA/view

For Humans Or Machines?

- One thing to think about is that the majority of the design and processing of image capture devices is to create images that are pleasing in some way to humans
  - It's also the majority of the data that we have to work with
- But for vision we want images that are optimized for algorithms to extract information
  - Is there a better tuning of the image capture process for this?

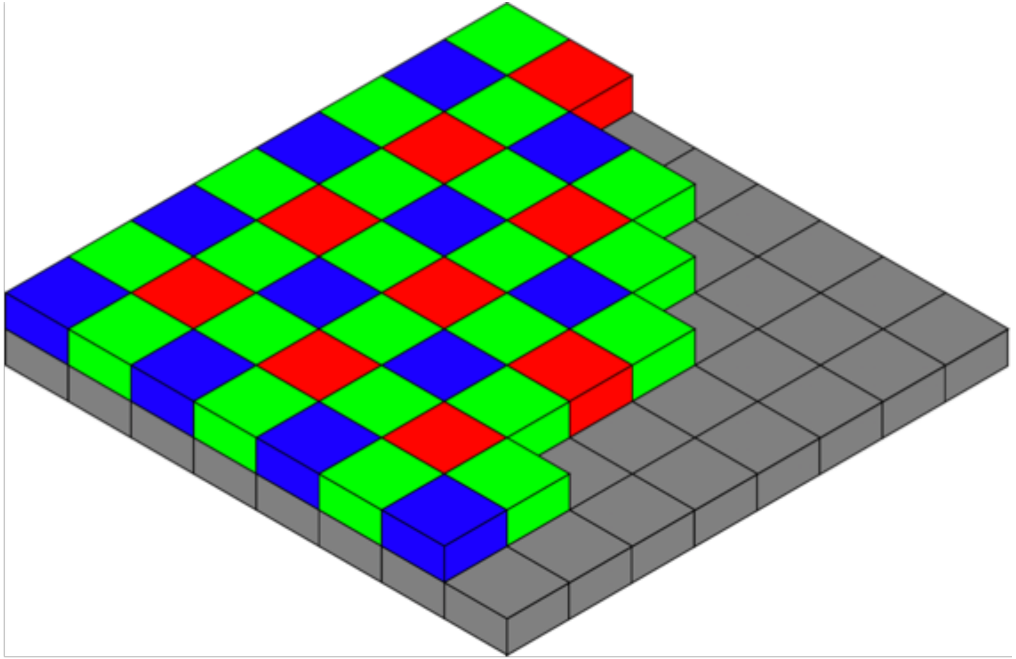


Figure from https://en.wikipedia.org/wiki/Bayer_filter

ARM Mali Camera

Configurable ASIC style

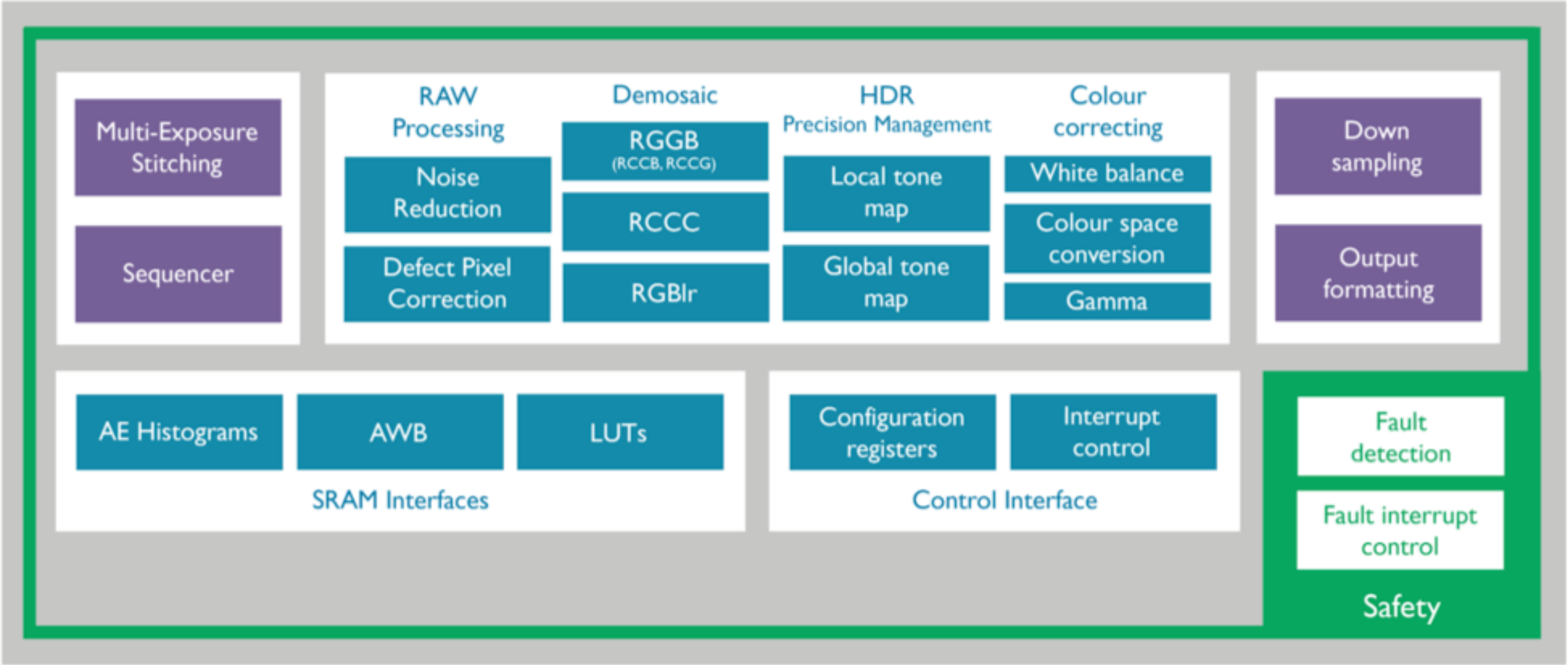


Figure from https://developer.arm.com/products/graphics-and-multimedia/mali-camera

Google Pixel Visual Core

- Domain specific architecture (DSA)
  - Inputs and outputs are in DRAM
  - Ring network between IPU cores and DMA
  - IPU is a line buffer + a stencil processors
  - Internal data is in line buffers
  - Stencil processors act on 16x16 compute regions within a 20x20 array (excess is halo) and perform 16b vector MAC operations
- Domain specific software (no abbreviation)
  - Program in a subset of Halide (http://halide-lang.org)
  - Halide backend creates an architecture independent intermediate representation
  - Final compilation into architecture specific instructions
  - Includes explicit memory movement

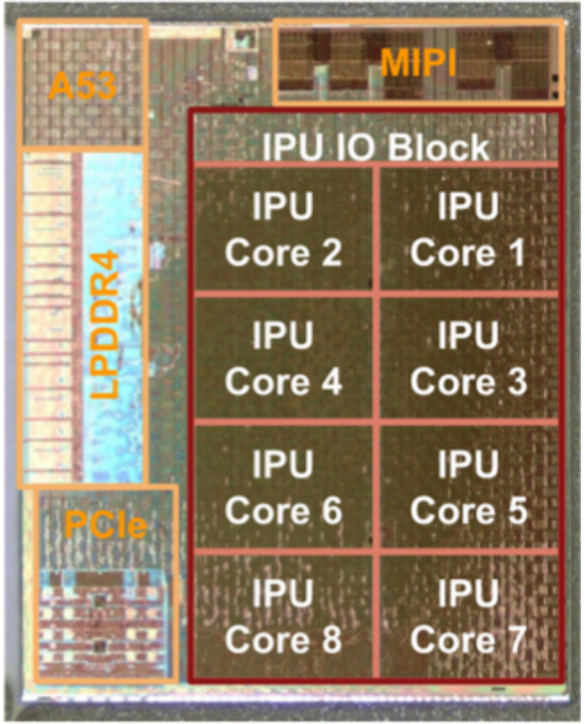


Figure from https://www.blog.google/products/pixel/pixel-visual-core-image-processing-and-machine-learning-pixel-2/

Human Understanding

- Will perhaps be added to a future version
- While there's no need to copy what the human visual system does, at the same time it could be useful to understand it a little better as an existence proof of what's possible with that architecture

Classification

Goal

- Image classification assigns a single label to a whole image corresponding to the dominant object in the image

Bald eagle

Figure from http://image-net.org

Data

- General
  - CIFAR
  - ImageNet
  - Open images dataset V4
- Specific
  - MNIST
  - Fashion MNIST
  - Street view house numbers
- Proprietary
  - Baidu
  - Google

Figure from http://image-net.org/explore.php

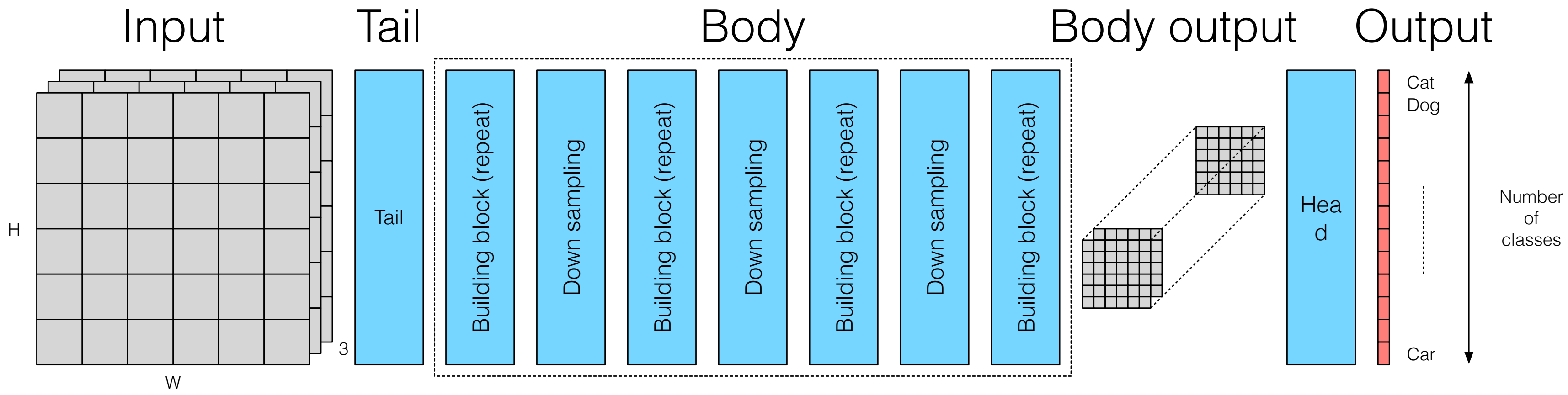
Pre Processing

- Common operations
  - Resizing
    - Not because of convolutional layers
    - Because of fully connected layers
  - Cropping
  - Normalizing to 0 mean and 1 variance

- Example pre processing used by PyTorch for networks applied to ImageNet
  - Resize image such that the shorter side is 256
  - Crop to 224 x 224
  - Flip BGR to RGB
  - Normalize each channel by diving by 255
  - Subtract mean
    - [0.485, 0.456, 0.406]
  - Divide by standard deviation
    - [0.229, 0.224, 0.225]

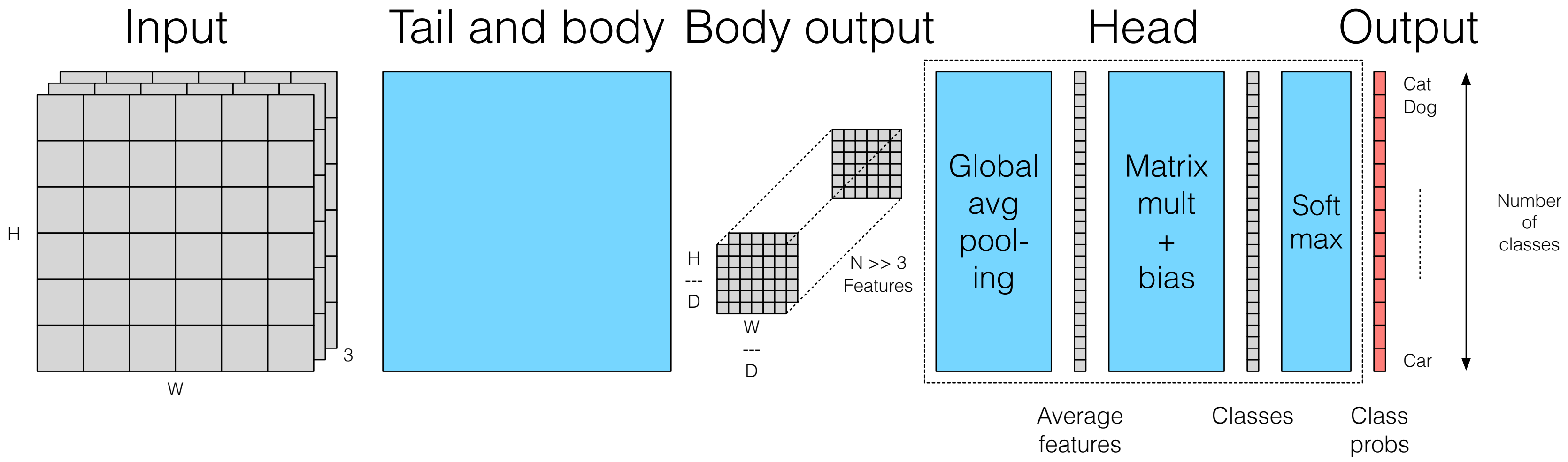
Feature Extraction

See the network design slides for tail and body design examples



Classification

See the network design slides for head design examples



Post Processing

- To win a contest use an ensemble of
    - Different networks or
    - The same network trained different ways

- Otherwise there’s not really a lot to do

Evaluation

- Top N accuracy
  - Network (if softmax was included) predicts a pmf for the different classes
  - Top N accuracy means the correct class was in the top N highest pmf values

- Uses
  - Top N = 1 is frequently used for datasets with a small number of classes
  - Top N = 5 is frequently also considered for datasets with a large number of classes with a high level of similarity (e.g., 2 dogs that look alike)

Pixel Segmentation

Goal

- Pixel segmentation: label every pixel in the image with the class that it belongs to
- Usually called semantic segmentation
- For a 3 x 512 x 1024 input image, that would mean labeling 512*1024 = 524288 pixels
- Note: sometimes the goal is modified to label every pixel in a lightly down sampled version of the image
  - Ex: (512/4) x (1024/4) down sampled image requiring 128*256 = 32768 pixels to be labeled

Figure from https://www.cityscapes-dataset.com/examples/#fine-annotations

Data

- Laundry list
  - Cityscapes
  - Pascal VOC
  - NYUDv2
  - SIFT Flow
  - CamVid
  - SUN RGB-D
  - ADE20K
  - ScanNet
- Note
  - It's also potentially possible to use some of the object based image segmentation datasets for generating labeled data for pixel segmentation
  - It's also possible to use multiple object detection bounding boxes to improve training

Figure from https://www.cityscapes-dataset.com/examples/#fine-annotations

Feature Extraction

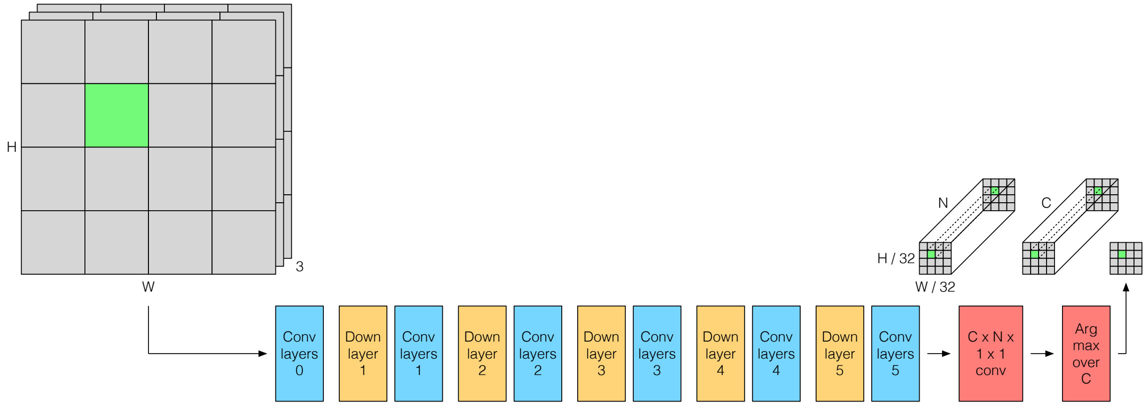
- How does feature extraction for pixel segmentation compare to feature extraction for classification?
  - Want strong features for prediction (like classification)
  - Want spatially accurate features for localization (new requirement)
  - Note: this same question also applies to multiple object detection, object based segmentation, depth estimation, motion estimation, ...

- Problem
  - Deep strong features that are good for prediction tend to be bad for localization
  - Shallow weak features that are good for localization tend to be bad for prediction

- The receptive field size is 1 more thing to keep track of
  - Shallower better localized features tend to have smaller receptive field sizes
  - Deeper worse localized features tend to have larger receptive field sizes
  - Scaling the size of the input image scales the size of the objects relative to the receptive field sizes
  - Classification typically has a global average pooling operation at the end to partially alleviate this problem, methods requiring good localization typically do not

A Conceptual Starting Point

- Pixel segmentation at 1/32 row and 1/32 col spatial resolution
  - Start with a classification network with 5 levels of down sampling probably pre trained on ImageNet
  - Remove the head (global avg pool and fully connected layer)
  - Add a CNN style 2D convolution layer with C x N x 1 x 1 filters and a soft / arg max in place of ReLU (C = number of output classes)
  - Effectively this layer is going to learn a linear transformation from a N x 1 vector to a C x 1 vector that's the same for every pixel in the feature map
  - Resume training on the new data set with labels at 1/32 the resolution in each dimension
  - Need to decide if the labels should be 1 hot based on the dominant object in the 32 x 32 region in the original image (so leaning a mapping to a 1 hot vector) or a pmf representing the class probability of all objects in the 32 x 32 region (so learning a mapping to a pmf)

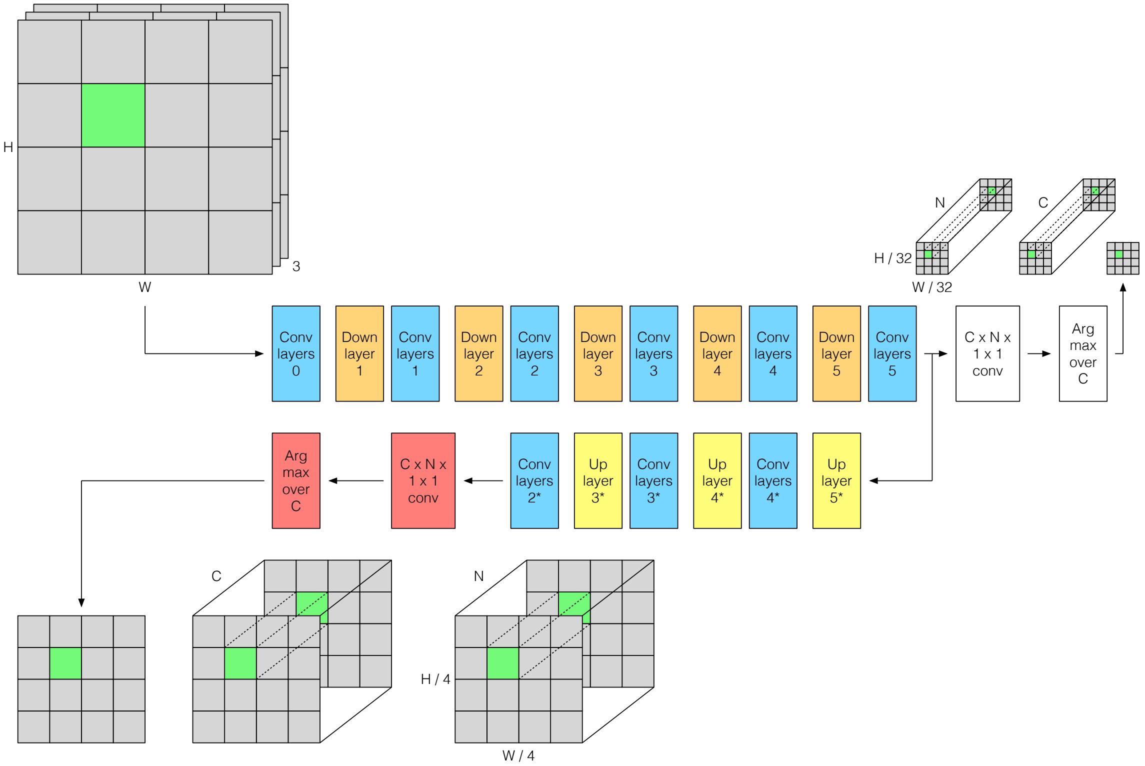


Up Sampling

- Up sampling options for increasing increasing the feature map resolution
  - Nearest neighbor interpolation
  - Un pooling
  - Up sample with 0s then fixed filter (e.g., a bilinear filter)
  - Up sample with 0s then learned filter (this is effectively what deconvolution is)

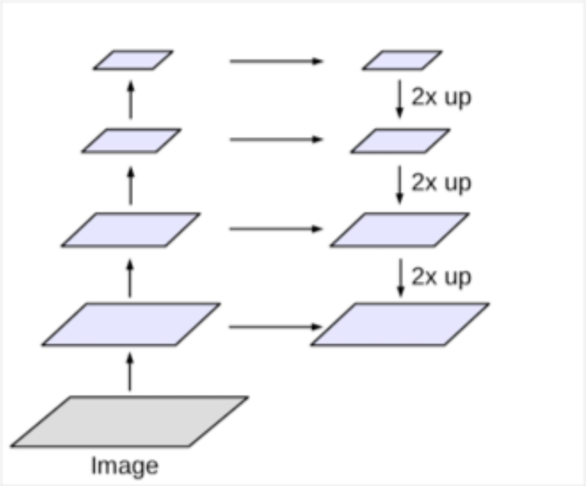
A First Step Towards Improving Localization

- So the question is how do you improve the localization of pixel classes from 1/32 in each dimension
- One option would be to up sample the final output feature map before applying the new head
  - Perhaps do this all at once
  - Perhaps do this in stages with extra transformations in between
  - Perhaps reduce N in the process of the transformations
  - Maybe not to the full image resolution but 1/4 the image resolution
  - Maybe all of this helps a little
  - But is there a better way? (yes, see next slide)

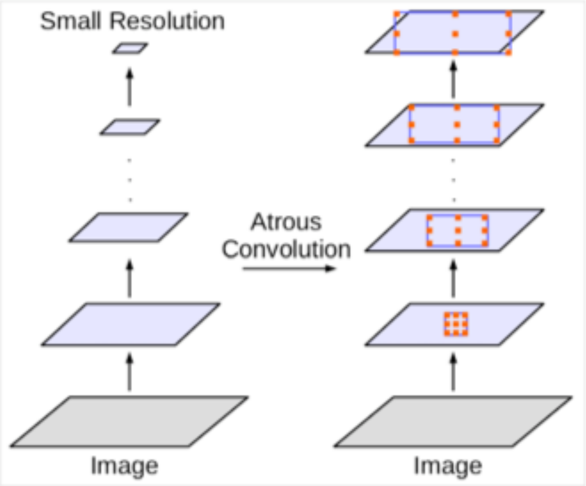


Better Methods For Improving Localization

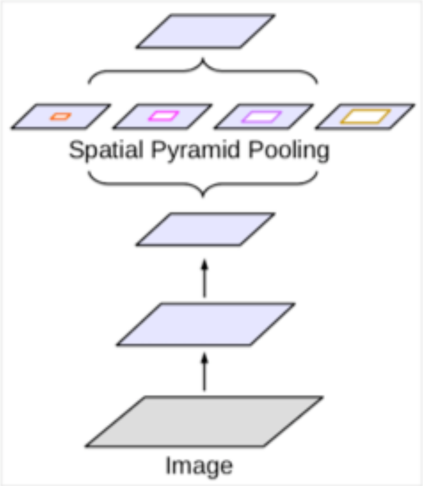
While still maintaining strong features good for prediction



Encoder decoder with skip connections



Atrous convolution



Spatial pyramid pooling

Figure from https://arxiv.org/abs/1706.05587

Pyramid Scene Parsing Network

Uses atrous convolution and pyramid pooling

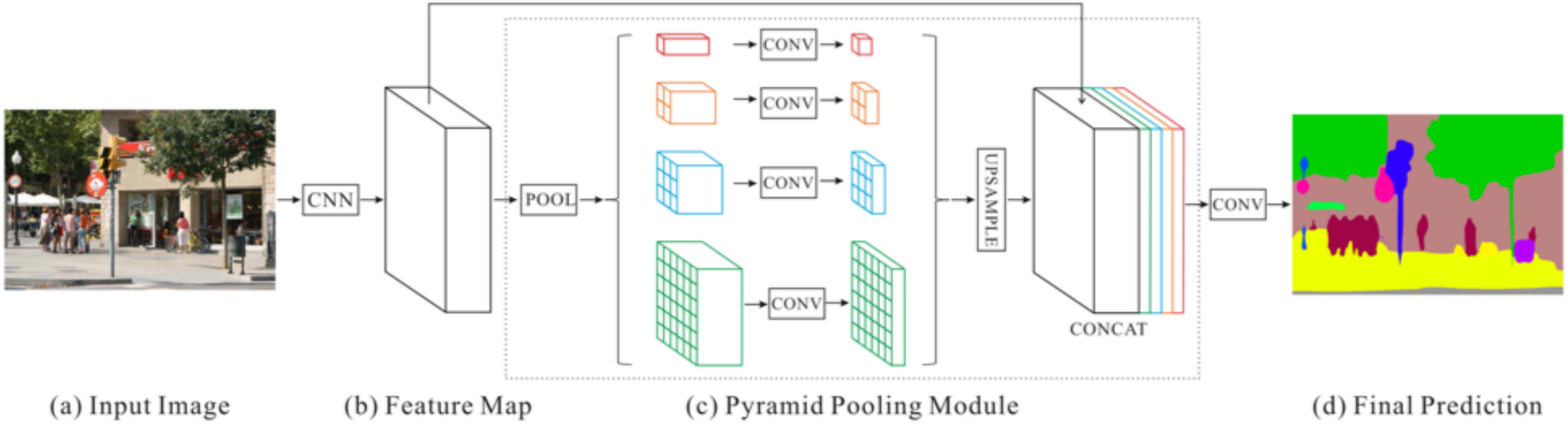


Figure from https://arxiv.org/abs/1612.01105

Fully Convolutional Networks

Encoder decoder with skip connections (possible to redraw the DAG to make this more clear)

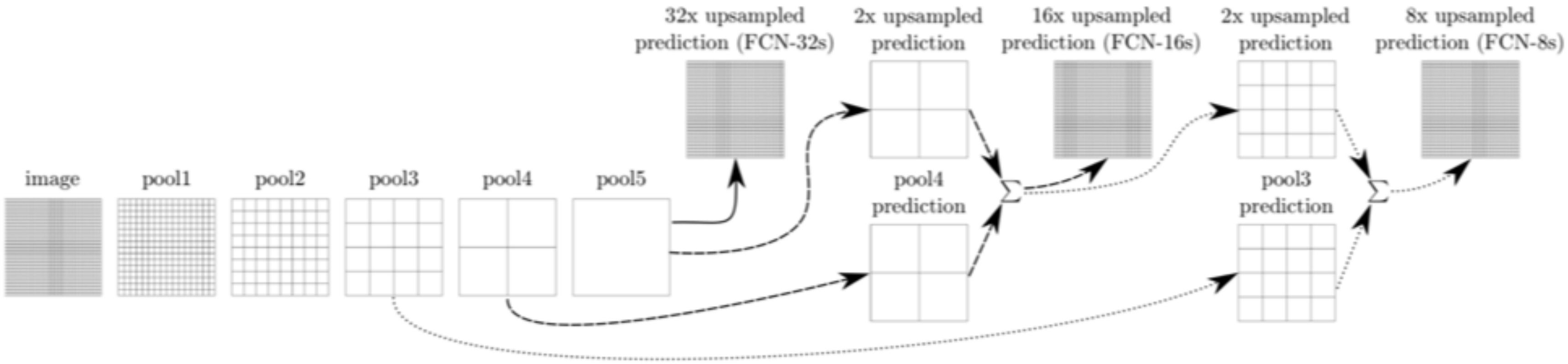
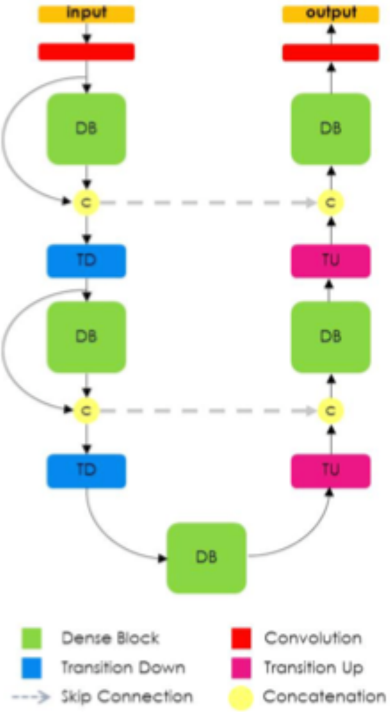


Figure from https://arxiv.org/abs/1411.4038

The One Hundred Layers Tiramisu

Encoder decoder with skip connections

Architecture
Input, $m = 3$
3×3 Convolution, $m = 48$
DB (4 layers) + TD, $m = 112$
DB (5 layers) + TD, $m = 192$
DB (7 layers) + TD, $m = 304$
DB (10 layers) + TD, $m = 464$
DB (12 layers) + TD, $m = 656$
DB (15 layers), $m = 896$
TU + DB (12 layers), $m = 1088$
TU + DB (10 layers), $m = 816$
TU + DB (7 layers), $m = 578$
TU + DB (5 layers), $m = 384$
TU + DB (4 layers), $m = 256$
1×1 Convolution, $m = c$
Softmax



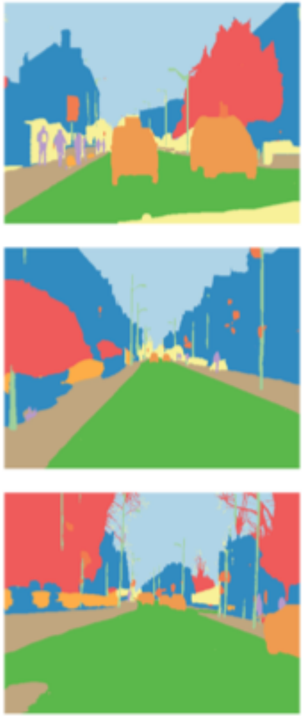


Figure from https://arxiv.org/abs/1611.09326

Encoder Decoder With Atrous Separable Convolution

Encoder decoder with skip connections, atrous convolution and spatial pyramid pooling

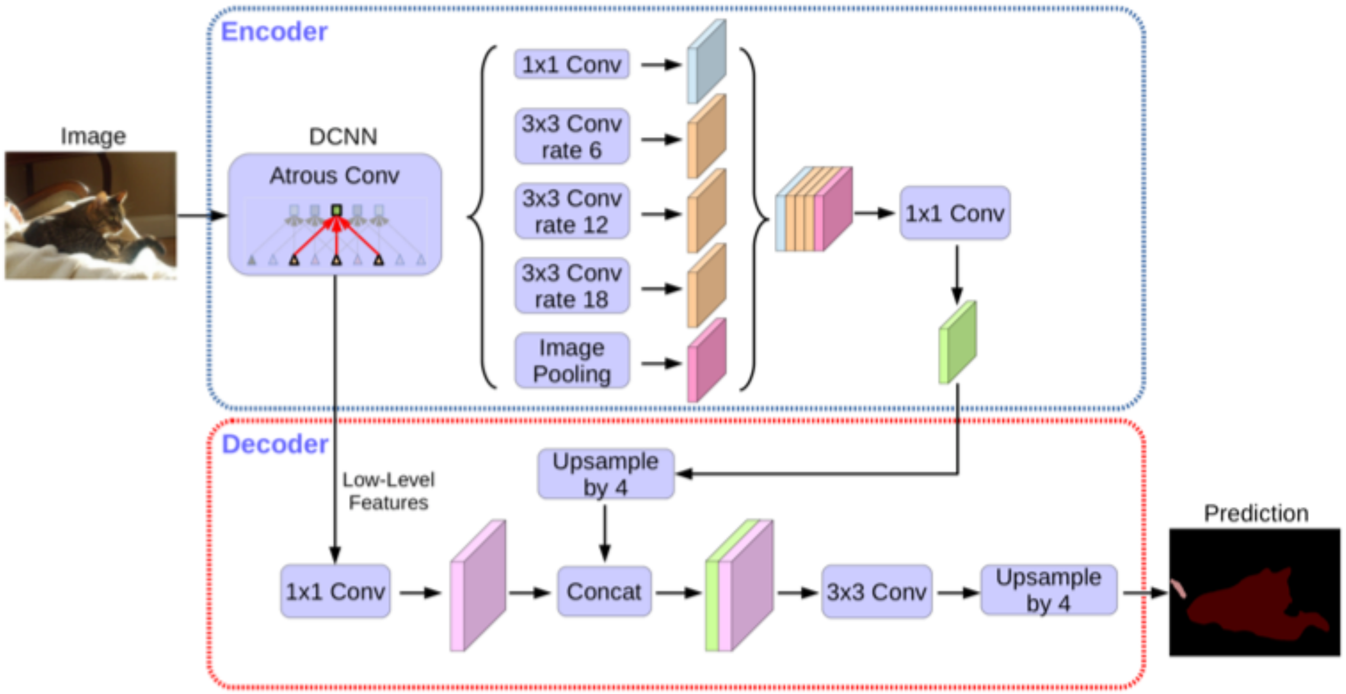


Figure from https://arxiv.org/abs/1802.02611

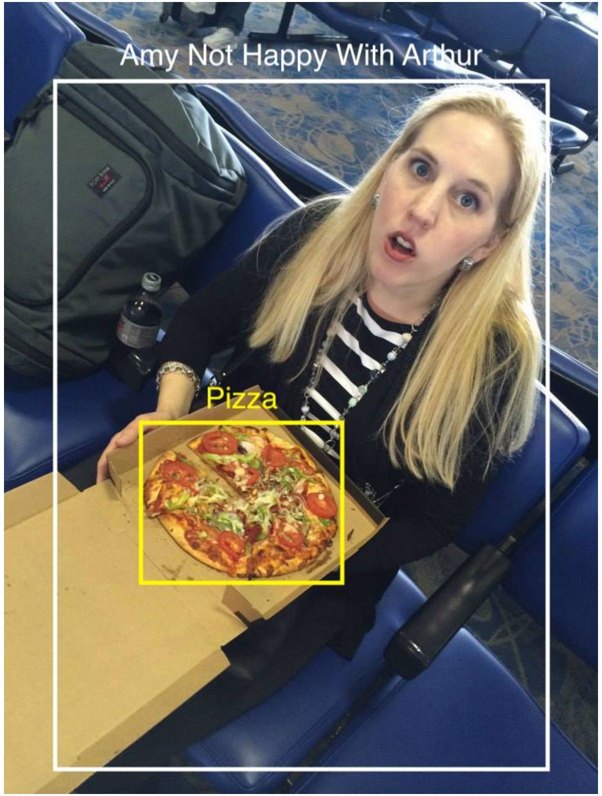
Demo: Cityscapes Pixel Segmentation

A modified ResNeXt encoder + custom sequential class based decoder with skip connections

Multiple Object Detection

Disclaimer: Not All Labels Are This Descriptive

When You're Eating Pizza In The Charlotte Airport Before Flying To Italy



Goal

- Draw a box around every object in the image and classify the object in the box

- Localization and classification
  - Localization can be cast as a classification problem
    - Cover an image with many potential (anchor) boxes at different locations with different shapes and sizes
    - Classification problem: does a potential (anchor) box contain an object or not
    - Regression problem: refine the sizing of the potential (anchor) box
  - Classification is classifying the objects in the boxes

Figure from https://storage.googleapis.com/openimages/web/index.html

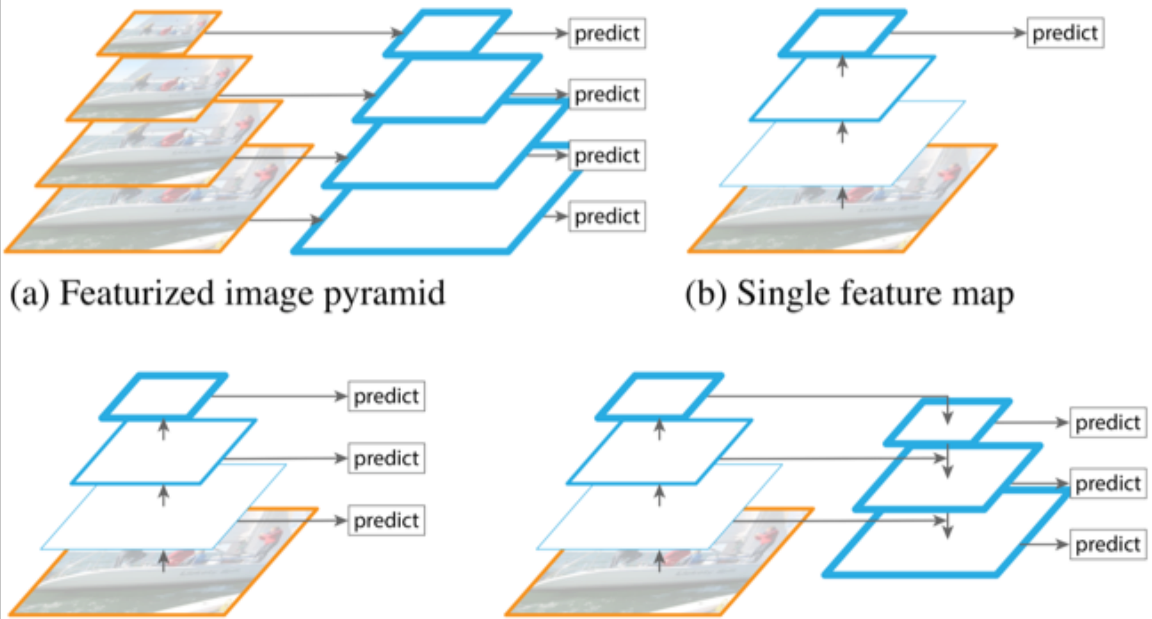
Data

- Laundry list
  - Pascal VOC
  - Open images dataset V4
  - Street view house numbers

Figure from https://storage.googleapis.com/openimages/web/index.html

Feature Extraction

- Can use all of the previously mentioned methods for generating features
- Will also add a new approach: feature pyramid networks
  - Give the ability of making predictions from feature maps at different scales
  - Either separately at each scale then post process or you can think of variants that do it at all scales in a combined manner then post process



(a) Featurized image pyramid

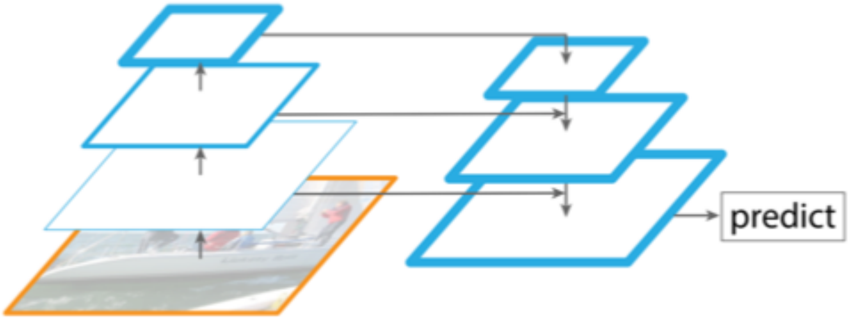
(b) Single feature map

(c) Pyramidal feature hierarchy

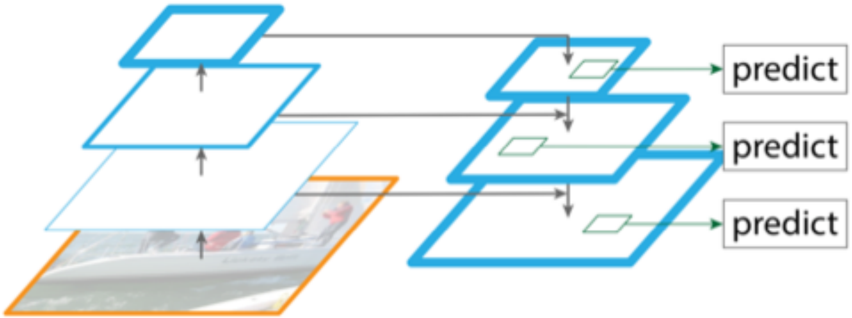
(d) Feature Pyramid Network

Figure from https://arxiv.org/abs/1612.03144

Feature Pyramid Vs Skip Connections



Encoder decoder with skip connections



Feature pyramid

Figures from https://arxiv.org/abs/1612.03144

Anchor Boxes

Candidate boxes that enclose objects, can be uniform or optimized in size and location distribution for a specific data set; multiple object detection methods determine if an object is present in the box, what class the object belongs to how to modify the box location and size to better enclose the object

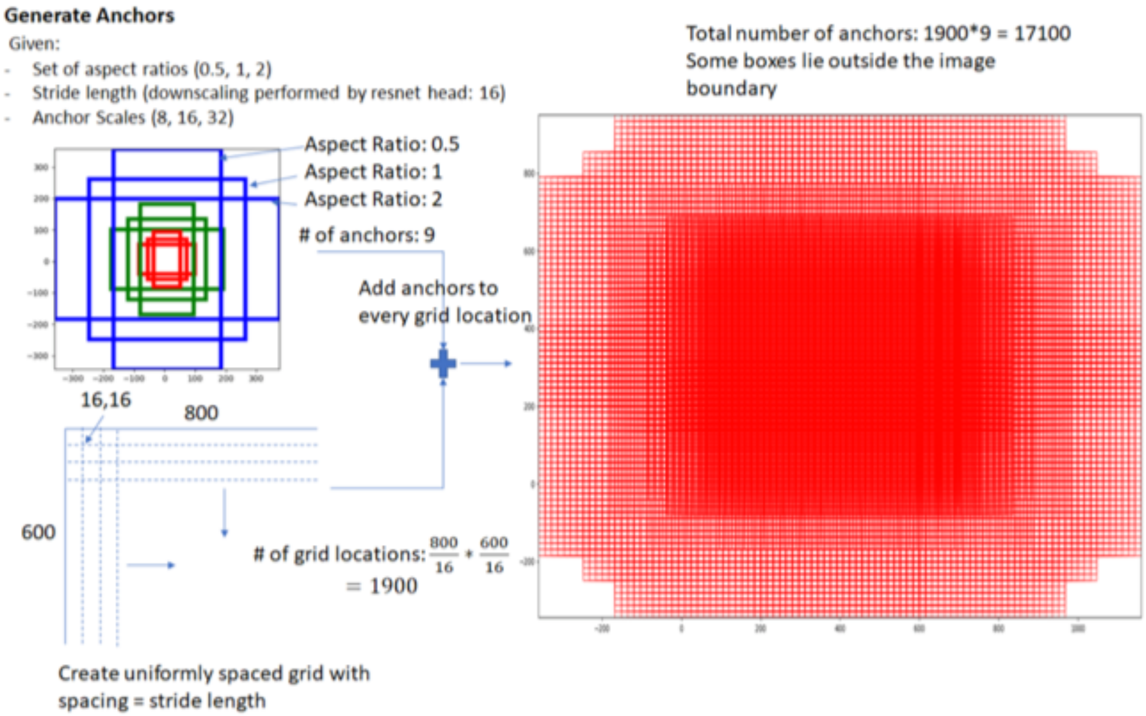


Figure from http://www.telesens.co/2018/03/11/object-detection-and-classification-using-r-cnns/

Single And Two Stage Approaches

- Two stage approaches
  - Classify anchor boxes {contains object, does not contain object} and refine {Δx, Δy, Δw, Δw} anchor box locations
  - Then classify objects in the refined anchor boxes that contain objects (and possibly refine their location again)
  - Then use post processing to combine / merge / prune results
- Single stage approaches
  - Classify anchor boxes {contains object, does not contain object} and refine {Δx, Δy, Δw, Δw} anchor box locations and classify the objects in those boxes at the same time
  - Then use post processing to combine / merge / prune results
- Typically, single stage approaches are faster than two stage approaches but two stage approaches are more accurate
  - Lots of caveats in that statement that I’m glossing over

Two Stage

- A historical arch of some key multiple object detection methods (this is a really beautiful arc of papers)
  - [R-CNN] Rich feature hierarchies for accurate object detection and semantic segmentation
    - Selective search for region proposals, warp to constant size, conv layers, SVM head
  - [SPPNet] Spatial pyramid pooling in deep convolutional networks for visual recognition
    - Spatial pyramid pooling so can process full image at once covering all regions via extracting arbitrary region sizes to fixed length vectors, multi stage training that's unable to update conv layers before the SPP layer
  - Fast R-CNN
    - Differentiable RoI pooling layer (single SPP level) with end to end training, no SVM head
  - Faster R-CNN: towards real-time object detection with region proposal networks
    - Replace selective search with a region proposal network built off of the same conv layers used for classification
  - R-FCN: object detection via region-based fully convolutional networks
  - [FPN] Feature pyramid networks for object detection

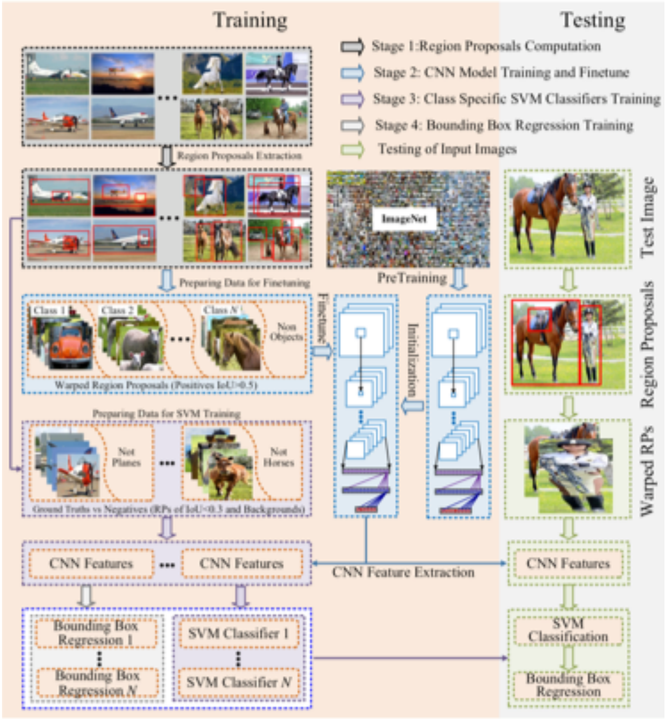


Figure from https://arxiv.org/abs/1809.02165

Spatial Pyramid Pooling And RoI Pooling

SPP input is arbitrary size feature map regions and output is 1 fixed length vector per region appropriate for fully connected layers (FC can batch process multiple regions via matrix mult); RoI pooling is SPP with only 1 level and each output region a fixed size N x W x H tensor instead of a N*W*H x 1 vector; note that applying an integer number of bins to an arbitrary region size results in some bin boundary quantization affects on the resulting output

Output is fixed length vectors irrespective of region size that are appropriate for fully connected layer classification

Allows convolutional features to be generated for the full image all at once instead of for each region separately (a huge amount of overhead when there's overlapping regions)

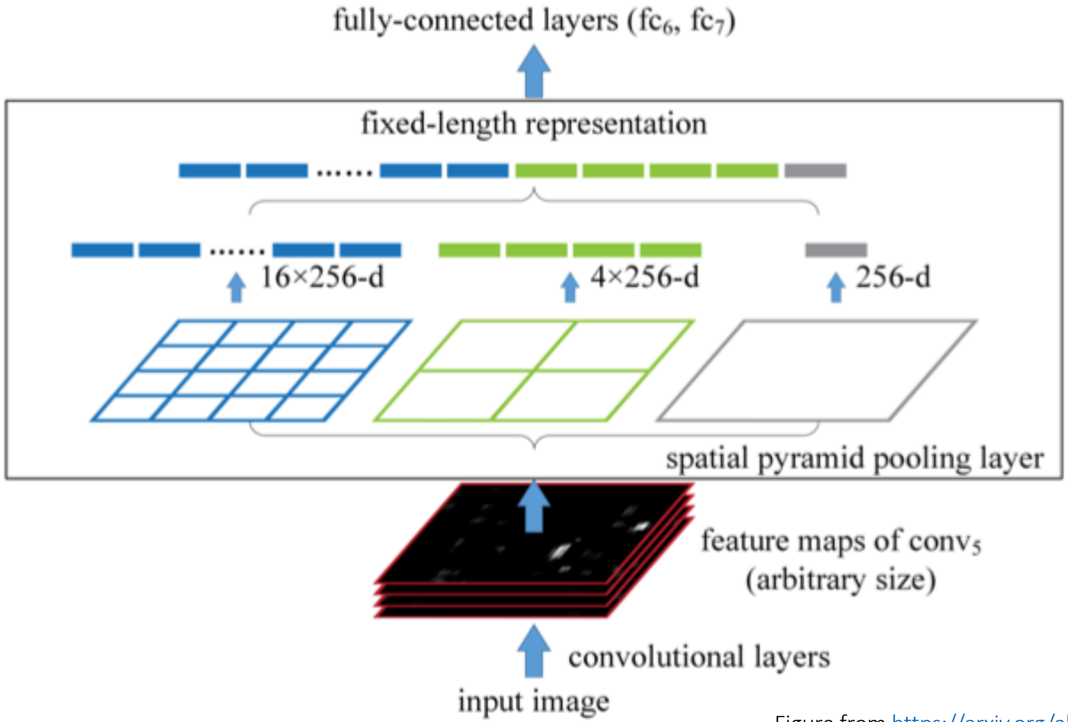


Figure from https://arxiv.org/abs/1406.4729

Region Proposal Network

Input is feature maps after convolution; output is a per anchor box classification {object in box, no object in box} and regression (x, y, w and h relative to the anchor box); separate weights are used for each of the k anchor classifiers (?) and regressors (yes)

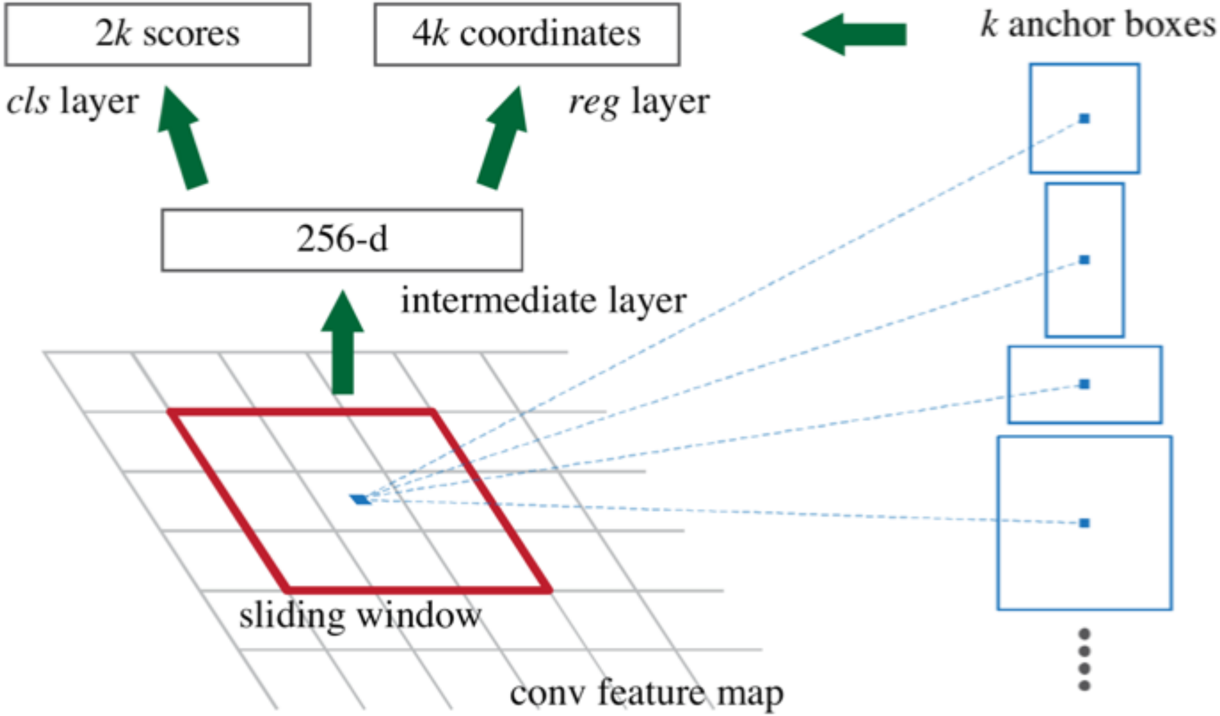


Figure from https://arxiv.org/abs/1506.01497

R-CNN | Fast R-CNN | Faster R-CNN | R-FCN

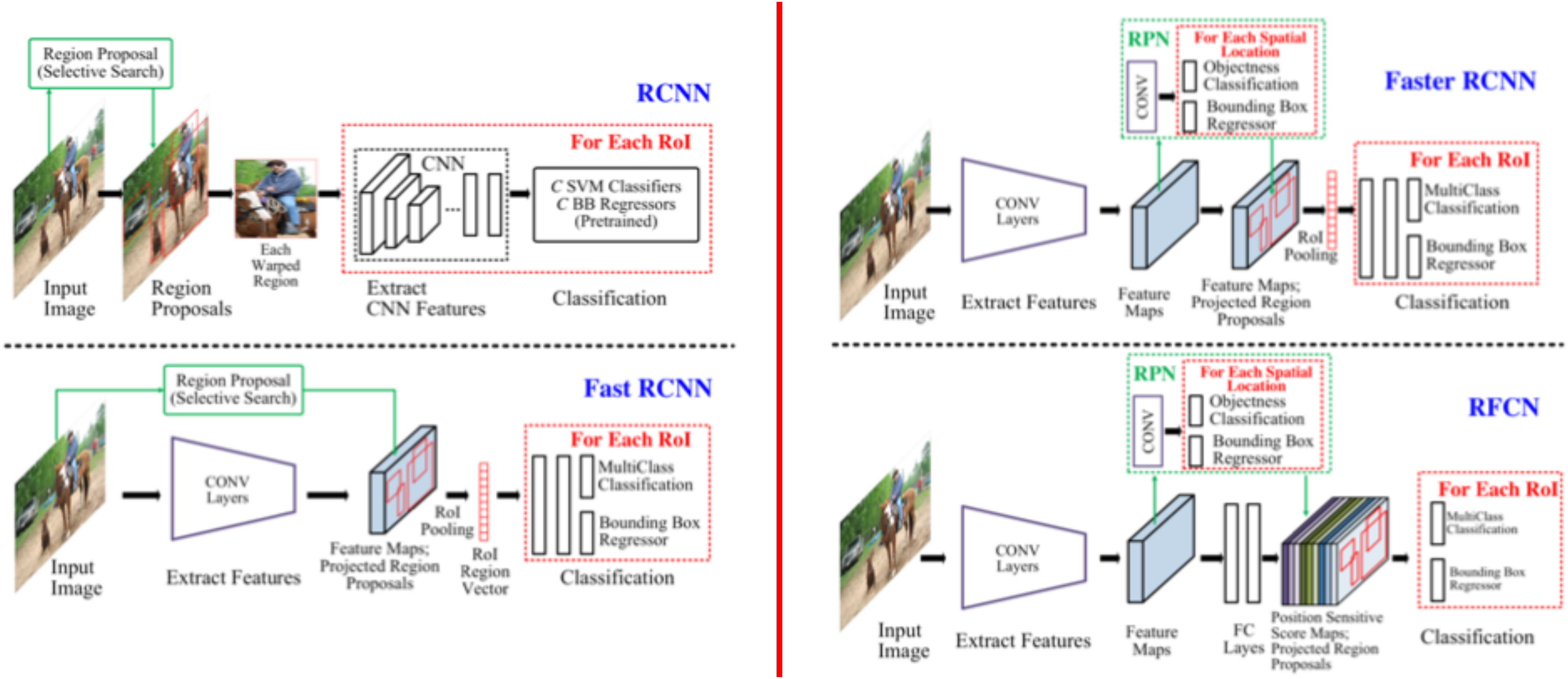
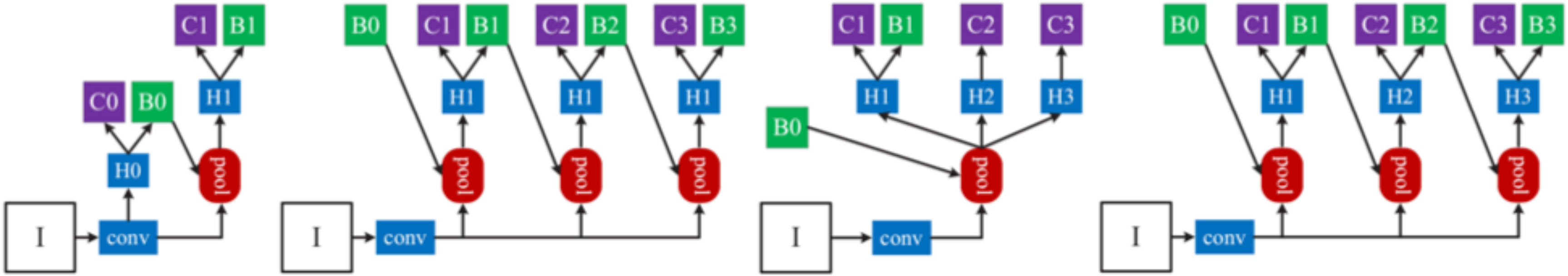


Figure from https://arxiv.org/abs/1809.02165

Cascade R-CNN

Bounding box localization is trained sequentially with increasing IoU thresholds; I = image, conv = shared convolutional layers, pool = region pooling, H = network head, Bx = bounding box stage x proposal and Cx = classification stage x proposal



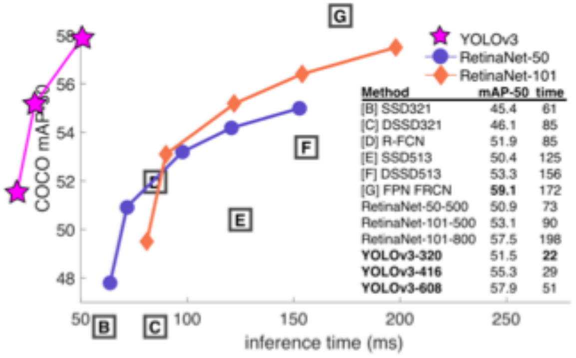
(a) Faster R-CNN (b) Iterative BBox at inference (c) Integral Loss (d) Cascade R-CNN

Figure from https://arxiv.org/pdf/1712.00726.pdf

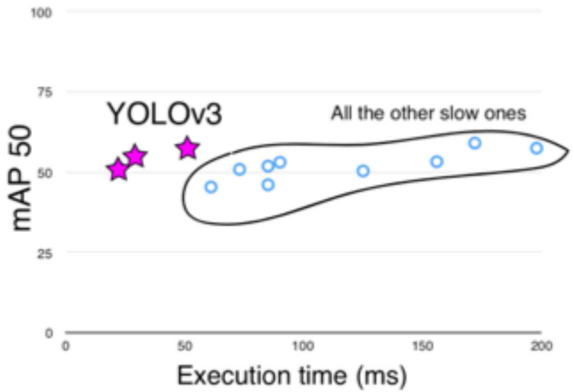
Single Stage

- Popular methods that estimate bounding boxes and classes in a single stage (then assemble the results with post processing)
  - YOLO
    - YOLO
    - YOLO9000
    - YOLO V3
  - SSD
  - RetinaNet

If you're ever feeling stressed and could use a laugh to take your mind off things, I highly recommend reading the YOLO V3 paper



Method	mAP-50	time
[B] SSD321	45.4	61
[C] DSSD321	46.1	85
[D] R-FCN	51.9	85
[E] SSD513	50.4	125
[F] DSSD513	53.3	156
[G] FPN FRCN	**59.1**	172
RetinaNet-50-500	50.9	73
RetinaNet-101-500	53.1	90
RetinaNet-101-800	57.5	198
YOLOv3-320	51.5	**22**
YOLOv3-416	55.3	29
YOLOv3-608	57.9	51



1. Introduction

Sometimes you just kinda phone it in for a year, you know? I didn't do a whole lot of research this year. Spent a lot of time on Twitter. Played around with GANs a little. I had a little momentum left over from last year [12] [1]; I managed to make some improvements to YOLO. But, honestly, nothing like super interesting, just a bunch of small changes that make it better. I also helped out with other people's research a little.

Actually, that's what brings us here today. We have a camera-ready deadline [4] and we need to cite some of the random updates I made to YOLO but we don't have a source. So get ready for a TECH REPORT!

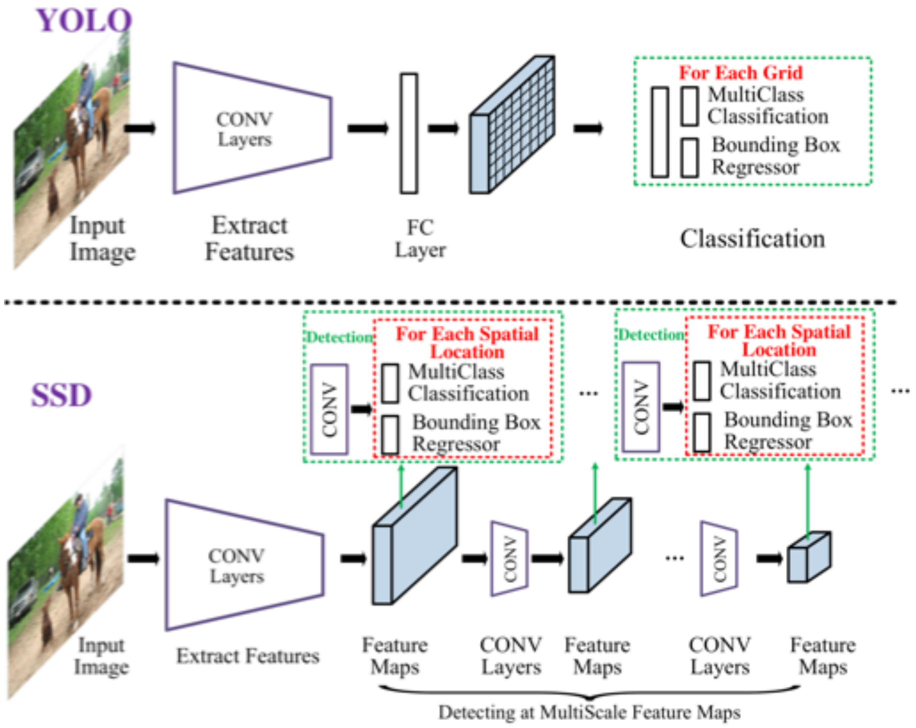
The great thing about tech reports is that they don't need intros, y'all know why we're here. So the end of this introduction will signpost for the rest of the paper. First we'll tell you what the deal is with YOLOv3. Then we'll tell you how we do. We'll also tell you about some things we tried that didn't work. Finally we'll contemplate what this all means.

2. The Deal

So here's the deal with YOLOv3: We mostly took good ideas from other people. We also trained a new classifier network that's better than the other ones. We'll just take you through the whole system from scratch so you can understand it all.

Text from https://arxiv.org/abs/1804.02767

YOLO And SSD



Detection heads are similar to RPNs except that multi class classification is predicted instead of a RPN predicting class / no class

RetinaNet

K = number of classes and A = number of anchor boxes per feature map pixel

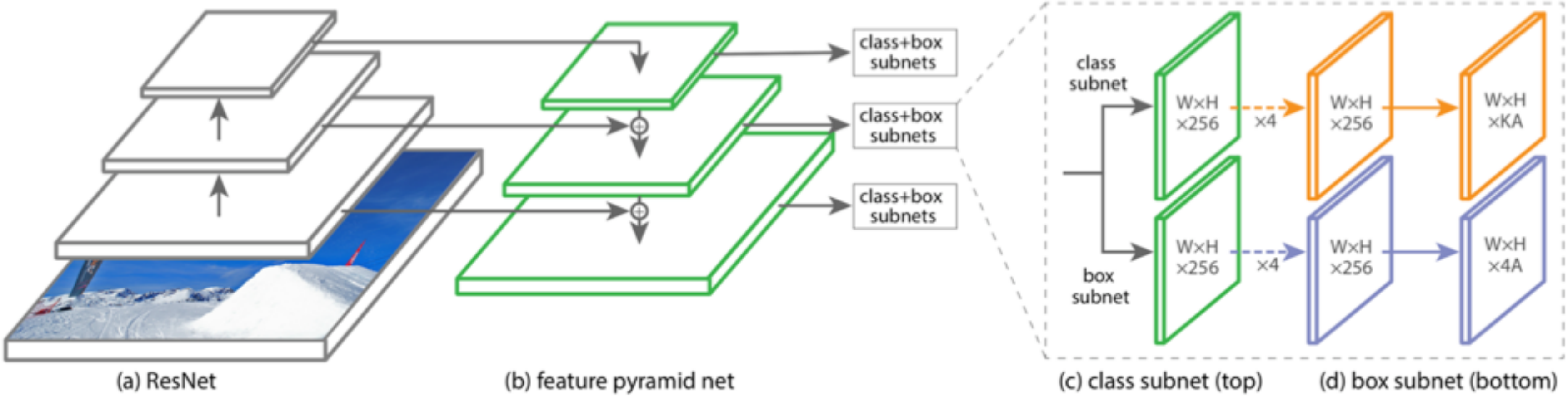


Figure from https://arxiv.org/abs/1708.02002

Post Processing

- Non maximal suppression
  - Inputs contain scores and box locations
  - Create a score list by sorting the entries based on the score
  - Repeat the following until no more entries with scores above a threshold are in the score list
    - Start with the entry with the best score on the score list
    - Remove other entries (suppress non maximals) from the score list with significant overlap
    - Add the best entry from the score list to the prediction list
    - Remove the best entry from the score list
- Variants
  - Can play games like averaging a few together, instead of removing others penalize them by reducing their score, ...
  - A difficulty is finding balance between suppressing windows and detecting close together objects (overlap parameter choice)

Figure from https://arxiv.org/pdf/1705.02950.pdf

Post Processing

Figure from http://www.telesens.co/2018/03/11/object-detection-and-classification-using-r-cnns/

Evaluation – Confidence Threshold

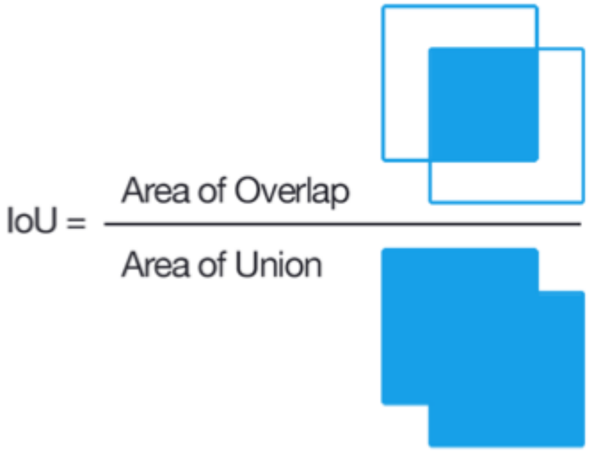
- The network output can be summarized as
  - Class 0
    - Confidence 0, bounding box 0
    - Confidence 1, bounding box 1
    - ...
  - Class 1
    - Confidence 0, bounding box 0
    - Confidence 1, bounding box 1
    - ...
  - ...

- Non maximal suppression (or another algorithm) is run on the network output to merge / remove / etc. predictions

- Remaining predictions are further reduced by only keeping predictions for a class above a confidence threshold for the class

Evaluation – Intersection Over Union

- For each of the remaining predictions the intersection over union with closest ground truth object is computed which allows the prediction to be marked as {0 == not true positive, 1 == true positive} if it is above a given IoU threshold
  - Class 0
    - Confidence 0, bounding box 0, TP for IoU > 0.50?, TP for IoU > 0.55?, ..., TP for IoU > 0.95?
    - Confidence 1, bounding box 1, TP for IoU > 0.50?, TP for IoU > 0.55?, ..., TP for IoU > 0.95?
    - ...
  - Class 1
    - Confidence 0, bounding box 0, TP for IoU > 0.50?, TP for IoU > 0.55?, ..., TP for IoU > 0.95?
    - Confidence 1, bounding box 1, TP for IoU > 0.50?, TP for IoU > 0.55?, ..., TP for IoU > 0.95?
    - ...
  - ...
- Typically only 1 prediction is allowed to be a true positive for a given ground truth object and the other predictions are marked as not true positives



Historical contests used a single IoU value of 0.50; more recent contests have used a spectrum of IoU values from 0.50, 0.55, ..., 0.95 to encourage better localization

Figure from https://commons.wikimedia.org/wiki/File:Intersection_over_Union_-_visual_equation.png

Evaluation – Precision

- Precision
  - How precise are the predictions for a particular class
  - True class positives / (true class positives + false class positives)
  - Correctly predicted objects in a class / All objects predicted in a class
  - Penalizes you for making too many predictions that aren't correct of a class
- Average precision (AP)
  - Precision averaged over multiple IoU thresholds
- Mean average precision (mAP)
  - Average precision averaged over all classes

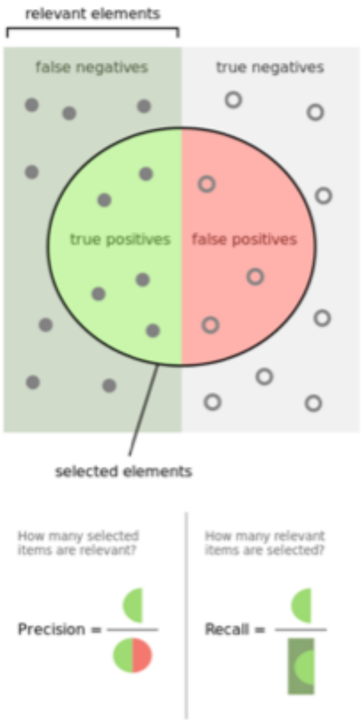


Figure from https://en.wikipedia.org/wiki/Precision_and_recall

Evaluation – Recall

- Recall
    - How complete are the predictions for a particular class
    - True class positives / (true class positives + false class negatives)
    - Correctly predicted objects in a class / All objects that should have been predicted of a class
    - Penalizes you for missing objects of a class
- Average recall (AR)
    - Recall averaged over multiple IoU thresholds
- Mean average recall (mAR)
    - Average recall averaged over all classes

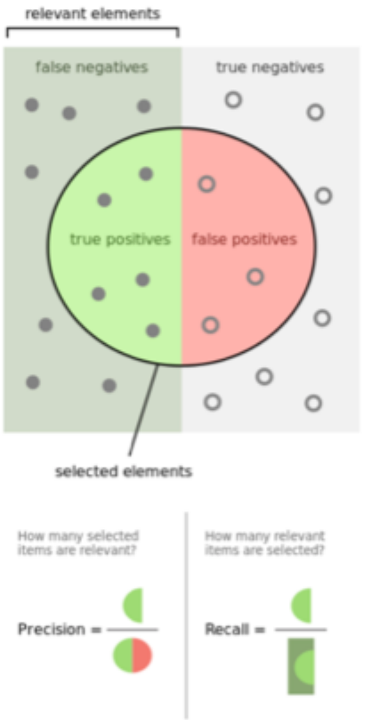
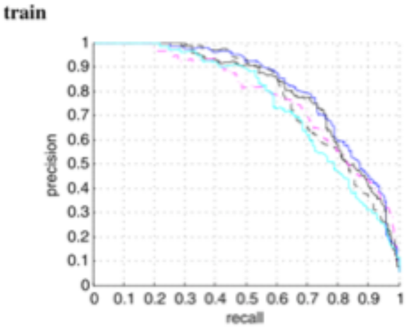


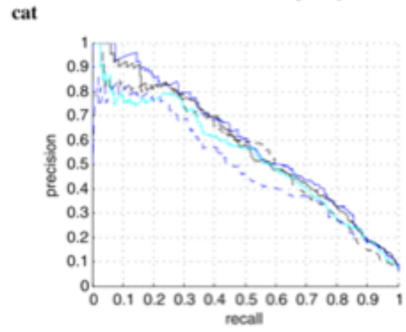
Figure from https://en.wikipedia.org/wiki/Precision_and_recall

Evaluation – Precision Recall Curve

- So remember a few slides back when we got rid of predictions below a specified confidence threshold?
- You can create a precision recall curve by varying this confidence threshold and plotting the resulting precision vs recall
    - Increasing the confidence threshold (fewer predictions) tends to lead to smaller values of recall and higher values of precision
    - Decreasing the confidence threshold (more predictions) tends to lead to larger values of recall and smaller values of precision
- You can plot a precision recall curve for a single class at a single IoU; or you can plot multiple precision recall curves for a single class each at a different IoU



(d) top 5 by AP



(f) top 5 by AP

Figure from http://host.robots.ox.ac.uk/pascal/VOC/pubs/everingham10.pdf

Object Based Segmentation

Goal

- Trace a contour around the boundary of every object in the image and classify the object in the contour

Figure from https://www.mapillary.com/dataset/vistas

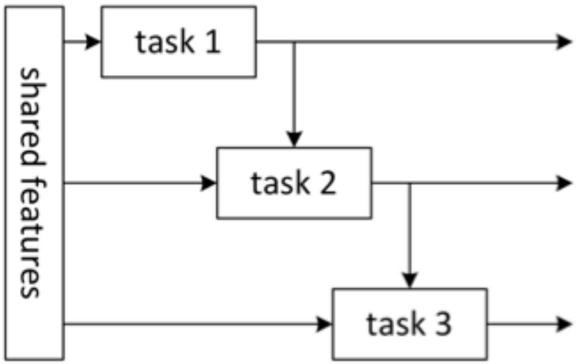
Data

- Laundry list
  - COCO
  - Mapillary Vistas

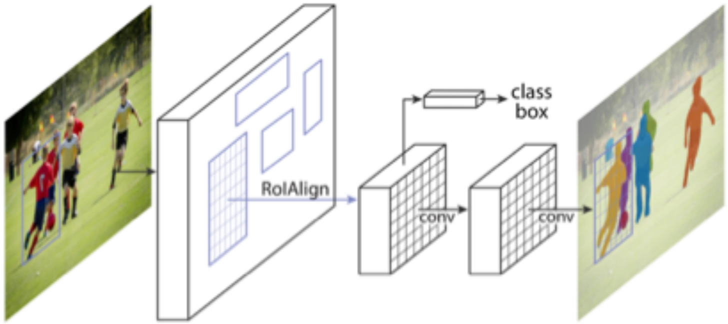
Figure from https://www.mapillary.com/dataset/vistas

Multistage Methods

- Three stage
    - Classify anchor boxes {contains object, does not contain object} and refine {Δx, Δy, Δw, Δh} anchor box locations
    - Then divide the refined anchor box into a grid and classify grid cells {part of the object, not part of the object} to determine a mask
    - Then classify objects in the grid cells that are part of the object for refined anchor boxes that contain objects (and possibly refine their location again)



- Two stage
    - Classify anchor boxes {contains object, does not contain object} and refine {Δx, Δy, Δw, Δh} anchor box locations
    - Then predict a mask and classify objects in the refined anchor boxes that contain objects (and possibly refine their location again)



Figures from https://arxiv.org/abs/1512.04412 and https://arxiv.org/abs/1703.06870

Instance Aware Semantic Segmentation

RoI warping is a differentiable transformation allowing end to end training that crops and warps a RoI to a target size via interpolation followed by pooling

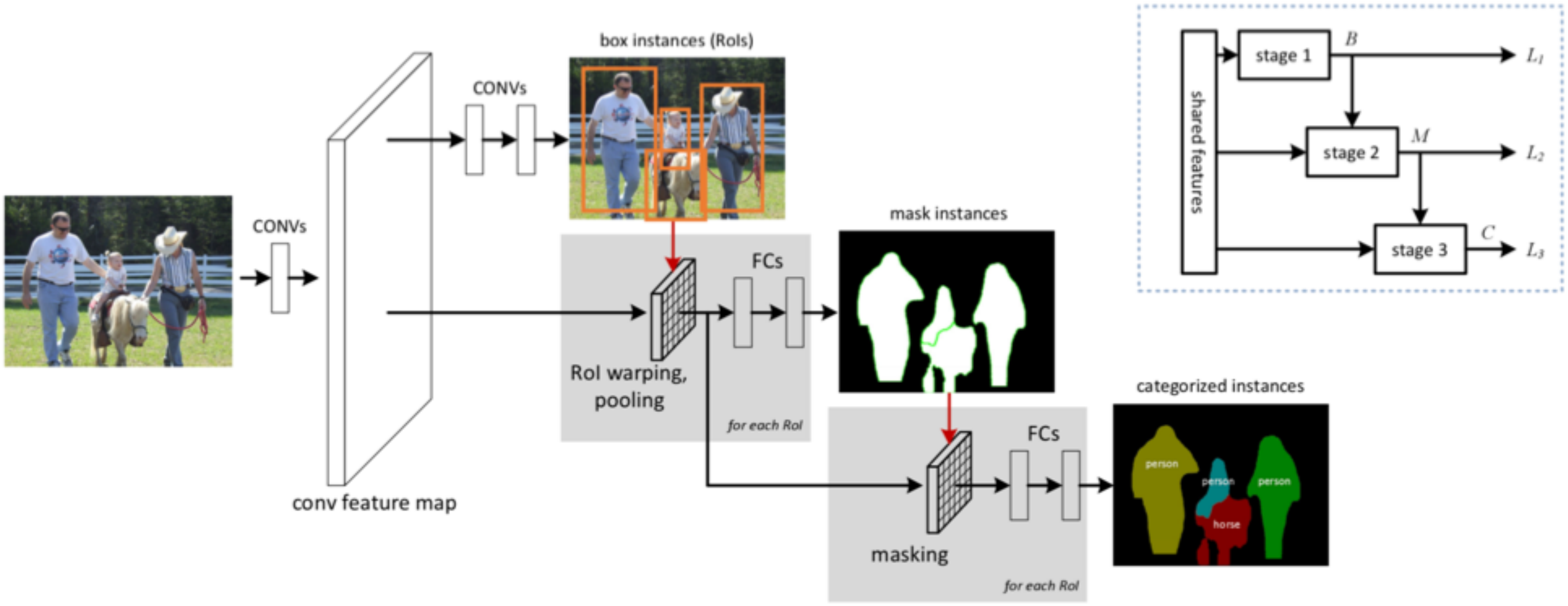


Figure from https://arxiv.org/abs/1512.04412

RoI Align

Input is N x h x w feature maps from convolutional layer and box coordinates for an arbitrary sized RoI, output is fixed size N x H x W feature maps with bilinear interpolation used to avoid bin boundary quantization (a key for improving performance relative to RoI pooling)

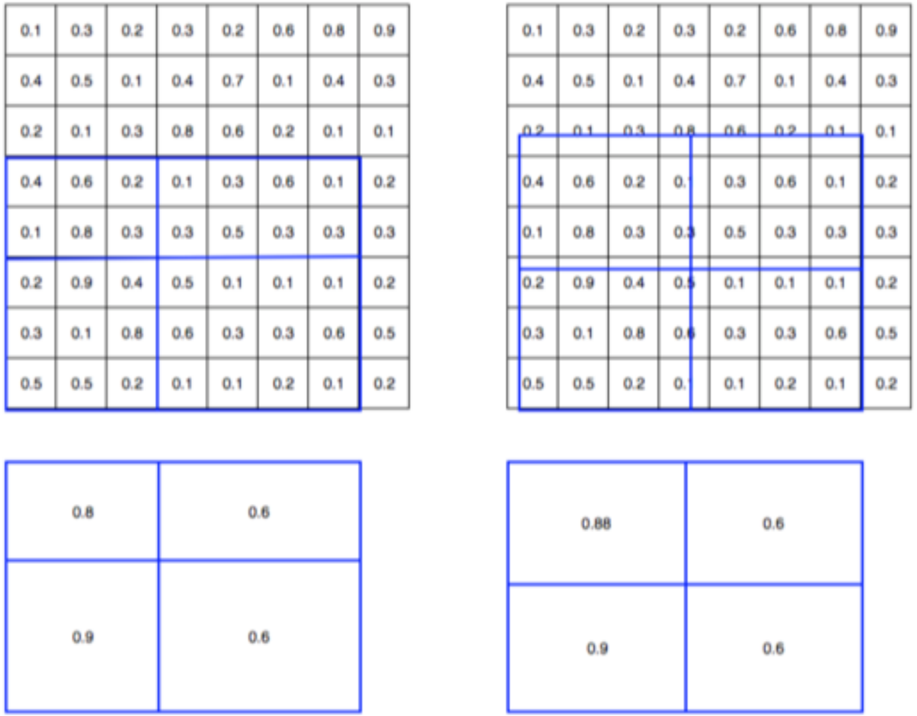


Figure from https://medium.com/@jonathan_hui/image-segmentation-with-mask-r-cnn-ebe6d793272

Mask R-CNN

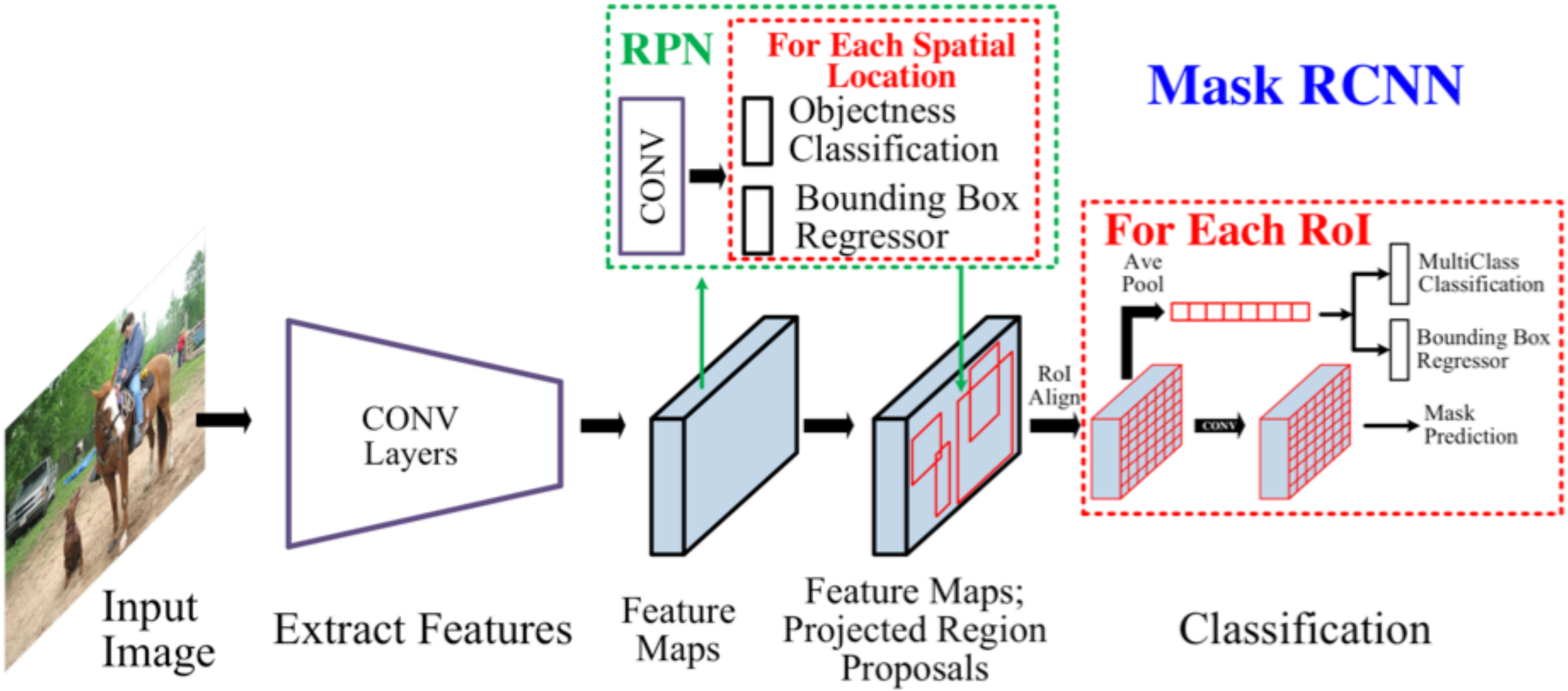


Figure from https://arxiv.org/abs/1809.02165

Depth Estimation

Goal

- Given a stereo image pair separated in space determine the distance of every pixel from the cameras

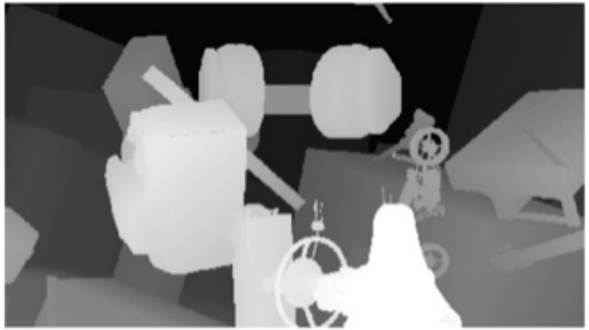


Figure from https://arxiv.org/pdf/1512.02134.pdf

Goal

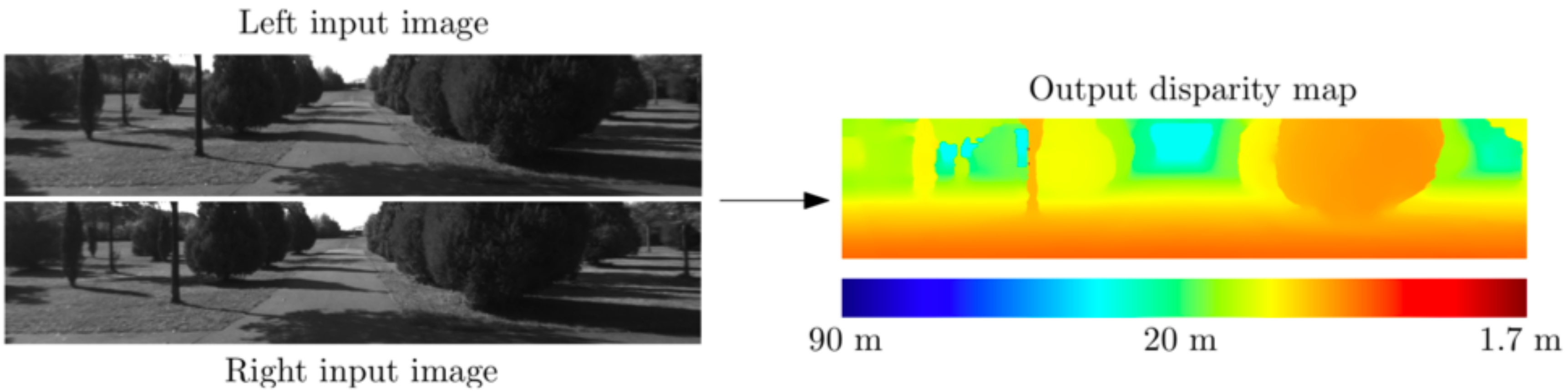


Figure from https://arxiv.org/abs/1409.4326

Fundamentals

- Pre processing
  - Start from a left and right image
  - Transform to emulate having a common image plane with focal length f and distance between cameras T
- Disparity
  - Search along horizontal (epipolar) lines to find the same point in both images
  - The disparity is difference in location of the same point in both images $d = x_R - x_L$
- Depth
  - The depth can be computed from the disparity as $Z = f T / d$
  - The smaller the disparity the farther the point is away (and vice versa)

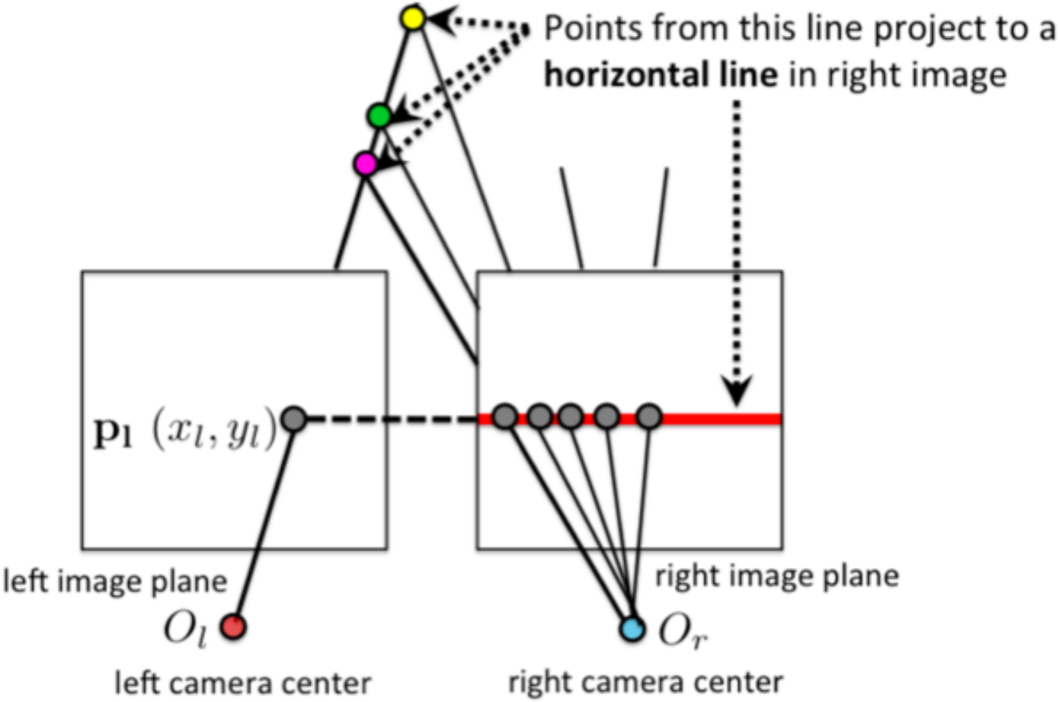


Figure from http://www.cs.toronto.edu/~fidler/slides/2015/CSC420/lecture12_hres.pdf

Fundamentals

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  - Start from a left and right image
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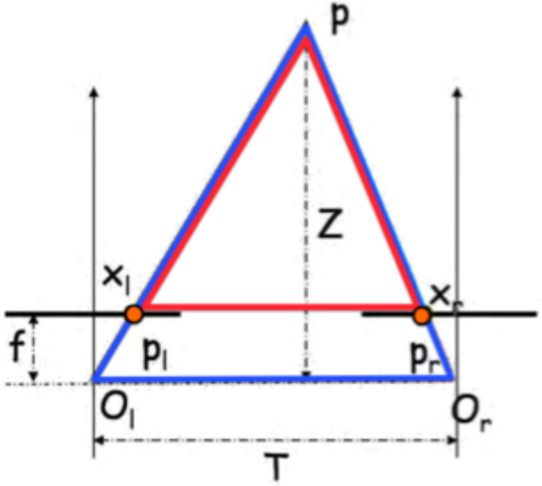


Similar triangles:

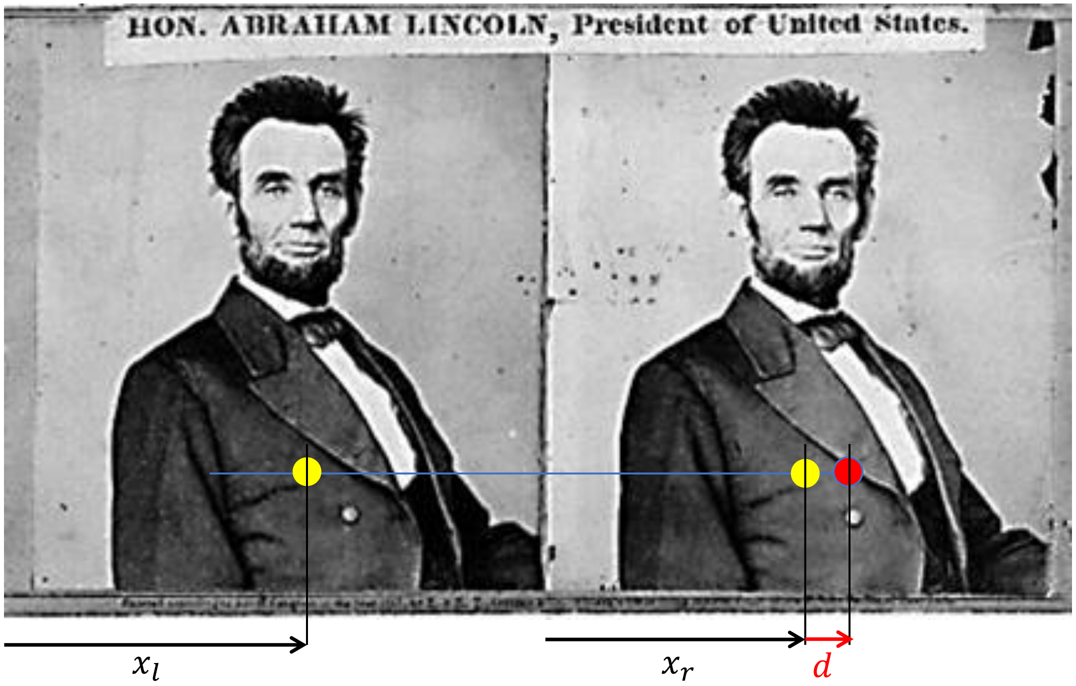
$$\frac{T}{Z} = \frac{T + x_l - x_r}{Z - f}$$

$$\boxed{Z = \frac{f \cdot T}{x_r - x_l}}$$

So if I know x_l and x_r, then I can compute Z!

Figure from http://www.cs.toronto.edu/~fidler/slides/2015/CSC420/lecture12_hres.pdf

Fundamentals



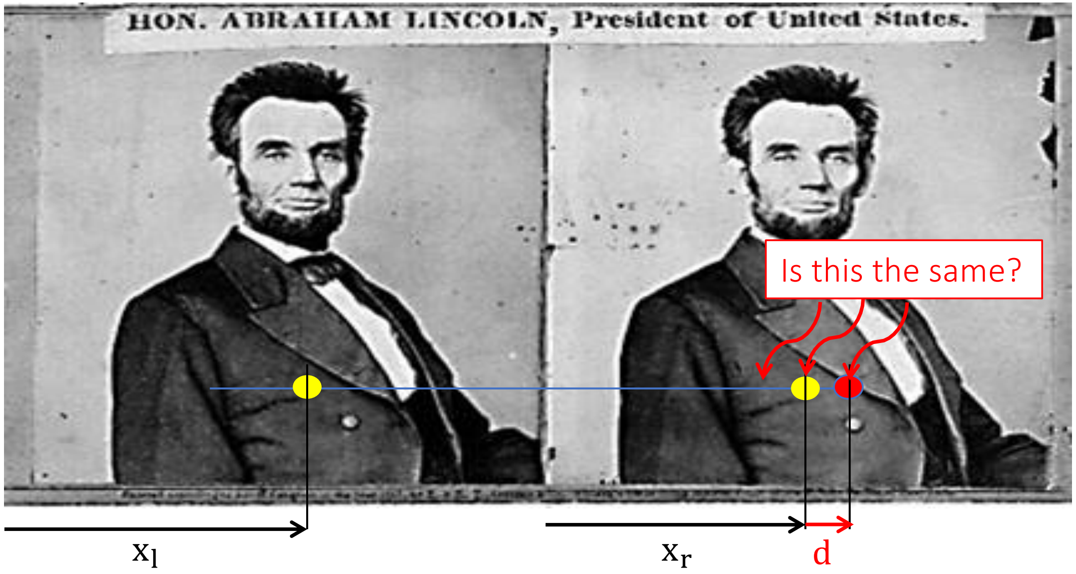
Apologies to the creator of this figure (I’m not sure where it originally came from)

Classical Stereo Disparity Estimation

- Cost cube creation
  - Cube = {disparity 0, ..., D – 1} x rows x cols
  - Values represent left / right match cost at the specified disparity
  - Patch comparisons via L1, L2 and variants are common matching
- Cost cube smoothing
  - Smooth consistent with image expectations
  - Across pixels via filtering like cross based cost averaging
  - Across pixels and disparities via nonlinear methods like SGM
- Cost cube to disparity
  - Winner take all selection of best match which is lowest cost
- Disparity refinement
  - Left / right consistency checks
  - Median filtering, sub pixel enhancement

What Role Can CNNs Play?

- Challenges of stereo depth estimation
  - Poor texture in local regions
  - Repeated structure
- CNNs can help with finding the same point in 2 or more images
  - This is a classification problem
  - CNNs are pretty good at a lot of image related classification problems
- CNNs can do direct regression or quantized classification from pixels to disparity
- CNNs can do iterative refinement of existing disparity estimations



Beyond these classical replacements, object instance segmentation via CNNs can be used as additional information to help improve stereo matching

Apologies to the creator of this figure (I'm not sure where it originally came from)

Data

- Laundry list
  - KITTI
  - FlyingThings3D
  - SceneFlow
  - ETH3D
- Note
  - Difficulty of acquisition and often sparse
  - 1 of the best uses of computer graphics for generating training data

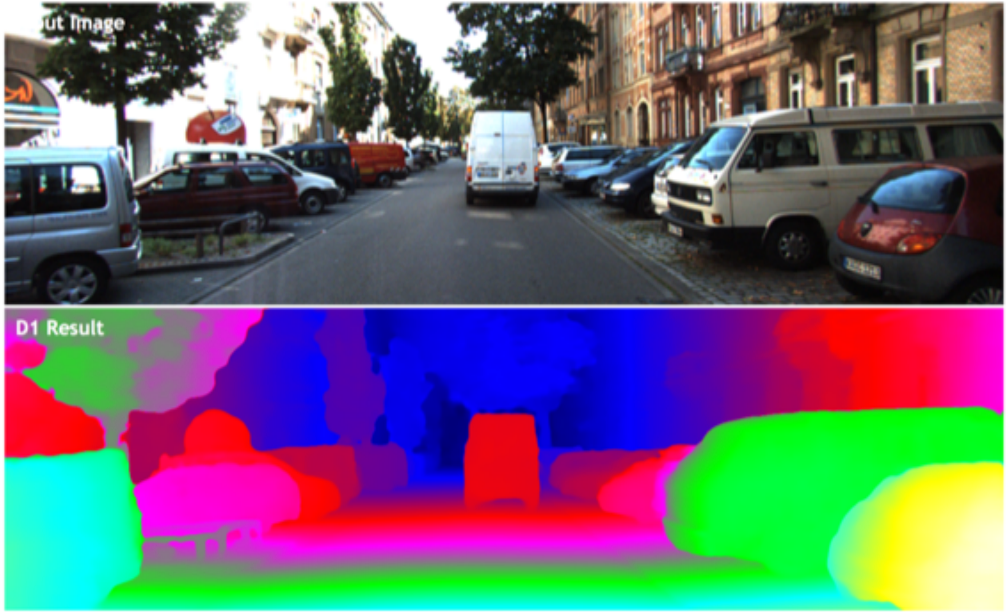


Figure from http://www.cvlibs.net/datasets/kitti/eval_scene_flow.php?benchmark=stereo

Network Architecture Options

- Structures
    - Siamese network (typically with shared weights) then merge
    - Stacked feature maps in a single network (not as popular)

- Note
    - It is possible to estimate depth (to a scale factor) from a single image
    - However, performance tends to be much worse than stereo methods
    - As expected

Image Patch Comparison

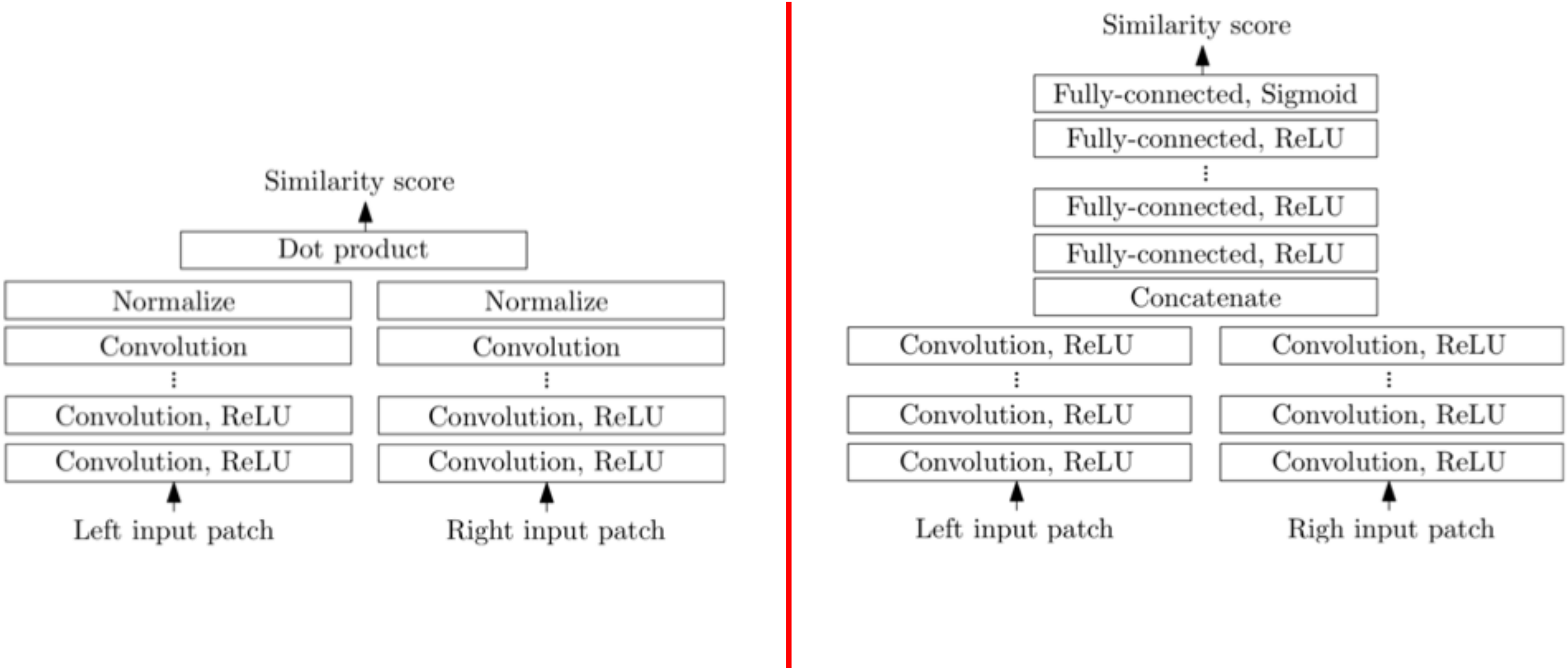
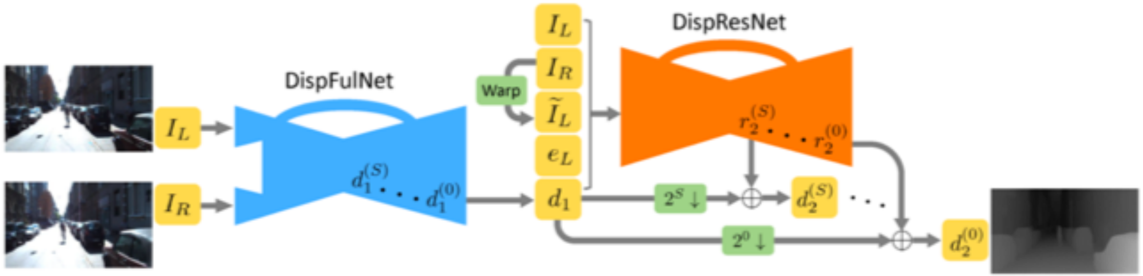


Figure from https://arxiv.org/abs/1510.05970

Cascade Residual Learning



Name	Kernel	Str.	Ch I/O	InpRes	OutRes	Input
conv1	7×7	2	6/64	768×384	384×192	Images
conv2	5×5	2	64/128	384×192	192×96	conv1
conv3a	5×5	2	128/256	192×96	96×48	conv2
conv3b	3×3	1	256/256	96×48	96×48	conv3a
conv4a	3×3	2	256/512	96×48	48×24	conv3b
conv4b	3×3	1	512/512	48×24	48×24	conv4a
conv5a	3×3	2	512/512	48×24	24×12	conv4b
conv5b	3×3	1	512/512	24×12	24×12	conv5a
conv6a	3×3	2	512/1024	24×12	12×6	conv5b
conv6b	3×3	1	1024/1024	12×6	12×6	conv6a
pr6+loss6	3×3	1	1024/1	12×6	12×6	conv6b
upconv5	4×4	2	1024/512	12×6	24×12	conv6b
iconv5	3×3	1	1025/512	24×12	24×12	upconv5+pr6+conv5b
pr5+loss5	3×3	1	512/1	24×12	24×12	iconv5
upconv4	4×4	2	512/256	24×12	48×24	iconv5
iconv4	3×3	1	769/256	48×24	48×24	upconv4+pr5+conv4b
pr4+loss4	3×3	1	256/1	48×24	48×24	iconv4
upconv3	4×4	2	256/128	48×24	96×48	iconv4
iconv3	3×3	1	385/128	96×48	96×48	upconv3+pr4+conv3b
pr3+loss3	3×3	1	128/1	96×48	96×48	iconv3
upconv2	4×4	2	128/64	96×48	192×96	iconv3
iconv2	3×3	1	193/64	192×96	192×96	upconv2+pr3+conv2
pr2+loss2	3×3	1	64/1	192×96	192×96	iconv2
upconv1	4×4	2	64/32	192×96	384×192	iconv2
iconv1	3×3	1	97/32	384×192	384×192	upconv1+pr2+conv1
pr1+loss1	3×3	1	32/1	384×192	384×192	iconv1

Figure from https://arxiv.org/abs/1708.09204

Pyramid Stereo Matching Network

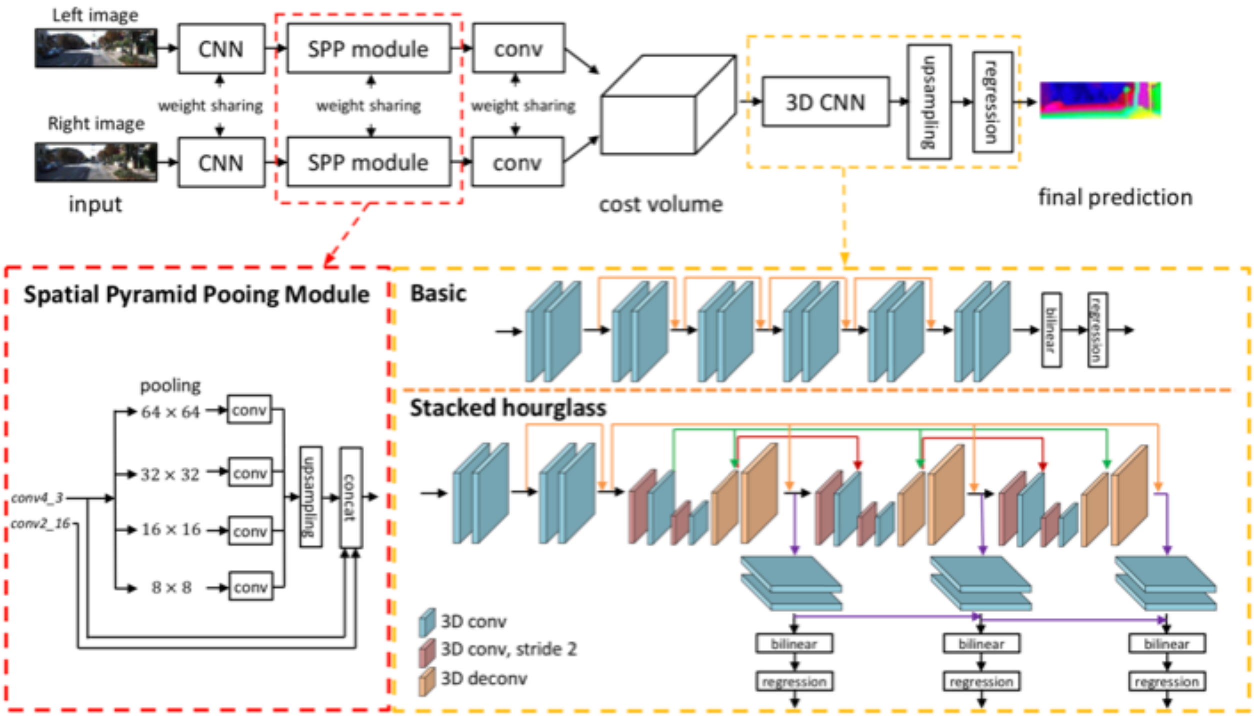


Figure from https://arxiv.org/abs/1803.08669

Evaluation

- KITTI criteria
  - Errors exceed 3 pixels and 5 % of the true value
  - Errors can be categorized as
    - Foreground pixels
    - Background pixels
    - All pixels

Motion Estimation

Goal

- Find the relative motion between pixels in 1 frame in time to the next
- This is referred to as optical flow (loosely)
- Note that there are single image motion estimation methods but these are not discussed here

Figure from http://sintel.is.tue.mpg.de

Fundamentals

- 2 images separated in time, find the same pixel in both
  - Again, this is a classification problem
  - Though unlike stereo where the search is over a line, now it can be in 2D
- Can improve with the addition of object based image segmentation
  - Do object segmentation on both images
  - Figure out where an object moves from 1 image to the next
  - Doesn’t fully handle deformations but also not bad if changes are small
- Can extend to more than 2 images
- Consistency between image at time 1, image at time 2 and motion estimation
  - Can use as an error estimate to potentially refine

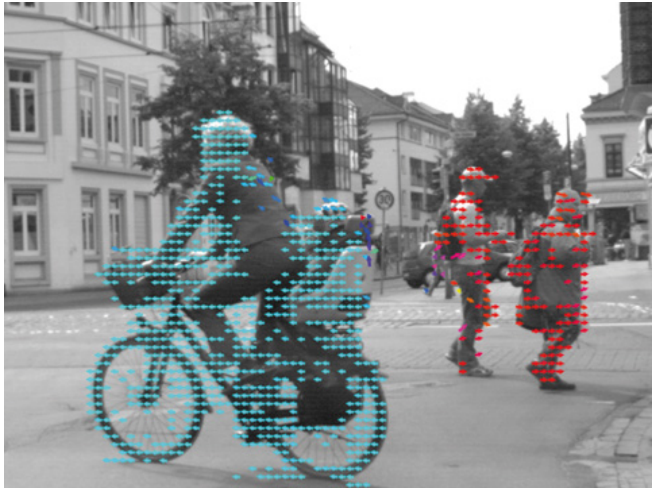


Figure from https://www.commonvisionblox.com/en/products/series/cvb-optical-flow/

Fundamentals

- Note that this seems to be 1 of the last places in vision where not deep learning based approaches are still comparable in terms of accuracy with deep learning based approaches
  - Unclear how long this will remain a true statement

Data

- Laundry list
  - KITTI
  - MPI Sintel
  - Flying Chairs
  - Middlebury
  - HD1K

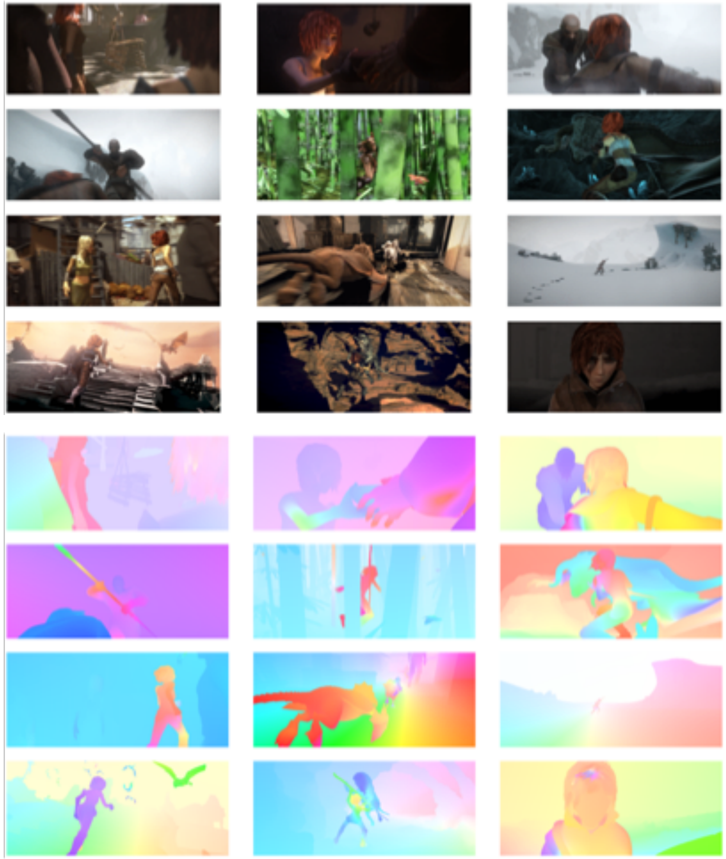


Figure from http://sintel.is.tue.mpg.de

FlowNet

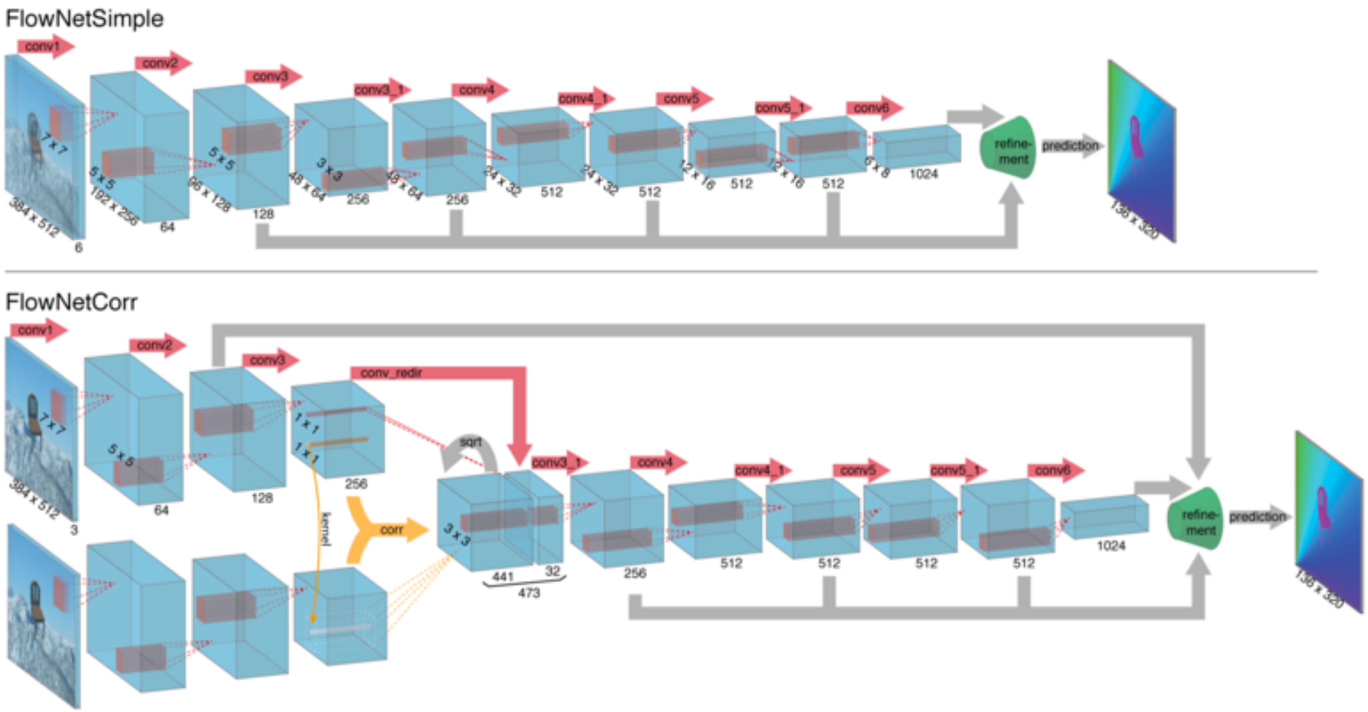


Figure from https://arxiv.org/abs/1504.06852

FlowNet

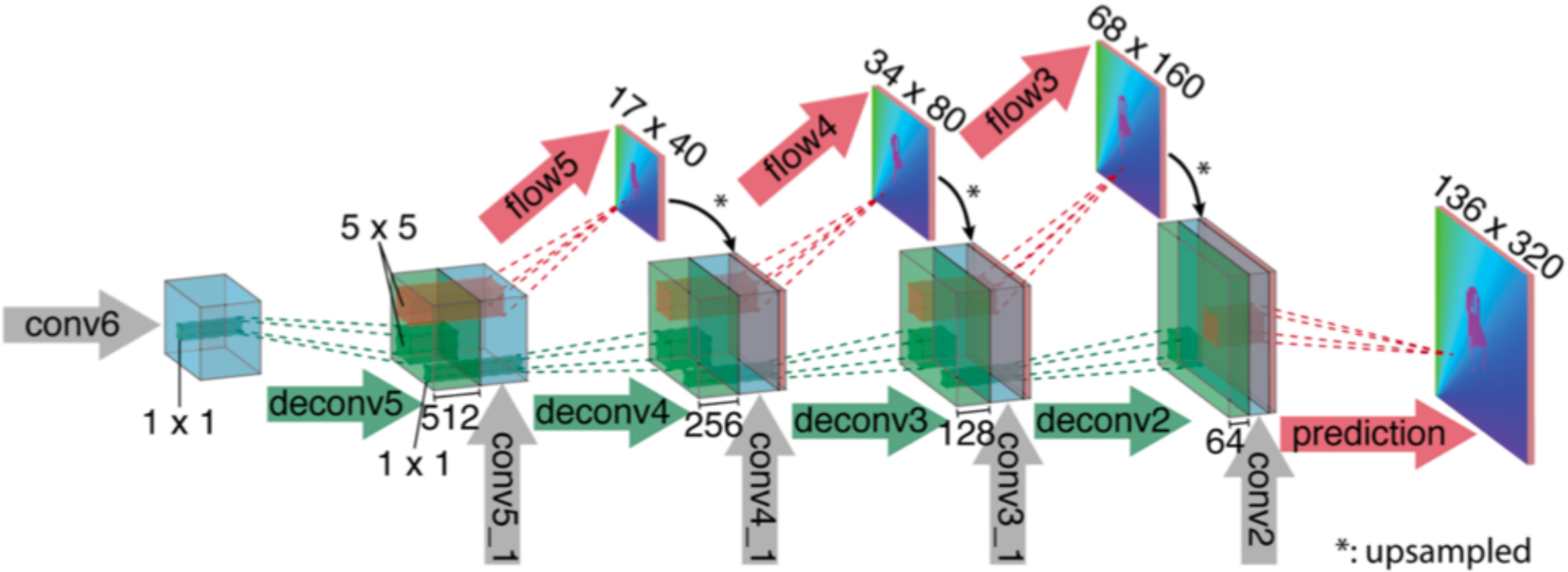


Figure from https://arxiv.org/abs/1504.06852

FlowNet 2.0

The sequel is better than the original (just like The Empire Strikes Back)

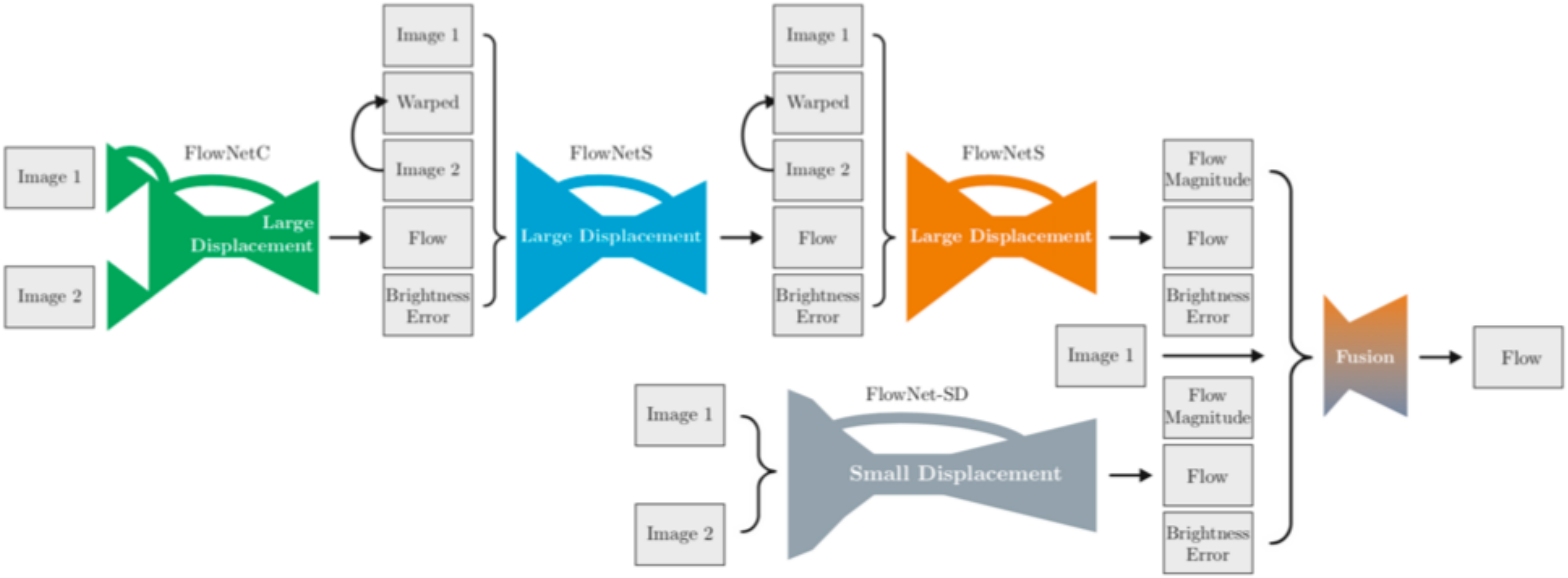


Figure from https://arxiv.org/abs/1612.01925

Evaluation

- Basically the same as stereo depth estimation

References

Data

- Yet another computer vision index to datasets (YACVID)
  - https://riemenschneider.hayko.at/vision/dataset/
- CV datasets on the web
  - http://www.cvpapers.com/datasets.html
- Computer vision online datasets
  - https://computervisiononline.com/datasets

- Google AI datasets
  - https://ai.google/tools/datasets/
- UC Irvine machine learning repository
  - https://archive.ics.uci.edu/ml/index.php
- 25 open datasets for deep learning every data scientist must work with
  - https://www.analyticsvidhya.com/blog/2018/03/comprehensive-collection-deep-learning-datasets/

Data

- CIFAR
  - https://www.cs.toronto.edu/~kriz/cifar.html
- Cityscapes dataset
  - https://www.cityscapes-dataset.com
- Common objects in context
  - http://cocodataset.org
- ETH3D
  - https://www.eth3d.net
- Flying chairs
  - https://lmb.informatik.uni-freiburg.de/resources/datasets/FlyingChairs.en.html
- HD1K
  - http://hci-benchmark.org
- ImageNet
  - http://www.image-net.org

Data

- The KITTI vision benchmark suite
  - http://www.cvlibs.net/datasets/kitti/
- Middlebury
  - http://vision.middlebury.edu/flow/
- Mapillary vistas
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- THE MNIST database of handwritten digits
  - http://yann.lecun.com/exdb/mnist/
- Fashion MNIST
  - https://github.com/zalandoresearch/fashion-mnist
- MPI Sintel flow dataset
  - http://sintel.is.tue.mpg.de
- Open images dataset V4
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Data

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  - http://host.robots.ox.ac.uk/pascal/VOC/
- ScanNet
  - http://kaldir.vc.in.tum.de/scannet_benchmark/
- The street view house numbers (SVHN) dataset
  - http://ufldl.stanford.edu/housenumbers/

Image Capture

- Brown CSCI 1290: computational photography and image manipulation
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  - https://sites.google.com/site/marclevoylectures/schedule

- ARM Mali camera
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- HotChips 2018: the Google pixel visual core live blog
  - https://www.anandtech.com/show/13241/hot-chips-2018-the-google-pixel-visual-core-live-blog
- Pixel visual core: image processing and machine learning on pixel 2
  - https://www.blog.google/products/pixel/pixel-visual-core-image-processing-and-machine-learning-pixel-2/

Classification

- See design lecture notes

Pixel Segmentation

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  - https://arxiv.org/abs/1411.4038
- Semantic image segmentation with deep convolutional nets and fully connected CRFs
  - https://arxiv.org/abs/1412.7062
- BoxSup: exploiting bounding boxes to supervise convolutional networks for semantic segmentation
  - https://arxiv.org/abs/1503.01640
- U-net: convolutional networks for biomedical image segmentation
  - https://arxiv.org/abs/1505.04597
- SegNet: a deep convolutional encoder-decoder architecture for image segmentation
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