Capturing Spatial Dependencies with Deep Neural Networks II

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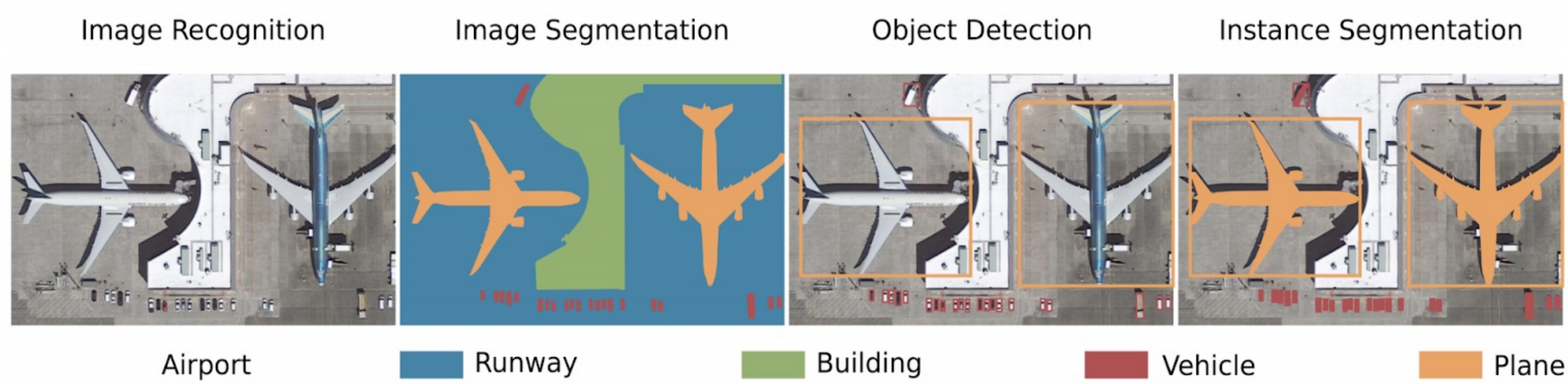
Semantic Segmentation and Object Detection

A short introduction

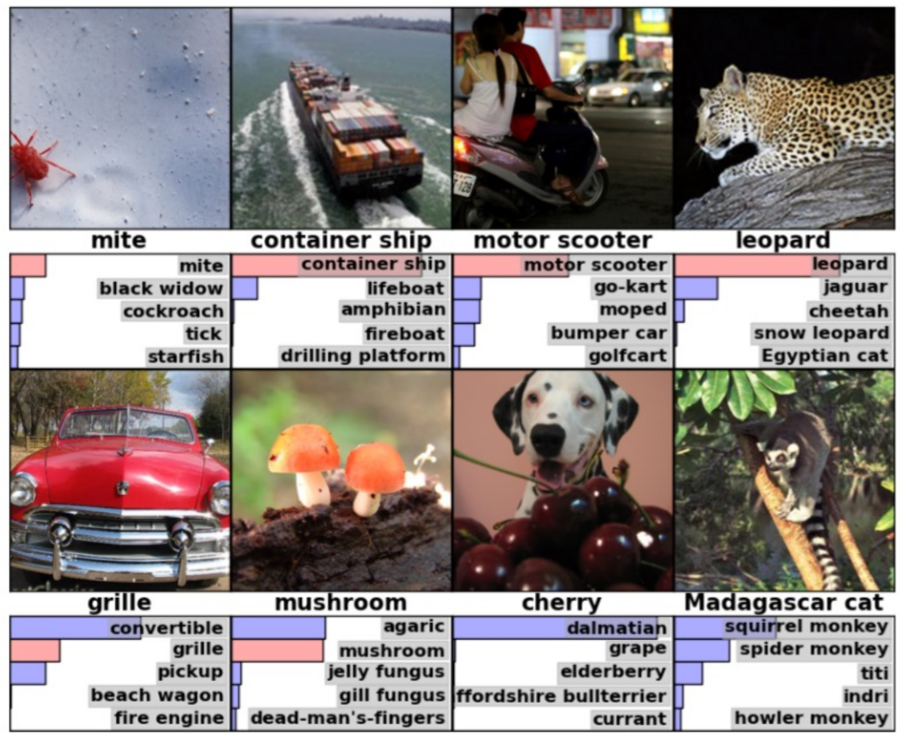
Recall: Overhead Imagery Understanding Tasks



Thorsten Hoeser and Claudia Kuenzer. 2020. Object detection and image segmentation with deep learning on earth observation data: A review-part i: Evolution and recent trends. *Remote Sensing*. Retrieved from https://www.mdpi.com/723500

CNN so far - Image Classification

- Take an input image, predict an object class

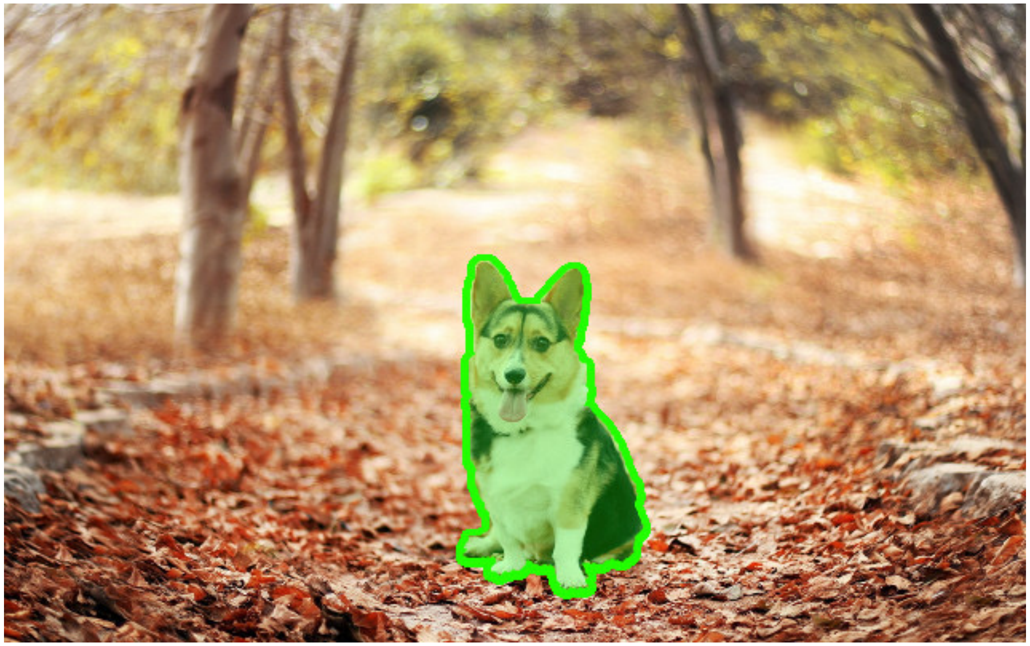


https://blog.acolyer.org/2016/04/20/imagenet-classification-with-deep-convolutional-neural-networks/

Semantic Segmentation

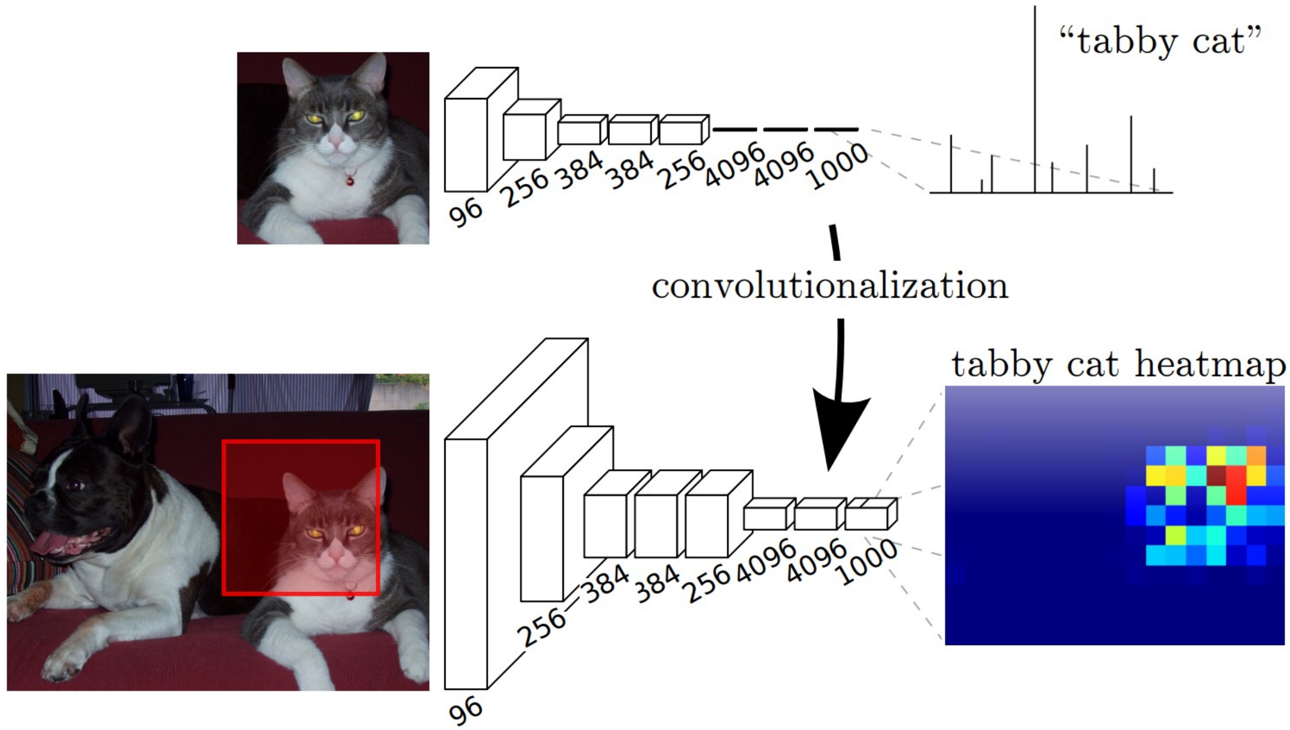
Semantic Segmentation

- Output a class map for each pixel (here: dog vs background)
- Also, **instance segmentation**: specify each object instance as well (two dogs have different instances)
  - This can be done through **object detection + segmentation**



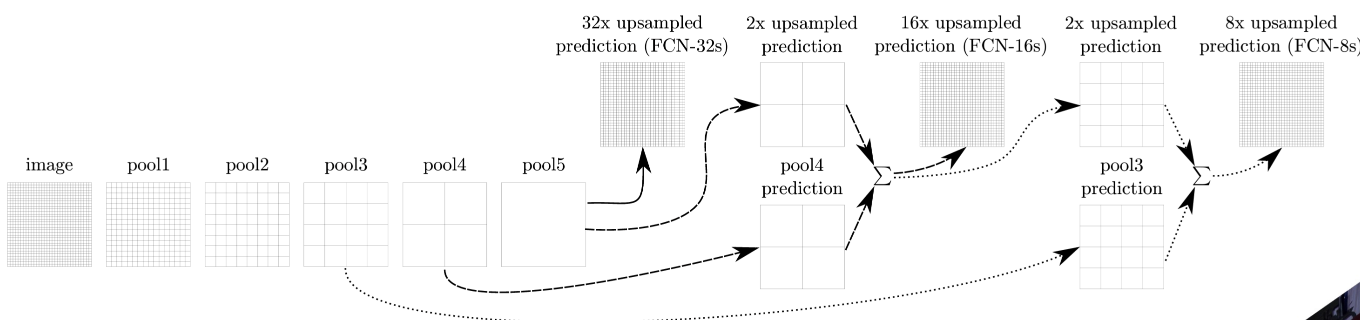
Sliding Window

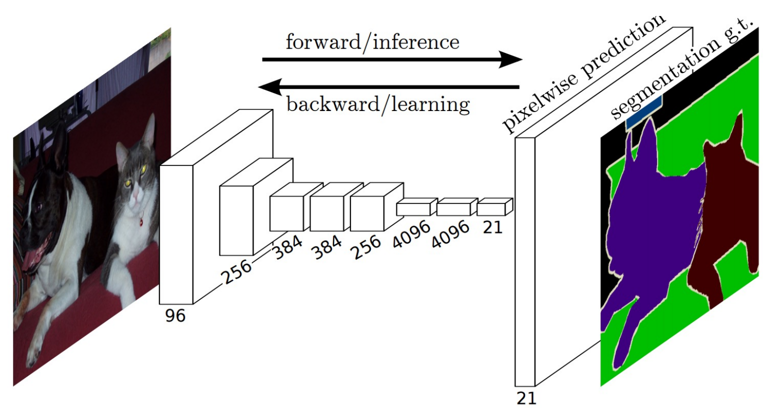
- Every window provides some context for classifying the center pixel
- Inefficient, why?



Fully Convolutional Network (FCN)

- Predict / backpropagate for every output pixel
- Aggregate maps from several convolutions at different scales
- Upsampling/unpooling back to dense pixels for classification

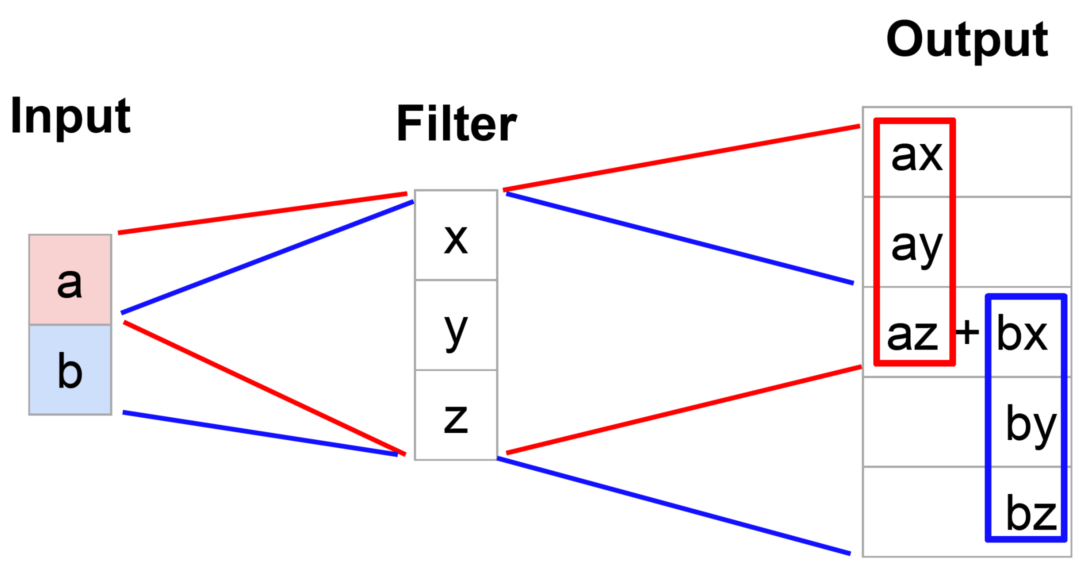




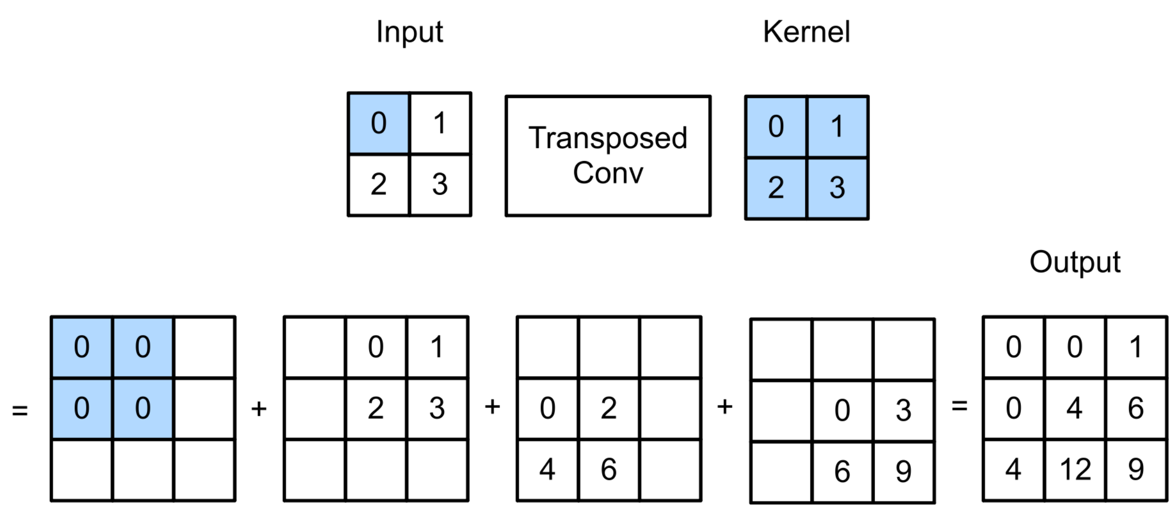
Long, Jonathan, et al. "Fully convolutional networks for semantic segmentation." CVPR 2015
Noh, Hyeonwoo, et al. "Learning deconvolution network for semantic segmentation." ICCV 2015

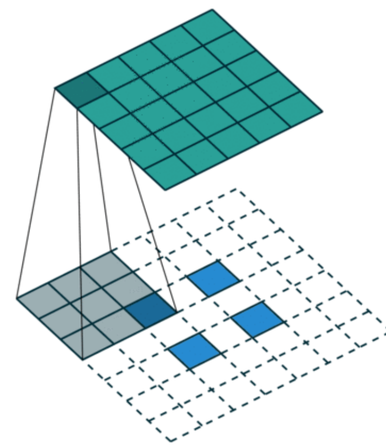
Learnable Upsampling

- 1D Example



Learnable Upsampling: Transposed Convolution





https://d2l.ai/chapter_computer-vision/transposed-conv.html

U-Net

- **Skip connections** between corresponding convolution and deconvolution layers
- **Sharper masks** by using precise spatial information (early layers)
- **Better object detection** by using semantic information (late layers)
- Weighted loss for clear boundaries

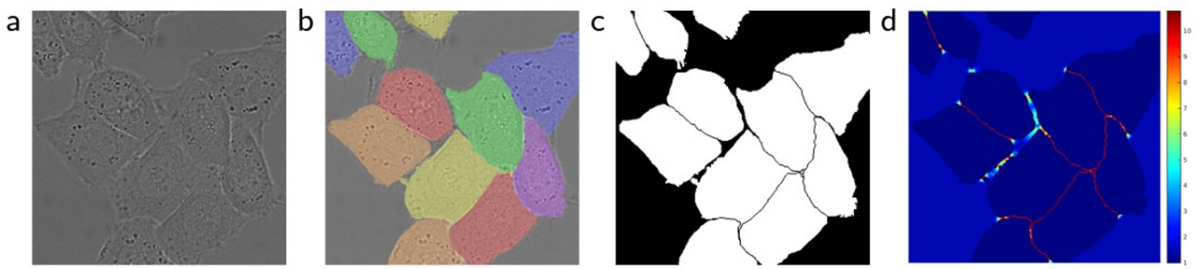
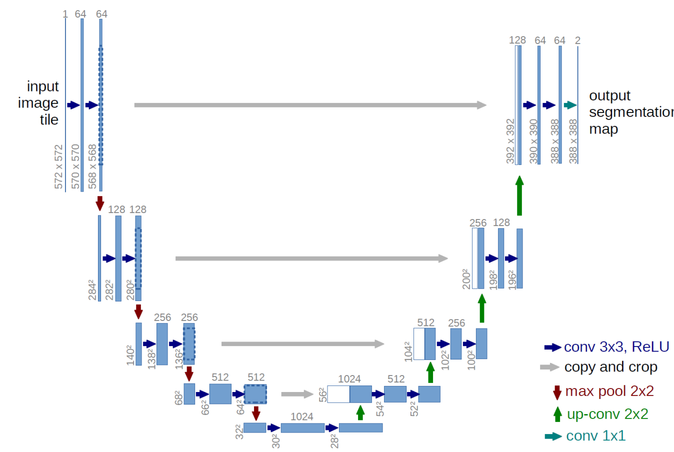
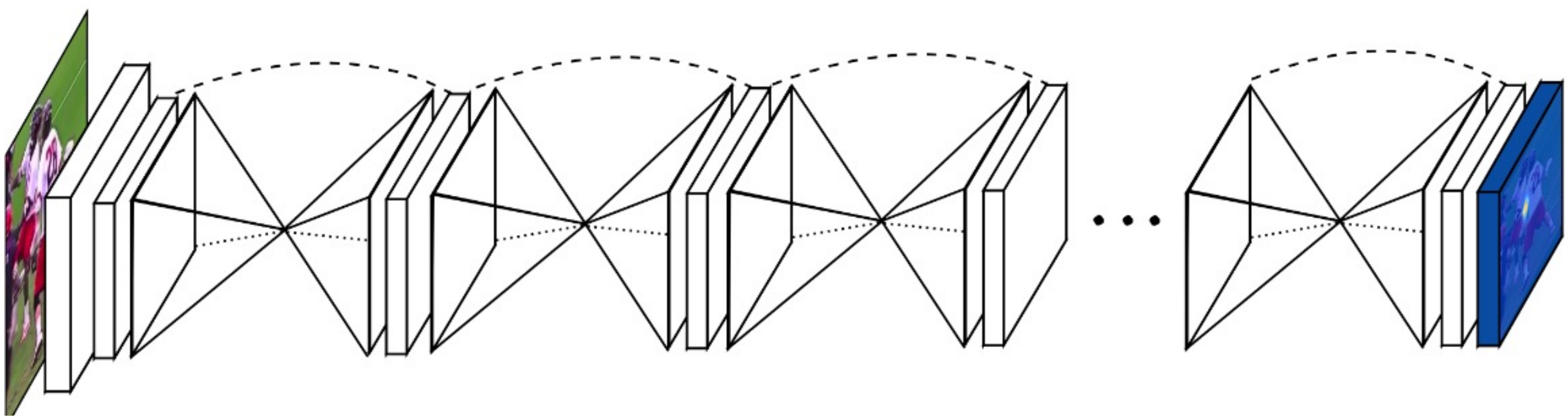


Fig. 3. HeLa cells on glass recorded with DIC (differential interference contrast) microscopy. (**a**) raw image. (**b**) overlay with ground truth segmentation. Different colors indicate different instances of the HeLa cells. (**c**) generated segmentation mask (white: foreground, black: background). (**d**) map with a pixel-wise loss weight to force the network to learn the border pixels.



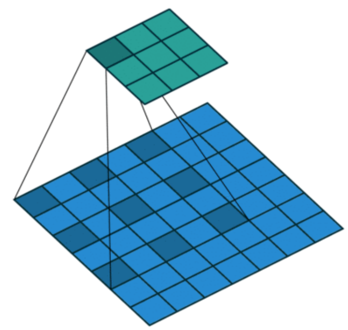
Hourglass Network

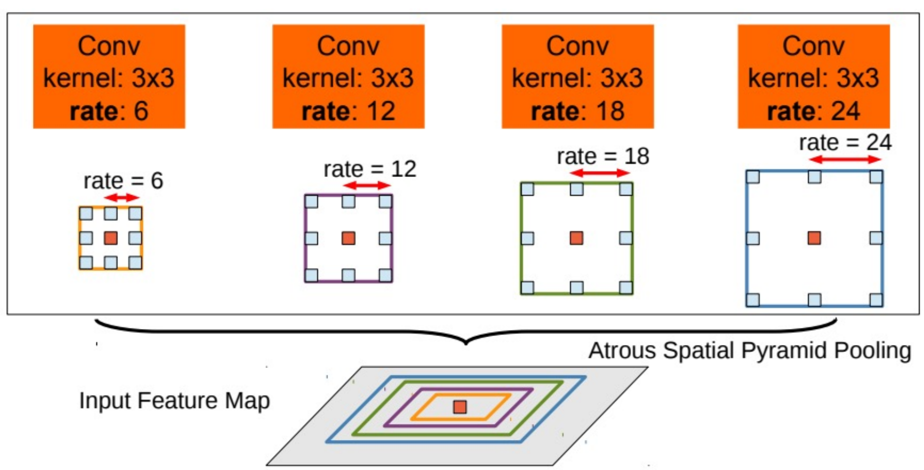
- U-Net like architectures repeated sequentially
- Each block refines the segmentation for the following
- Each block has a segmentation loss



DeepLab V3

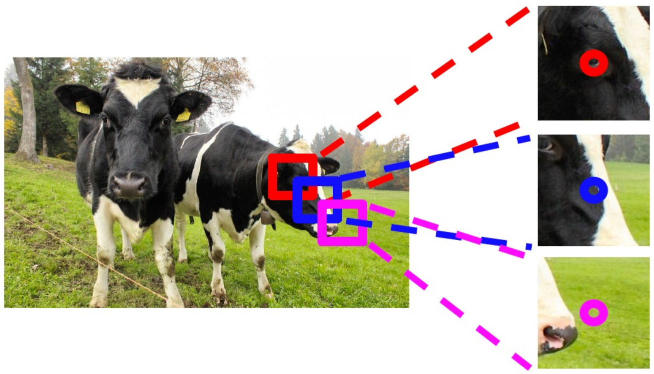
- Atrous convolutions, or dilated convolutions
  - Arbitrarily enlarge the field-of-view of filters
  - Compute the responses of any layer at any desirable resolution
- Atrous Spatial Pyramid Pooling (ASPP)
  - To classify the center pixel (orange), ASPP exploits multi-scale features by employing multiple parallel filters with different rates
  - The effective Field-Of-Views are shown in different colors

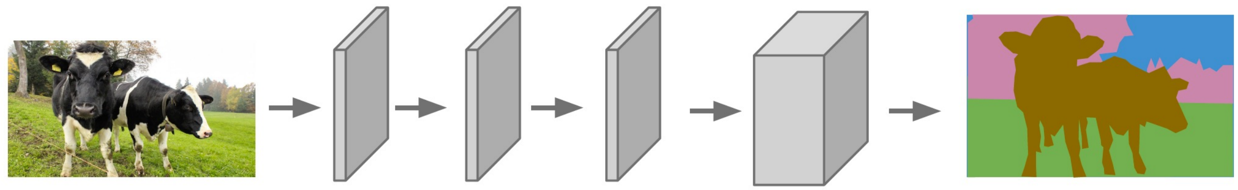


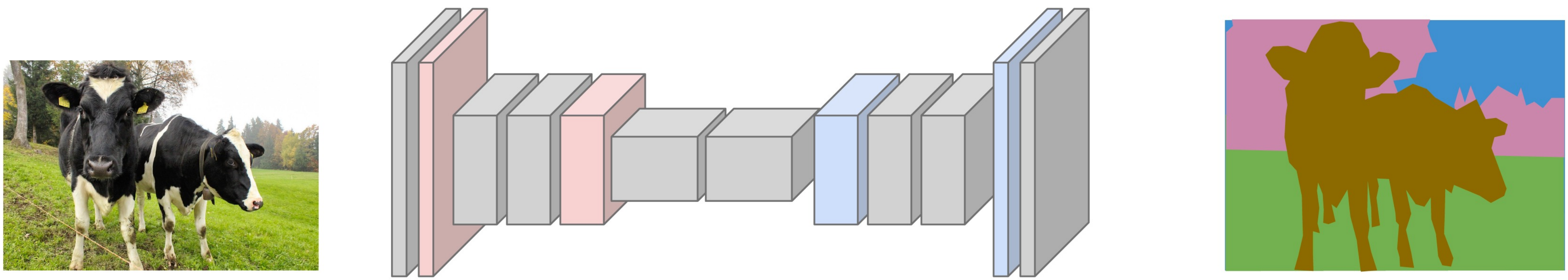


https://arxiv.org/abs/1606.00915v2

Semantic Segmentation Summary



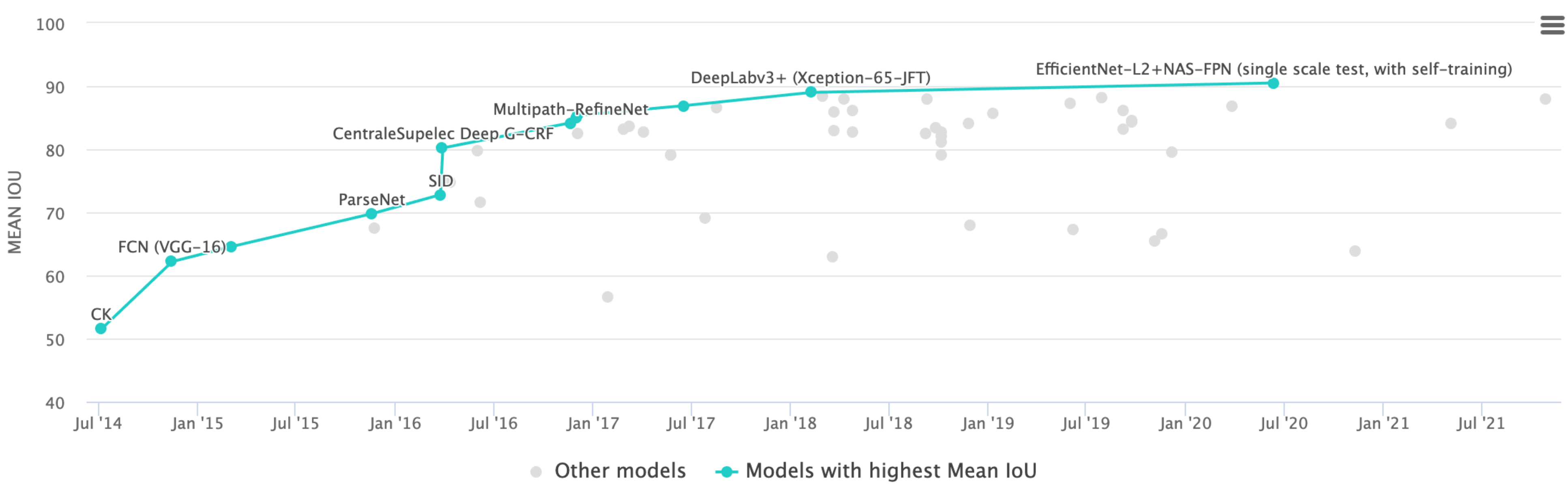




Semantic Segmentation on PASCAL VOC 2012 test

Leaderboard Dataset

View Mean IoU by Date for All models

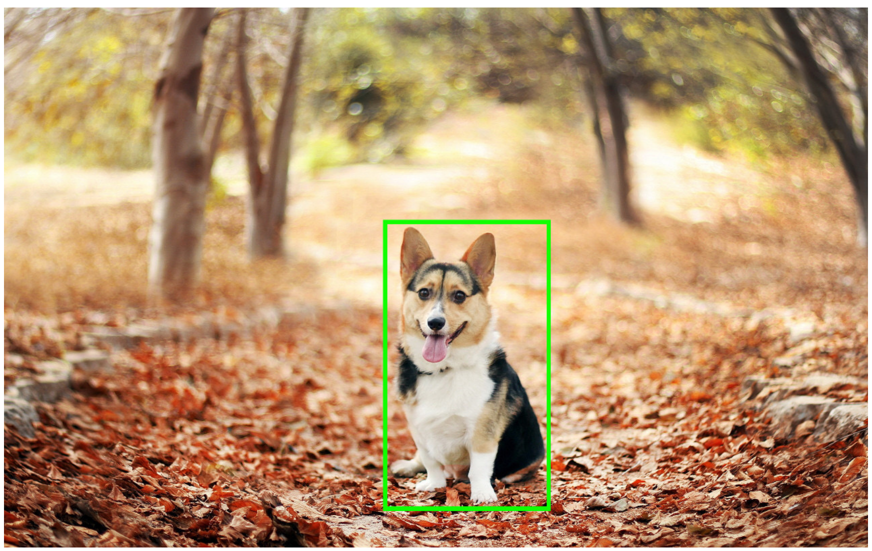


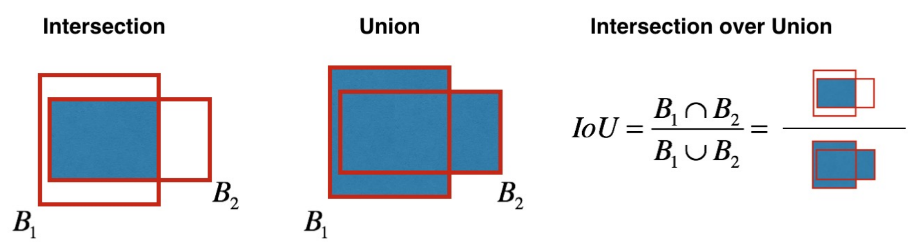
https://paperswithcode.com/sota/object-detection-on-coco

Object Detection

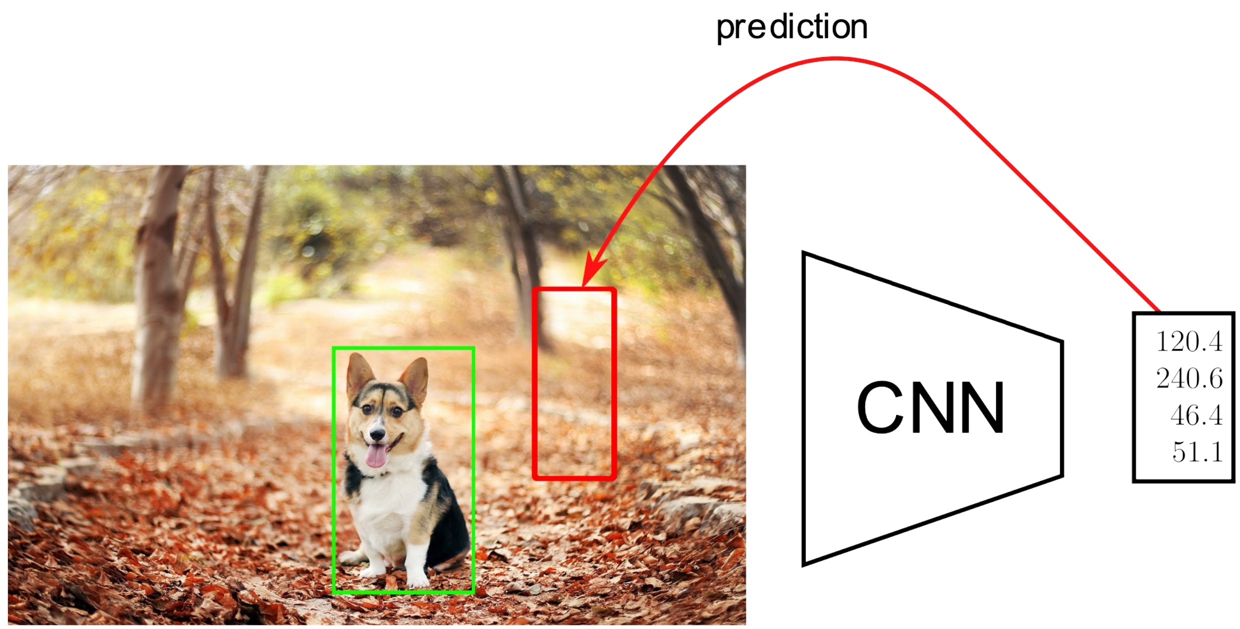
Localization

- Single object per image
- Predict coordinates of a bounding box (x, y, w, h)
- Evaluate via Intersection over Union (IoU) (Jacard Similarity)

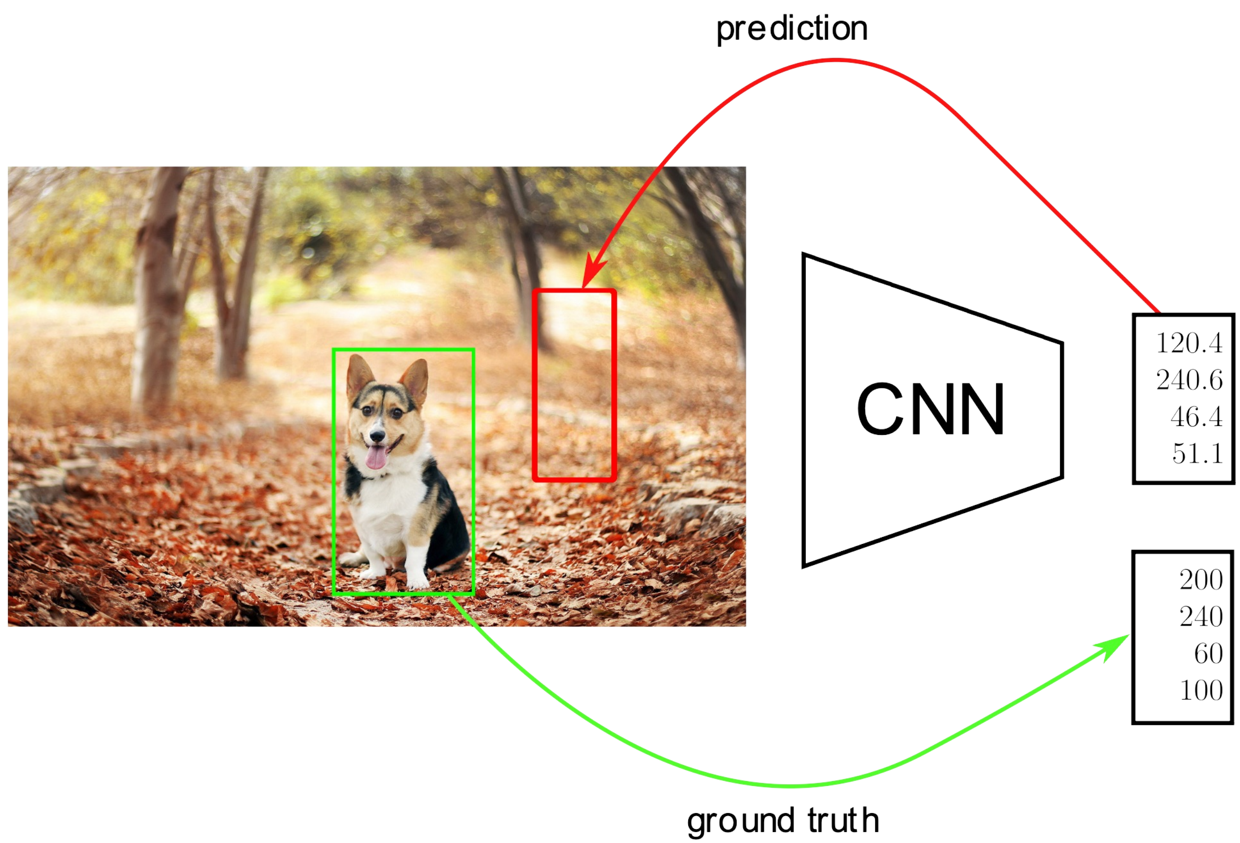




Localization as regression



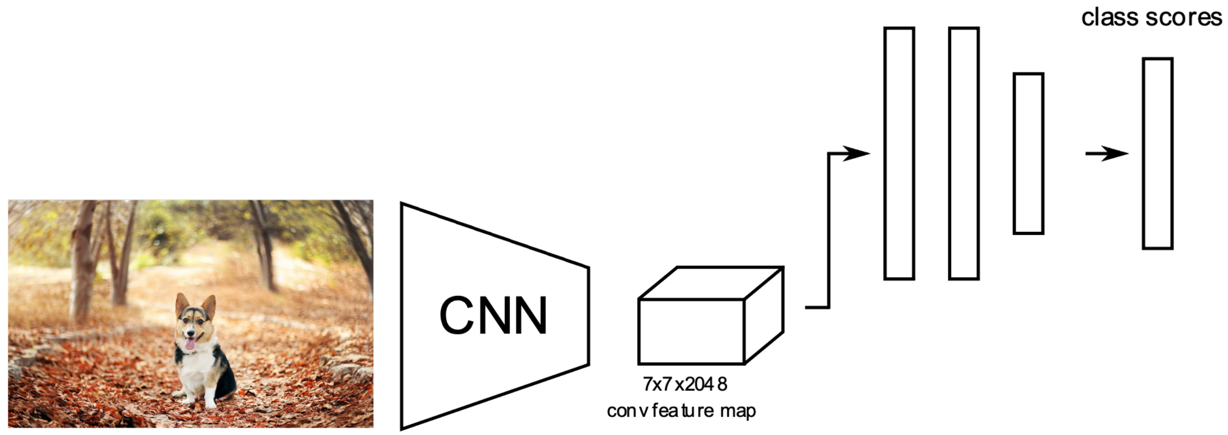
Localization as regression



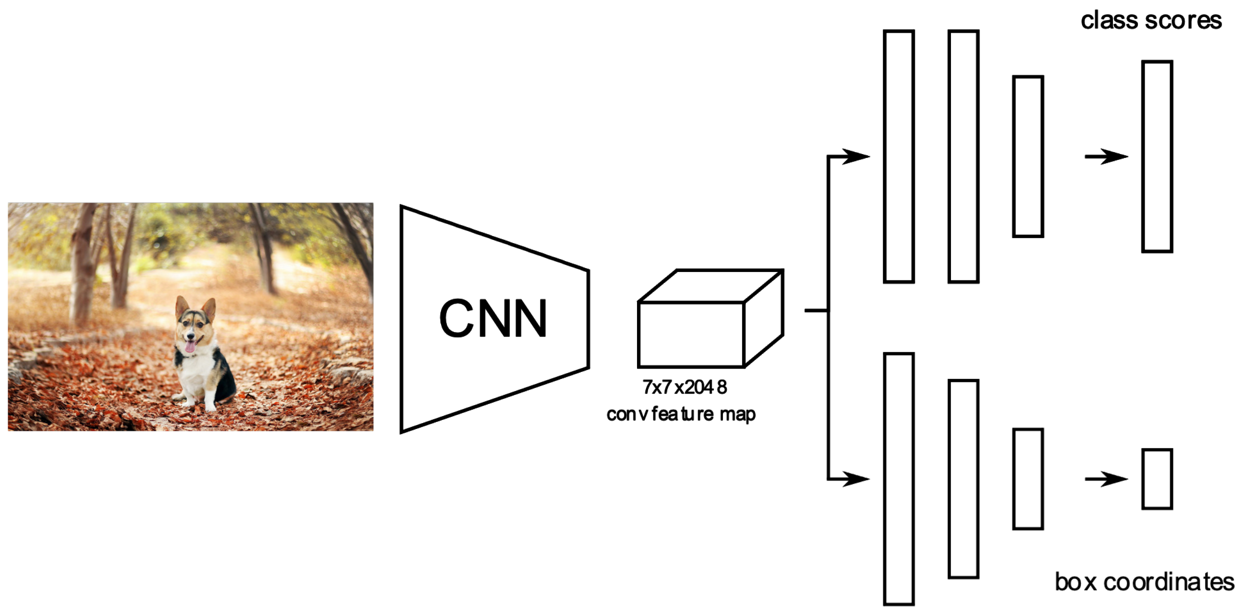
L2 loss

the sum of the all
the **squared** differences
between the true value and
the predicted value

Classification + Localization

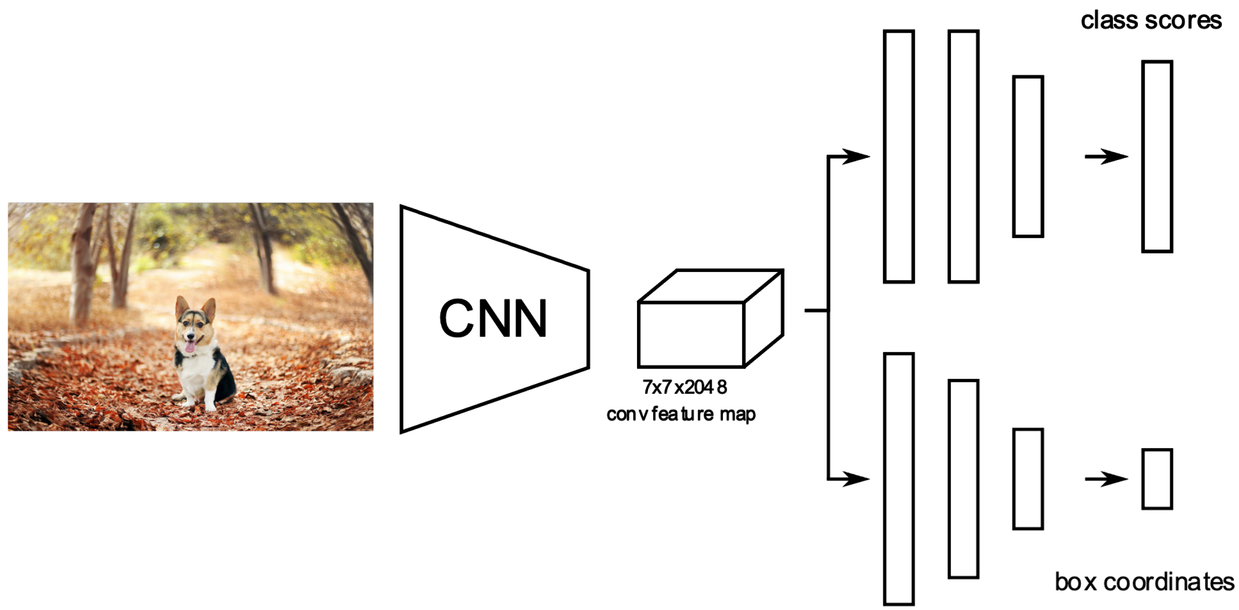


Classification + Localization



- Use a pre-trained CNN on ImageNet (e.g., ResNet)
- The "localization head" is trained separately with regression (i.e., generate coordinates in a continuous space)
- Possible end-to-end finetuning of both tasks
- At test time, use both heads

Classification + Localization



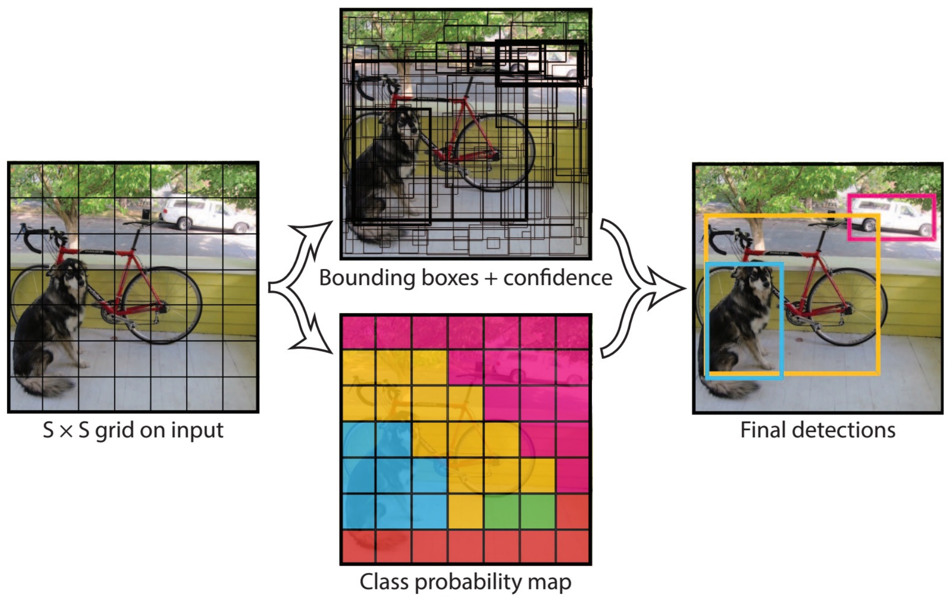
- C classes, 4 output dimensions (1 box)
- **Predict exactly** N **objects:** predict (N×4) coordinates and (N×K) class scores

Object Detection

- We don't know in advance the number of objects in the image.
- Object detection relies on *object proposal* and *object classification*
- **Object proposal:** find regions of interest (RoIs) in the image
- **Object classification:** classify the object in these regions
- Two main families:
  - Single-Stage: A grid in the image where each cell is a proposal (SSD, YOLO, RetinaNet)
  - Two-Stage: Region proposal then classification (Faster-RCNN)

YOLO – You Only Look Once

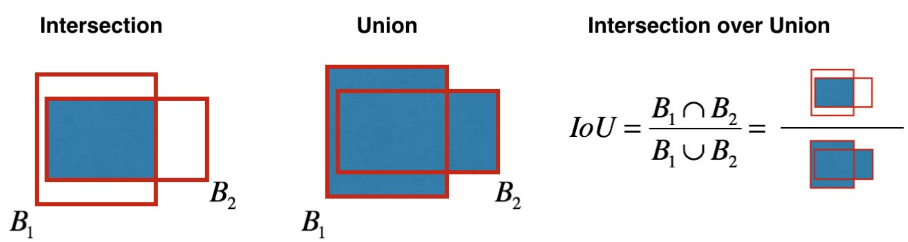
- Slice the image into cells
- Every cell predicts for
  - Locations of bounding boxes and confidence scores
  - Class probabilities



Redmon, Joseph, et al. "You only look once: Unified, real-time object detection." CVPR (2016)

YOLO – You Only Look Once

- Every cell predicts a number of B bounding boxes: $[P_c, B_x, B_y, B_w, B_h]$
  - P_c: Pr(obj) x IOU, the probability of an object in the cell x IOU between the predicted box and any ground truth box

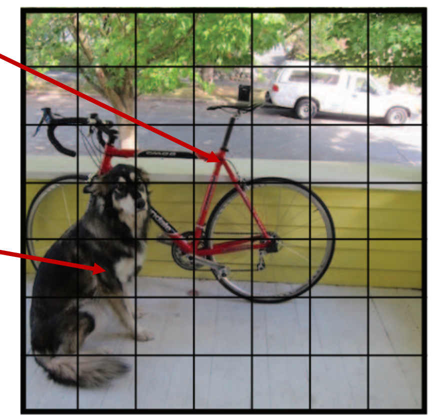


  - B_x, B_y, B_w, B_h, object bounding box location (relative to the cell) and size (relative to the image)
- Every cell also predicts C conditional class probabilities for all boxes:
  - $C_1, C_2, \ldots C_n$: $Pr(Class_i \mid obj = true)$ Give the cell contains an object, what is the probability of the object

[1, 0.5, 0.5, 5, 4, 0 ,1]

[1, 0.05, 0.5, 2.35, 4, 1 ,0]

dog, bike

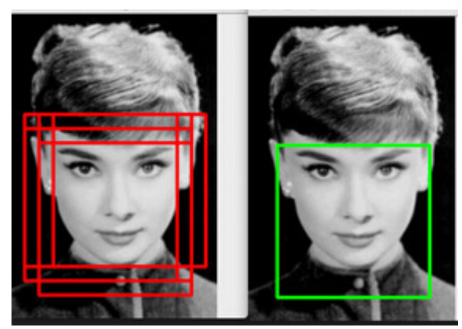


S × S grid on input

https://www.coursera.org/learn/convolutional-neural-networks
https://polakowo.io/datadocs/docs/deep-learning/object-detection

YOLO – You Only Look Once

- Non-maximum suppression to merge detected boxes with high confidence
- For each object class:
  - discard bounding boxes where probability of object being present is below some threshold, say 0.6
  - take the bounding box with the highest score,
  - discard any remaining bounding boxes with IOU value above some threshold (0.5)



https://www.coursera.org/lecture/convolutional-neural-networks/non-max-suppression-dvrjH

YOLO – You Only Look Once

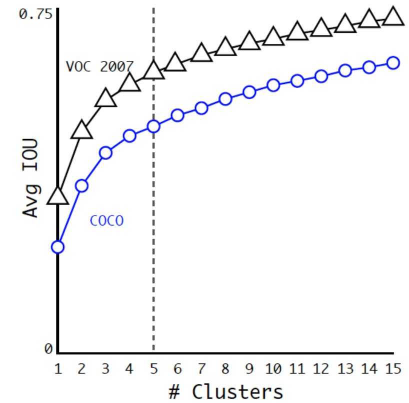
- After ImageNet pretraining, the whole network is trained end-to-end
- The loss is a weighted sum of different regressions

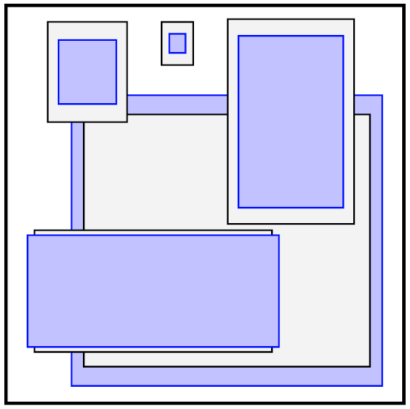
$$
\begin{aligned}
&\lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] \\
&+ \lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right] \\
&+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2 \\
&+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2 \\
&+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \qquad (3)
\end{aligned}
$$

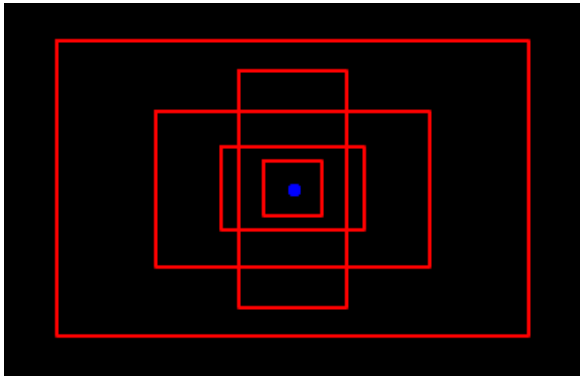
Redmon, Joseph, et al. "You only look once: Unified, real-time object detection." CVPR (2016)

YOLO9000 / YOLOv2

- Better, Faster, Stronger
- Instead of directly predict any bounding box sizes from a cell, use anchor boxes as prior knowledge and then predict to adjust the boxes
- Anchor boxes
  - Predefined dimensions of bounding boxes
  - Calculated from training data using K-Means with IOU as the distance measure
  - When K=5, every cell predicts to adjust 5 anchor boxes
  - Help detect multiple objects centered at a cell







Center all boxes and se IOU as the distance measure

https://vivek-yadav.medium.com/part-1-generating-anchor-boxes-for-yolo-like-network-for-vehicle-detection-using-kitti-dataset-b2fe033e5807

RetinaNet

- One-stage object detection
- Feature Pyramid Networks (FPN)
  - Effectively handle multiscale objects
- FocalLoss
  - Help the networks to focus on hard classification

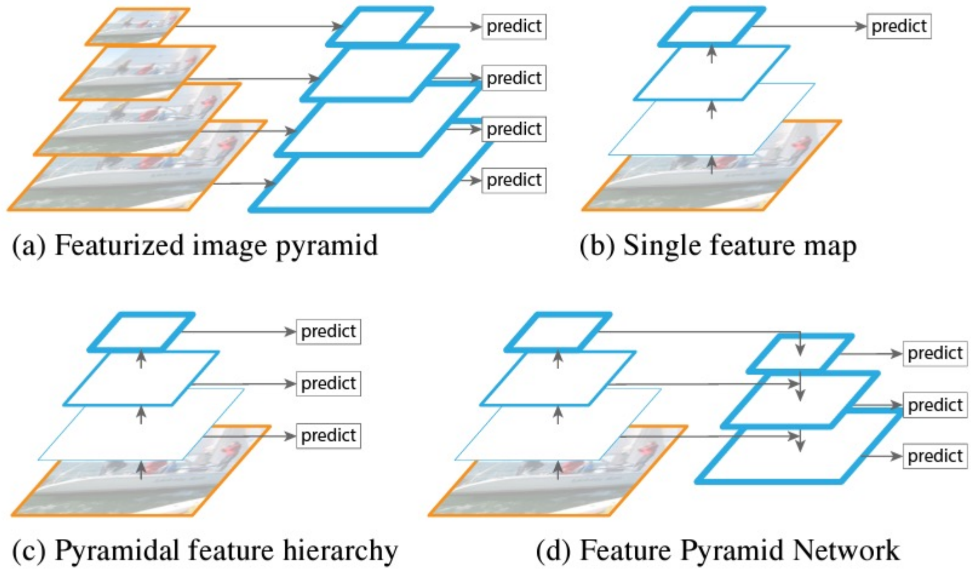
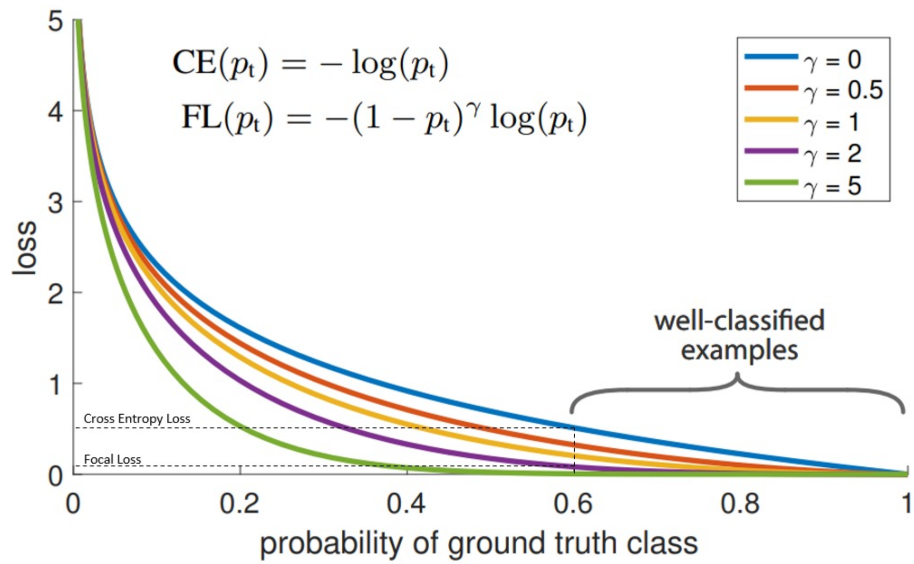


Figure 1. (a) Using an image pyramid to build a feature pyramid. Features are computed on each of the image scales independently, which is slow. (b) Recent detection systems have opted to use only single scale features for faster detection. (c) An alternative is to reuse the pyramidal feature hierarchy computed by a ConvNet as if it were a featurized image pyramid. (d) Our proposed Feature Pyramid Network (FPN) is fast like (b) and (c), but more accurate. In this figure, feature maps are indicate by blue outlines and thicker outlines denote semantically stronger features.

https://arxiv.org/abs/1612.03144

FocalLoss

- Class Imbalance Problem
  - Information related to one class in a dataset used in training is over-represented than the other classes
  - Make the network biased towards learning more representations of the data-dominated class and other classes will be underlooked
- Focal Loss
  - Reduce the loss for “well-classified examples” (e.g., p > 0.5 and it's correct)
  - Increase loss for “hard-to-classify examples” (e.g., p < 0.5)
  - Help the models focus on the rare class in case of class imbalance.

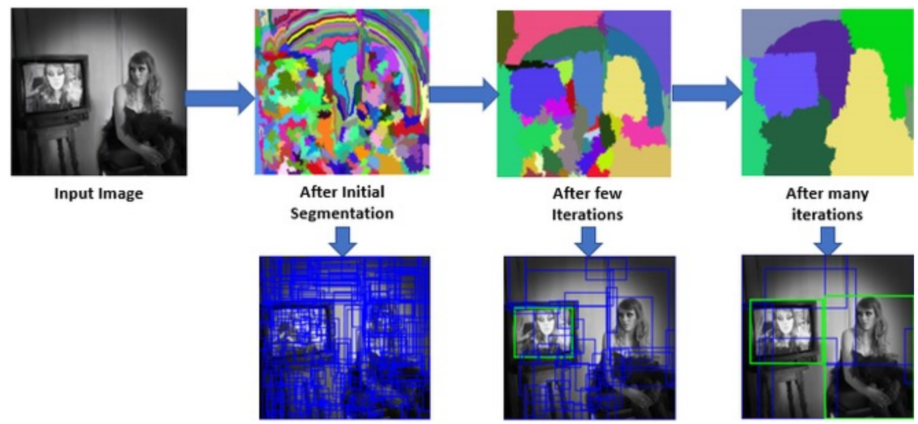


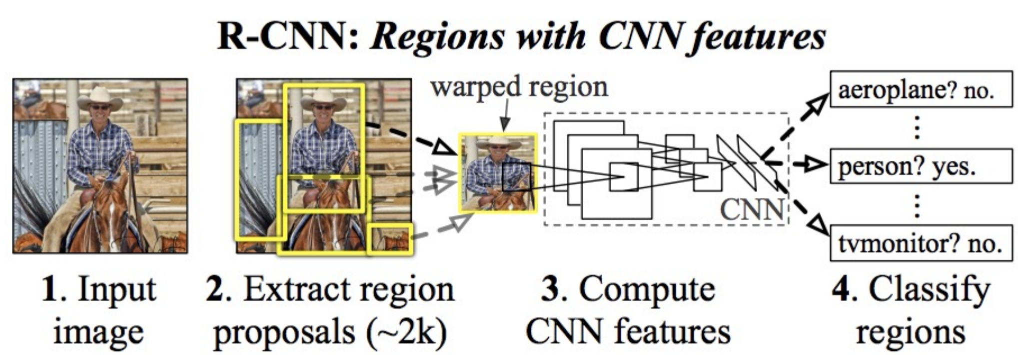
https://medium.com/visionwizard/understanding-focal-loss-a-quick-read-b914422913e7
https://amaarora.github.io/2020/06/29/FocalLoss.html

See also Dice Loss for semantic segmentation: https://www.youtube.com/watch?v=NqDBvUPD9jg

R-CNN

- Selective search to find boxes of object candidates (slow, CPU time, 47 sec. per image) – recursively combine similar regions
- ConvNet trained on individual regions
- Predict a class label for each box using a support vector machine (SVM)
- Predict offsets of the bounding boxes to improve box precision

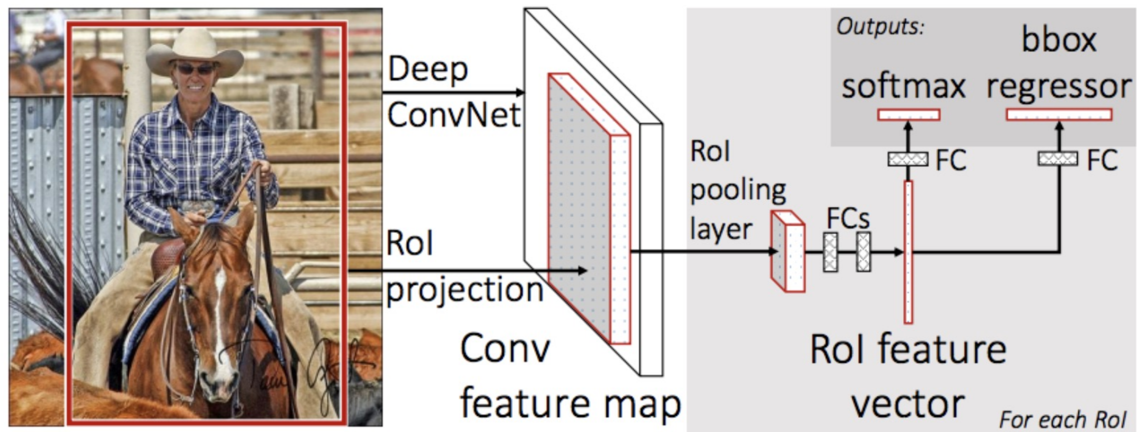


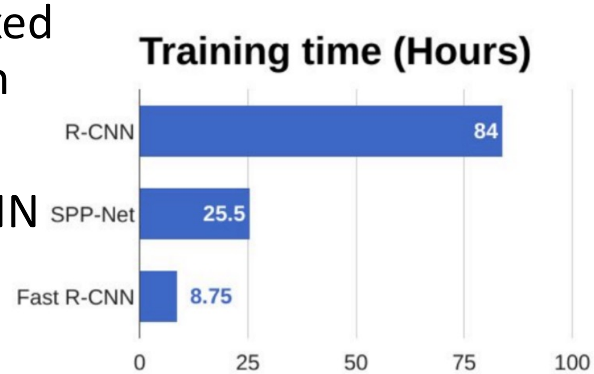


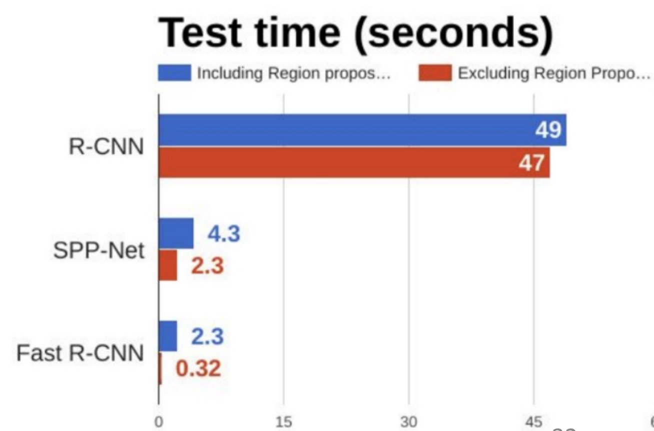
https://www.geeksforgeeks.org/selective-search-for-object-detection-r-cnn/

Fast R-CNN

- Find regions of interest from the feature map (selective search, but instead of from the input image)
- ConvNet trained on the entire image and use ROI pooling to generate fixed feature vector for each region for prediction
- Much faster than R-CNN

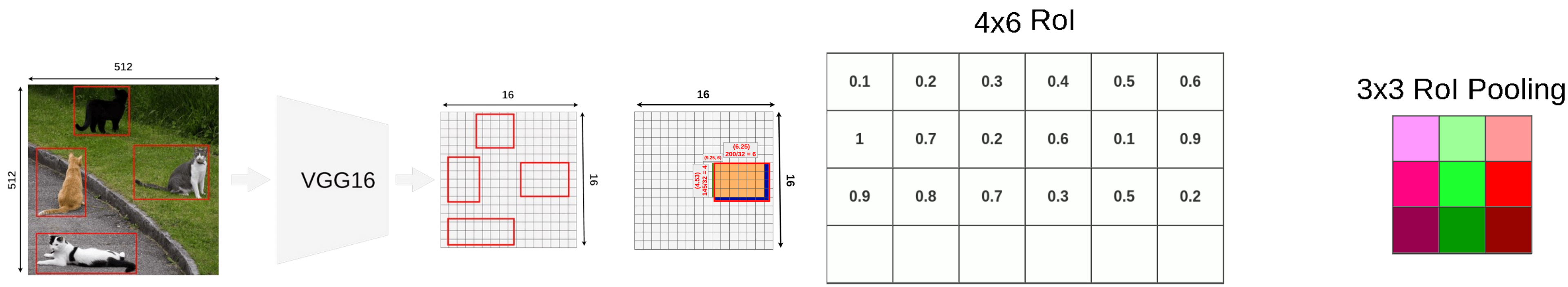






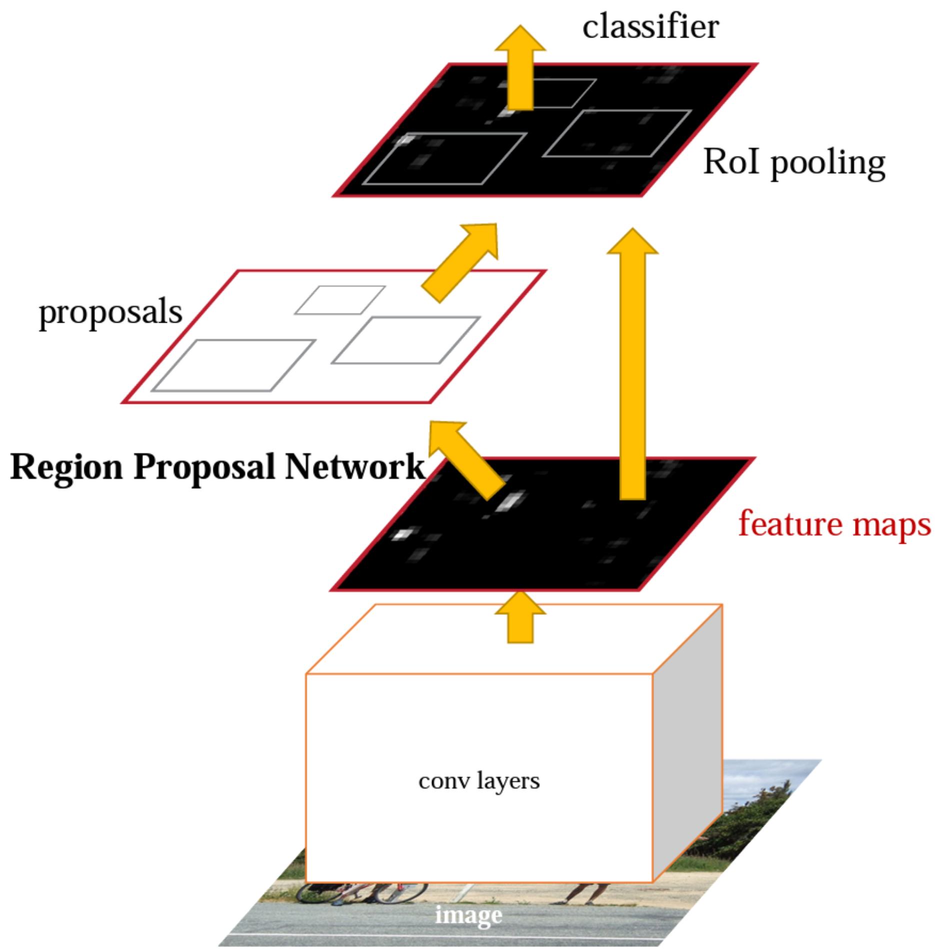
ROI pooling

- Use ROI pooling to generate a fixed-size feature vector for each proposal for final classification
- Allows to propagate gradient only on interesting regions, and efficient computation



Faster-RCNN

- Region proposal network (RPN): Take an image (of any size) as input and outputs a set of rectangular object proposals, each with an objectness score
  - Use anchor boxes
  - Lots of proposals (high recall, low precision)
- Classification: decide if a proposed region has an object



Ren, Shaoqing, et al. "Faster r-cnn: Towards real-time object detection with region proposal networks." NIPS 2015

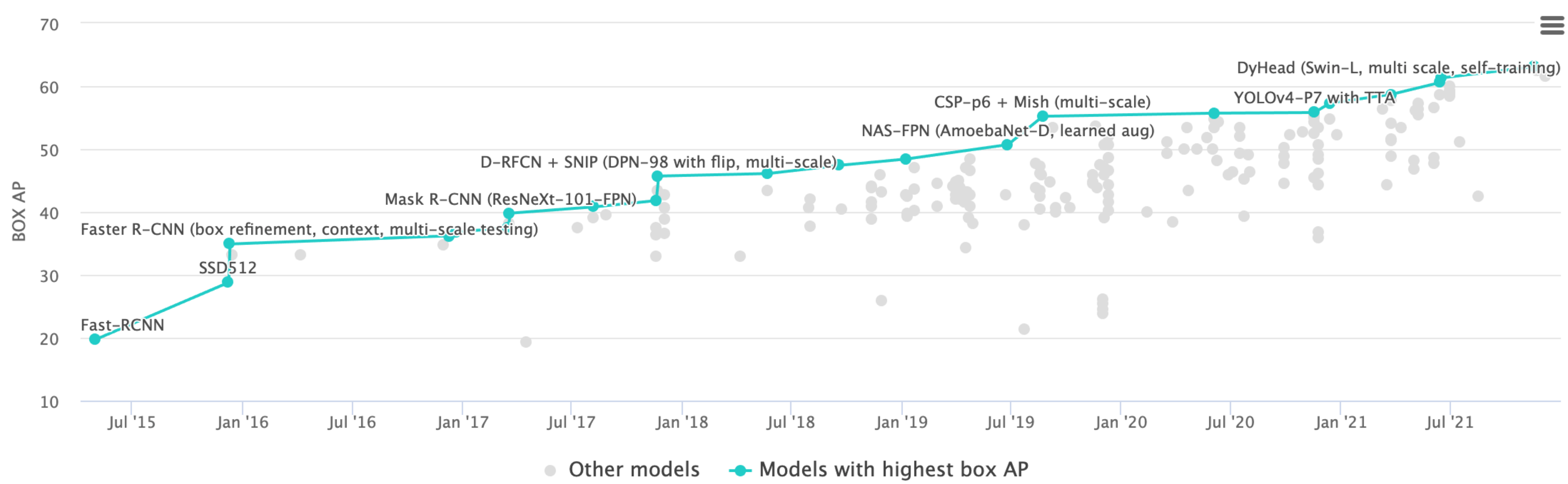
Object Detection Summary

- YOLO family
  - One stage
  - Very fast, better than real-time (45 – 150 frames per second)
  - Might have lower recall compared to Faster RCNN
    - Need to work on the entire image – imbalanced training data, see FocalLoss for dealing with this problem: Lin, Tsung-Yi, et al. "Focal loss for dense object detection." ICCV 2017.
  - Might not work well for small objects
- Faster RCNN family
  - Two stage
  - The second stage can focus on ROI proposals
  - Might be slower than YOLO

Object Detection on COCO test-dev

Leaderboard Dataset

View box AP by Date for All models



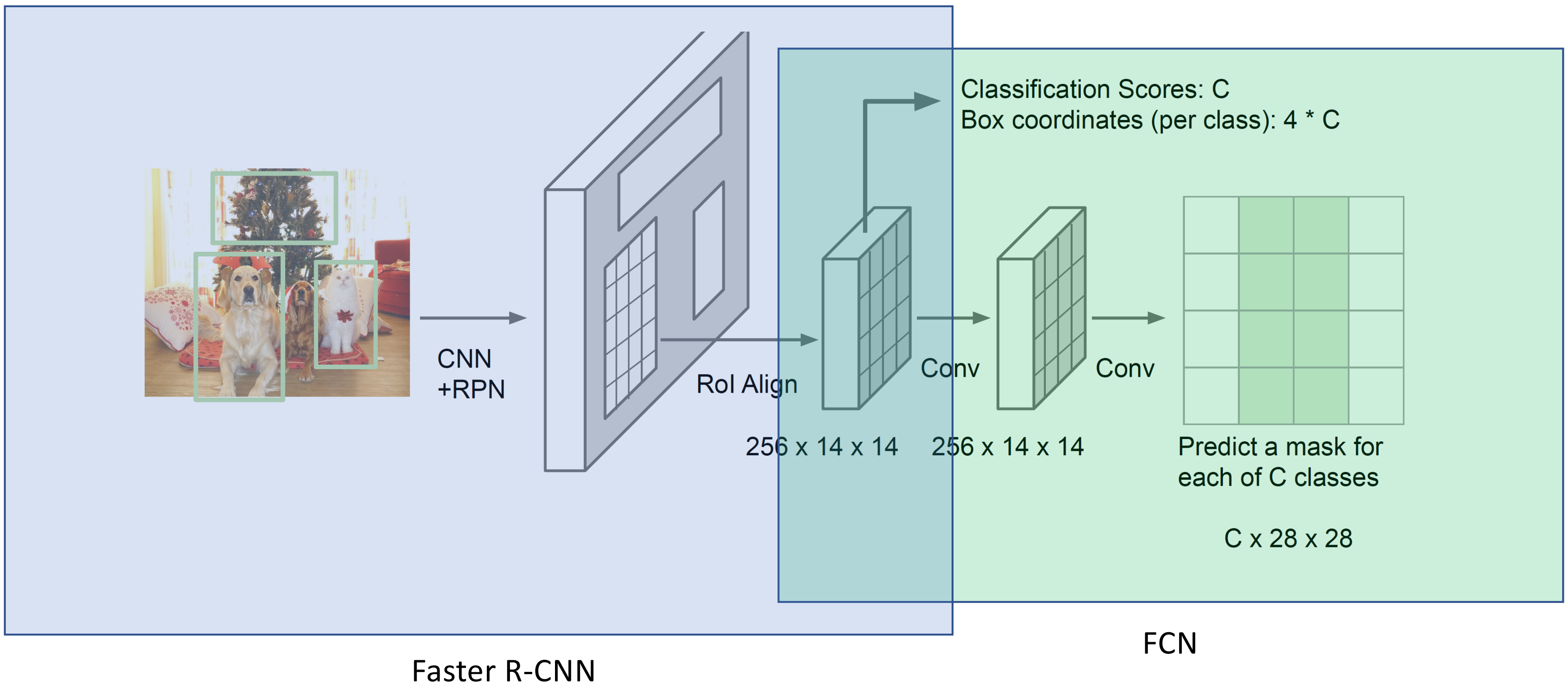
Filter: multiscale ResNet ResNeXt FPN single scale DCN YOLO Swin-Transformer Transformer NAS-FPN GCN Vision Language Dynamic Head BERT-Base Focal-Transformer untagged Hardware Burden Operations per network pass

Edit Leaderboard

https://paperswithcode.com/sota/object-detection-on-coco

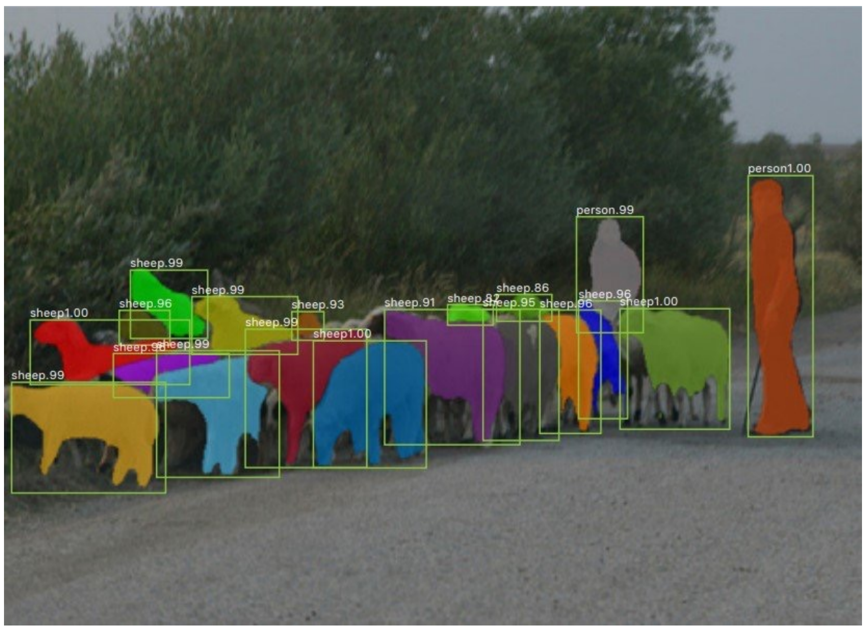
Object Detection + Semantic Segmentation

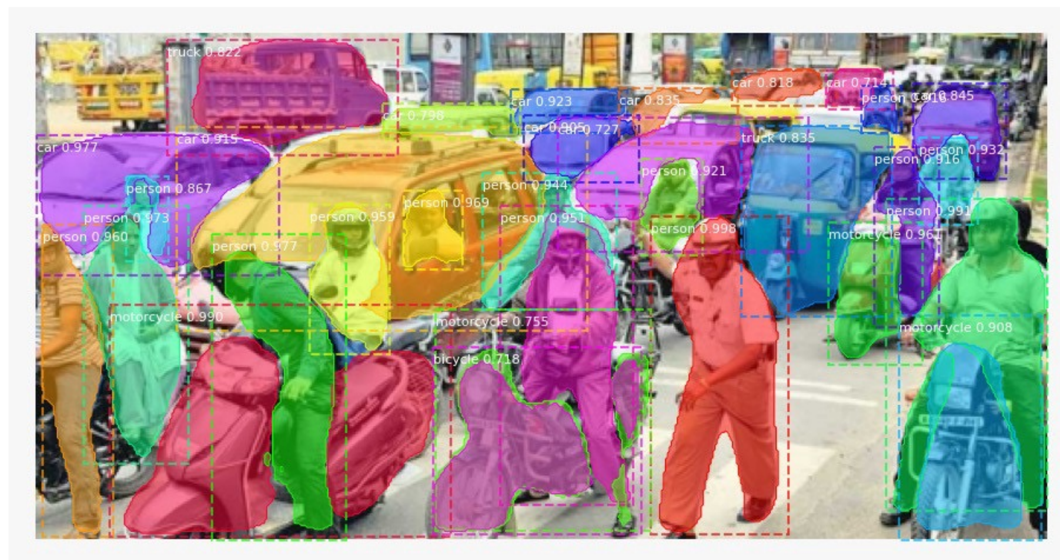
Instance Segmentation: Mask R-CNN



He et al, "Mask R-CNN", arXiv 2017

Mask R-CNN Results

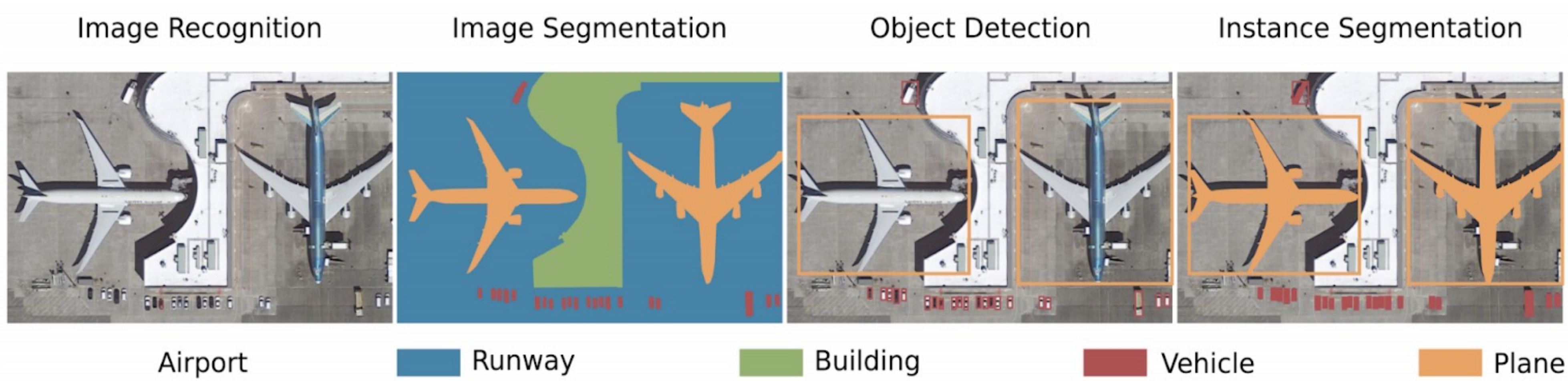




Overhead Imagery Understanding

Overhead Imagery Understanding Tasks

- Typically customize existing CV models with pretrained weights
  - YOLO or Faster R-CNN for object detection
  - Unet or similar architecture for semantic segmentation



Thorsten Hoeser and Claudia Kuenzer. 2020. Object detection and image segmentation with deep learning on earth observation data: A review-part i: Evolution and recent trends. *Remote Sensing*. Retrieved from https://www.mdpi.com/723500

Open Challenges

- The need of customization of network architectures come from open challenges in dealing with overhead imagery
  - Small objects
  - Imbalanced data, inconsistent training data domain (e.g., scenic photos vs overhead imagery)
  - Large search space/large image
  - Multi-scale
  - Multi-orientation
  - Multi-bands
  - Occlusion (camera angle or vertical occlusion)
  - Varying imagery quality (shadows, cloud covers, over/under-exposition)

You Only Look Twice: Rapid Multi-Scale Object Detection In Satellite Imagery

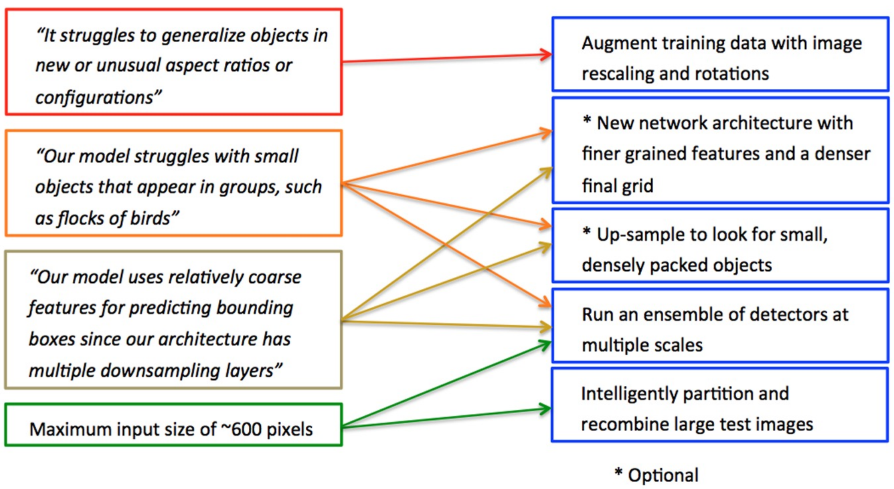
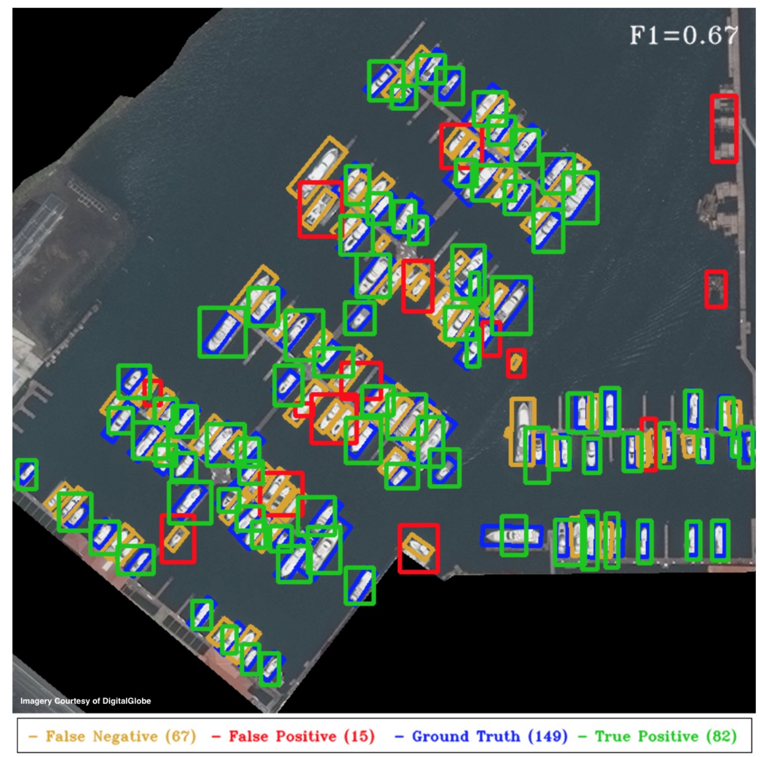


Figure 3: Limitations of the YOLO framework (left column, quotes from [10]), along with YOLT contributions to address these limitations (right column).



https://arxiv.org/abs/1805.09512
https://medium.com/the-downlinq/you-only-look-twice-multi-scale-object-detection-in-satellite-imagery-with-convolutional-neural-38dad1cf7571

Generating Location Specific Training Data

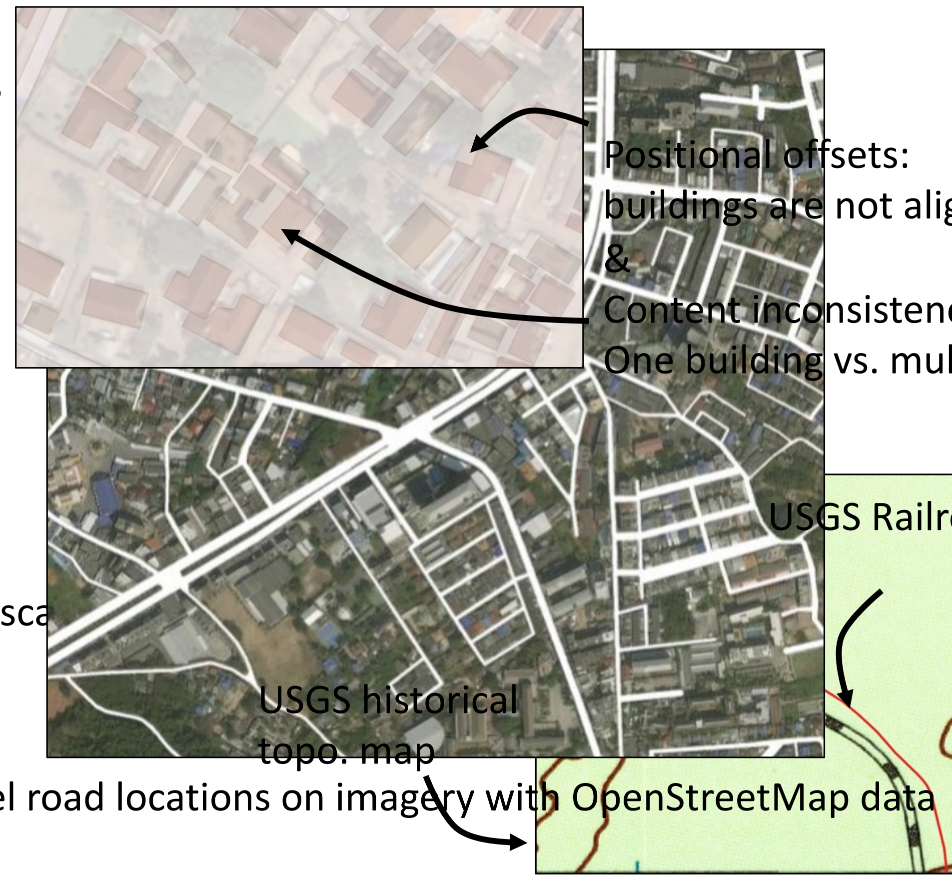
- **Location** is the key to link various types of data
  - e.g., can provide context-rich annotated (training) data (if we do it correctly)

"By using the data in OSM, we were able to collect more than 100 million labeled examples to add to our training data set."
"However, using OSM data for labels presented several challenges that required novel approaches to overcome."

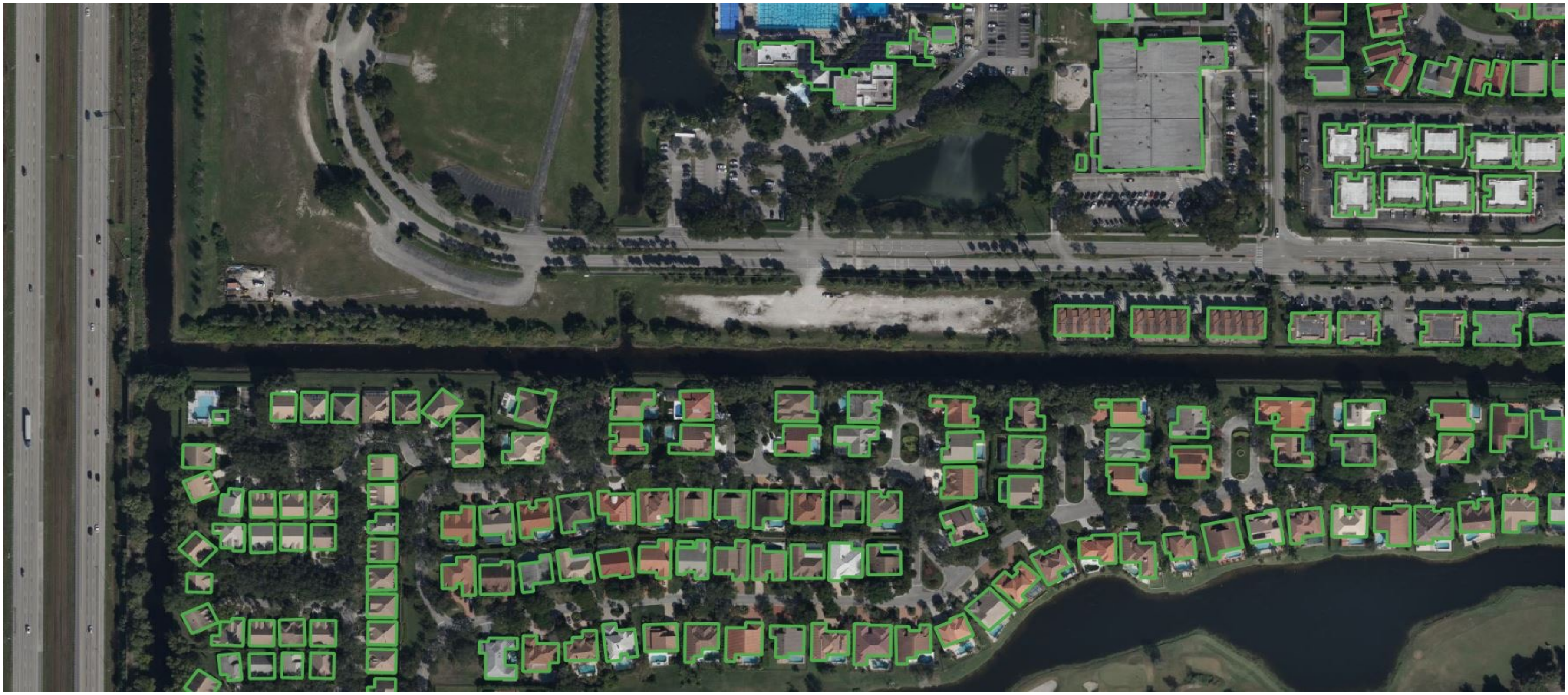
Meta AI

~~Facebook~~ Map with AI

https://ai.facebook.com/blog/mapping-the-world-to-help-aid-workers-with-weakly-semi-supervised-learning/



Microsoft Building Footprints



https://www.microsoft.com/en-us/maps/building-footprints

Conflation: Generating your own training data

A short introduction

Conflation

- Integrating multiple geo-spatial datasets by establishing the correspondence between matched entities (control point pairs) and transforming the other objects accordingly

Conflation

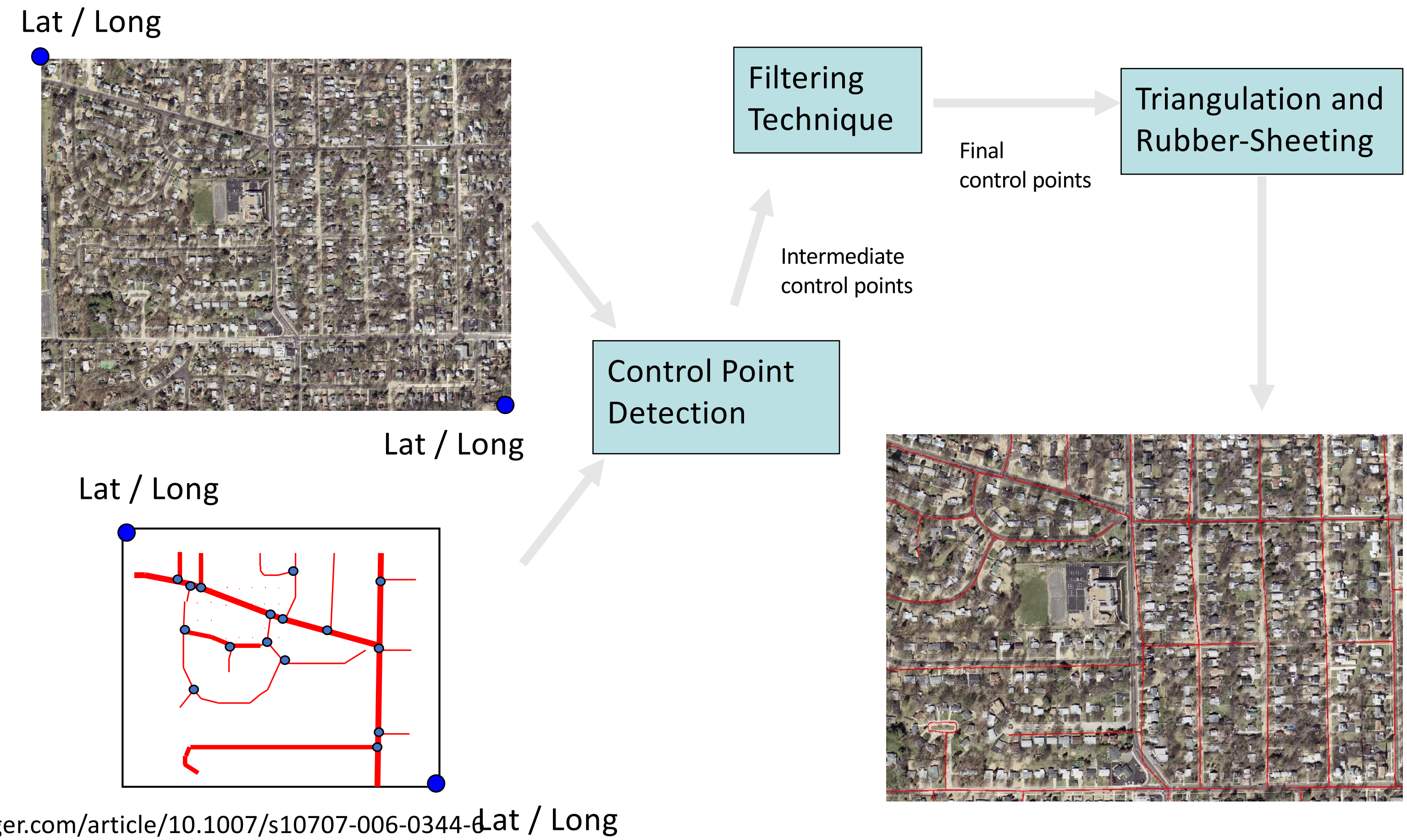
Challenges

- Different projections, accuracy levels, resolutions
- Result in spatial inconsistencies

D.C.

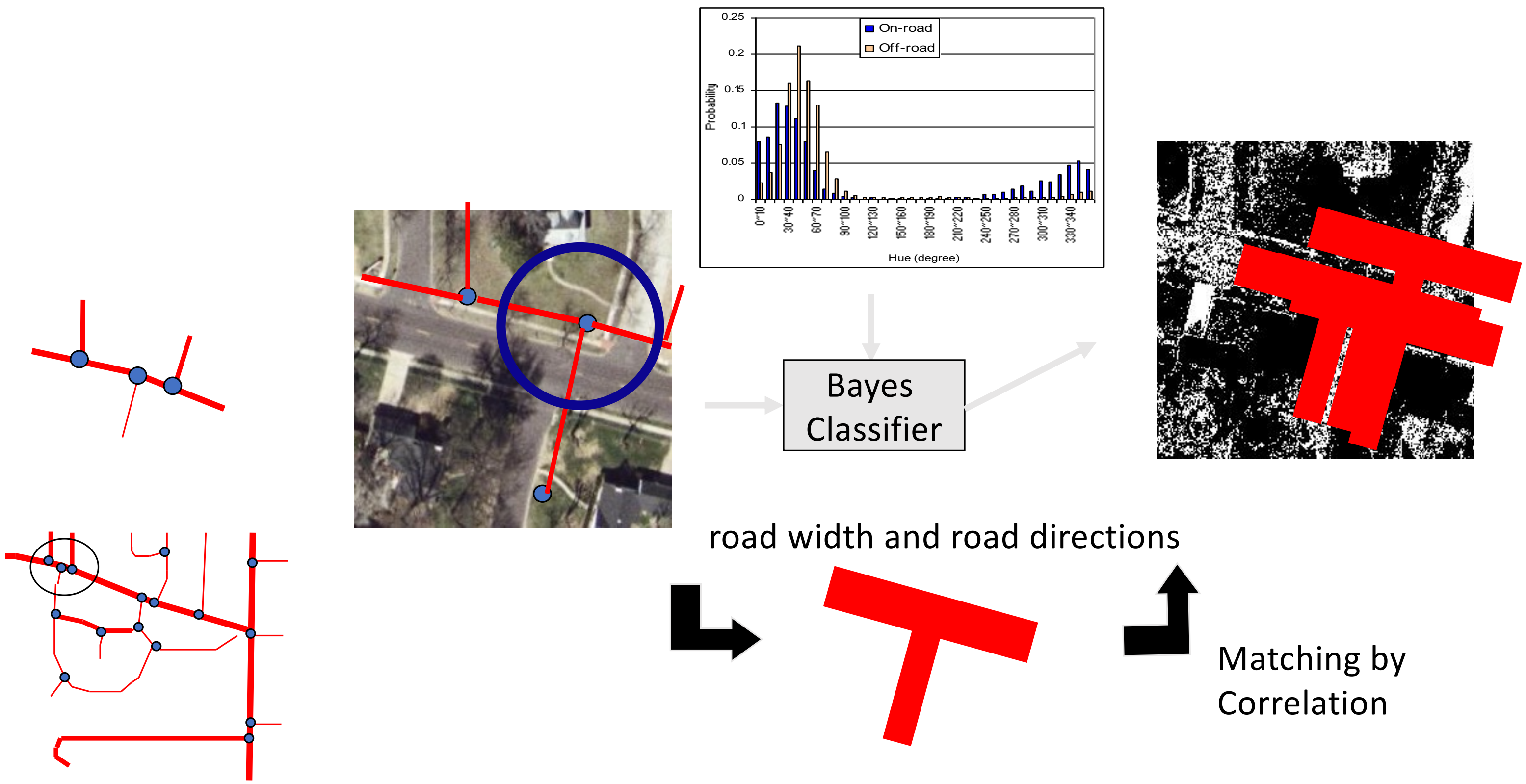
Ft. Campbell, KY (only zoom into 1m/p)

AMS-Conflation to Align Vector and Imagery



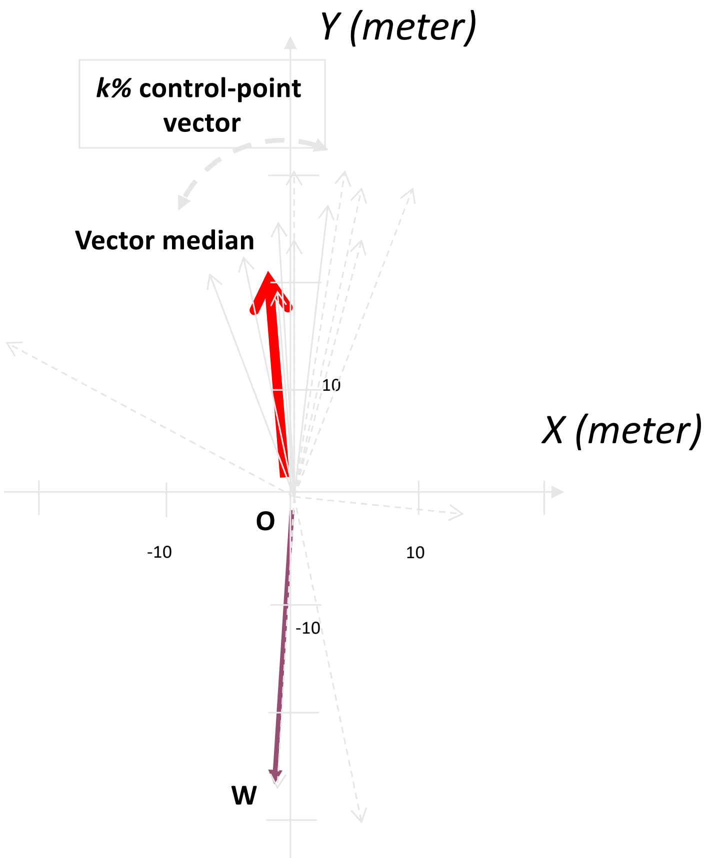
https://link.springer.com/article/10.1007/s10707-006-0344-6

Localized Template Matching (LTM)



https://link.springer.com/article/10.1007/s10707-006-0344-6

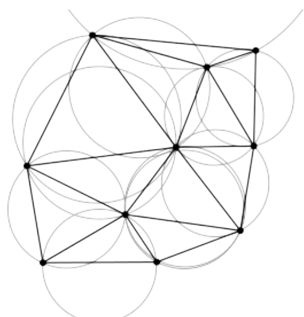
Filtering Control Point Pairs Using Vector Median Filter (VMF)

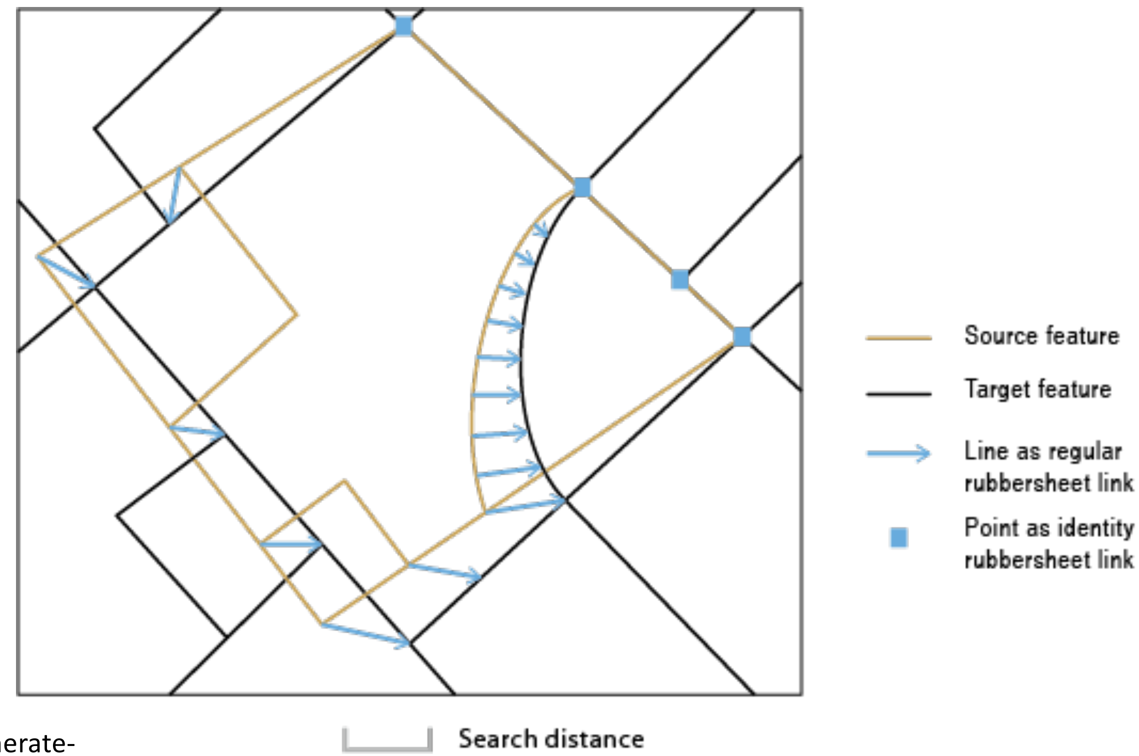


https://link.springer.com/article/10.1007/s10707-006-0344-6

Triangulation & Rubbersheeting

- Delaunay triangulation on the CP pairs (maximize the minimum angle of all the angles of the triangles)
- Use the 3 CP pairs for each triangle to calculate a transformation matrix
- Transform data within each triangle according to the matrix





https://desktop.arcgis.com/es/arcmap/10.3/tools/editing-toolbox/generate-rubbersheet-links.htm
https://en.wikipedia.org/wiki/Delaunay_triangulation

MO-DOT+ High-resolution USGS Color Image

Red lines: Original MO-DOT
Blue lines: Conflated lines

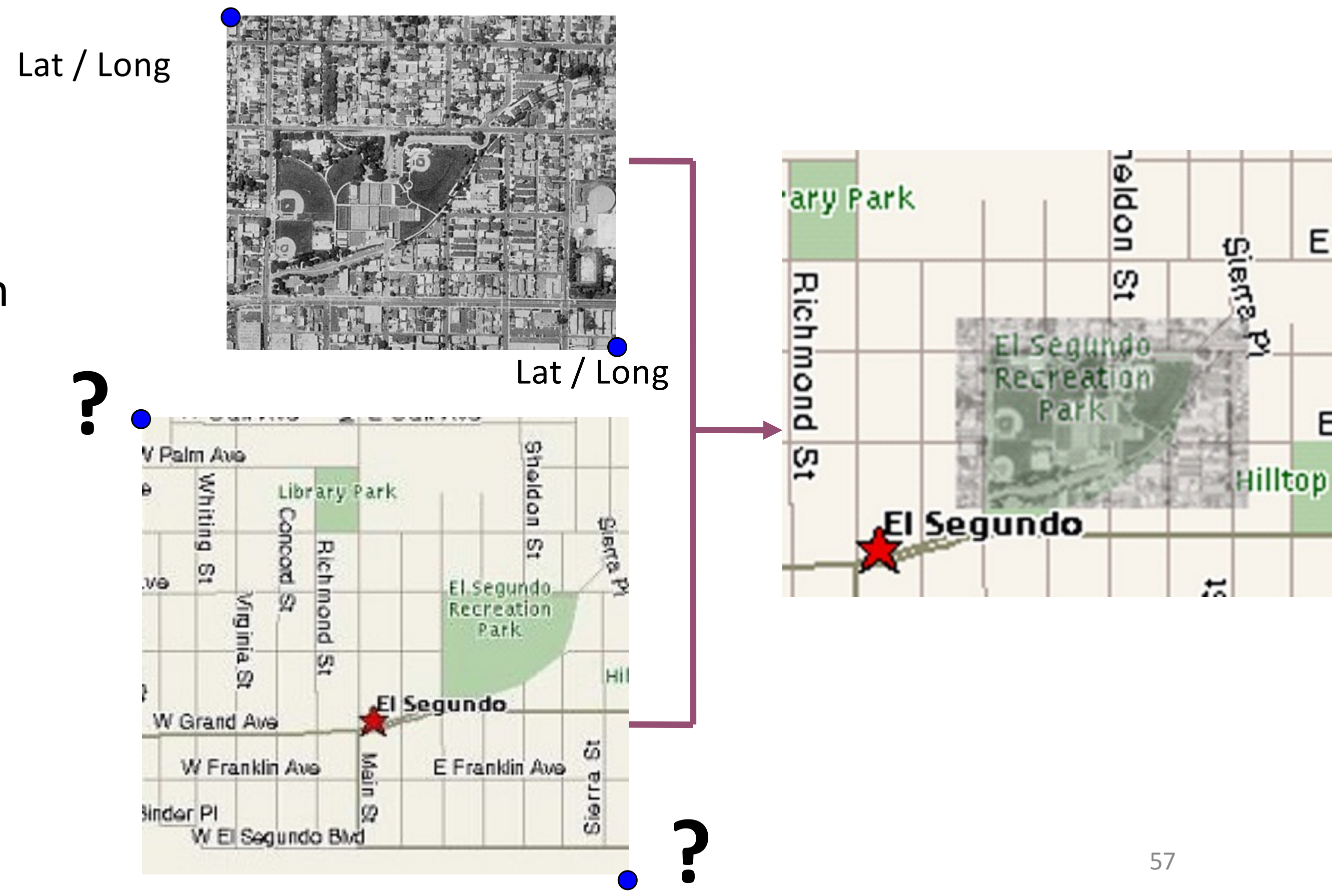
NAVSTREETS+ High-resolution USGS Color Image

Red lines: Original NAVSTREETS roads
Yellow lines: Conflated lines

Conflation Results: Parcel data

Matching Point Sets for Conflation

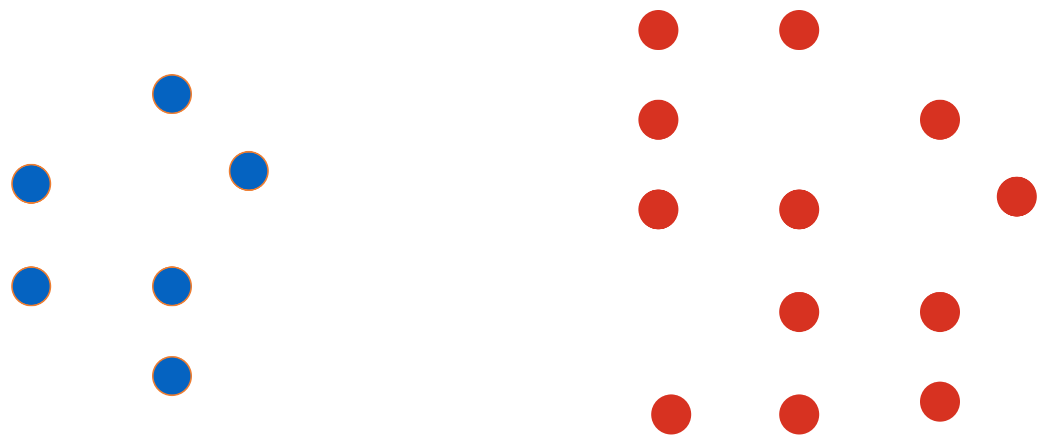
- Sometimes one data source does not provide the exact geocordinates
- Find salient features from both datasets for matching
  - e.g., road intersections
- A point pattern matching problem



https://doi.org/10.1145/1032222.1032231

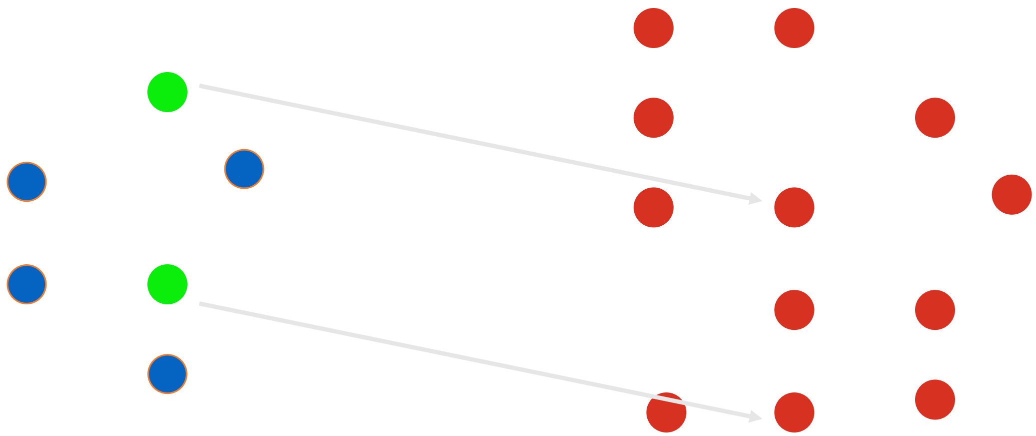
Point Pattern Matching

- Pick a pair of points in first dataset



Point Pattern Matching

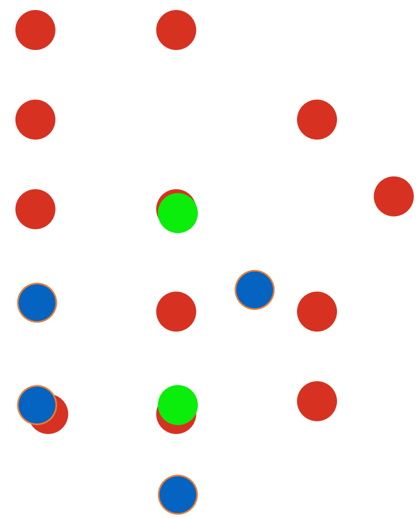
- Pick a pair of points in first dataset
- Pick two random points in the second dataset



Point Pattern Matching

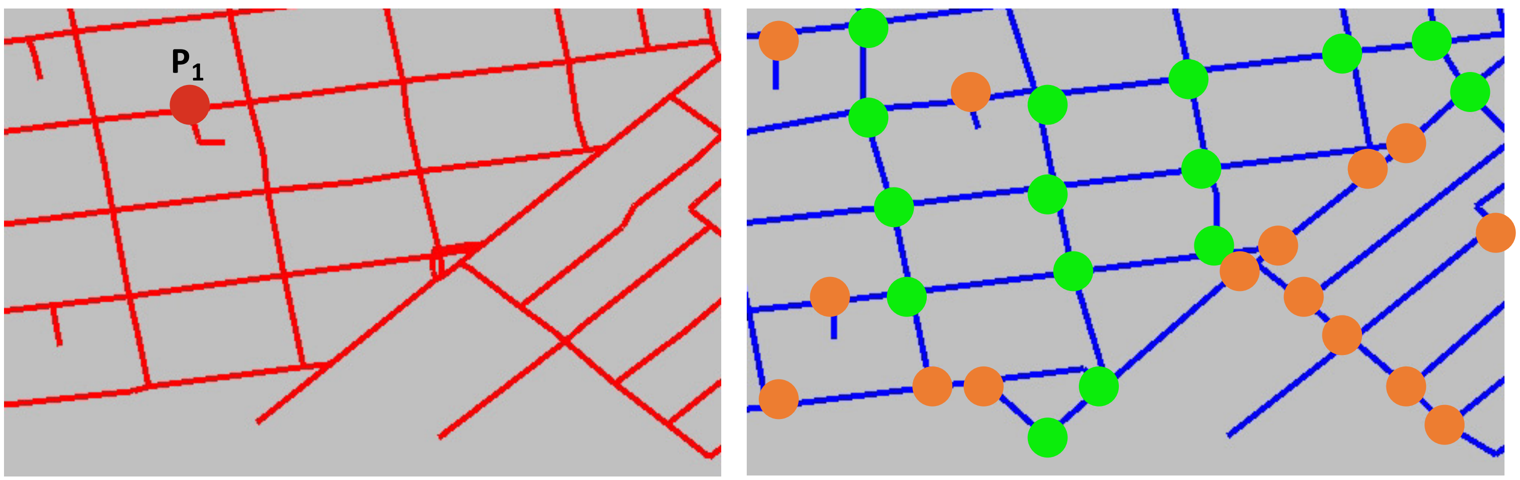
- Pick a pair of points in first dataset
- Pick two random points in the second dataset
- Apply the same transformation all points
- Calculate the number of matches

$\boxed{\text{Repeat until every point has a match}}$



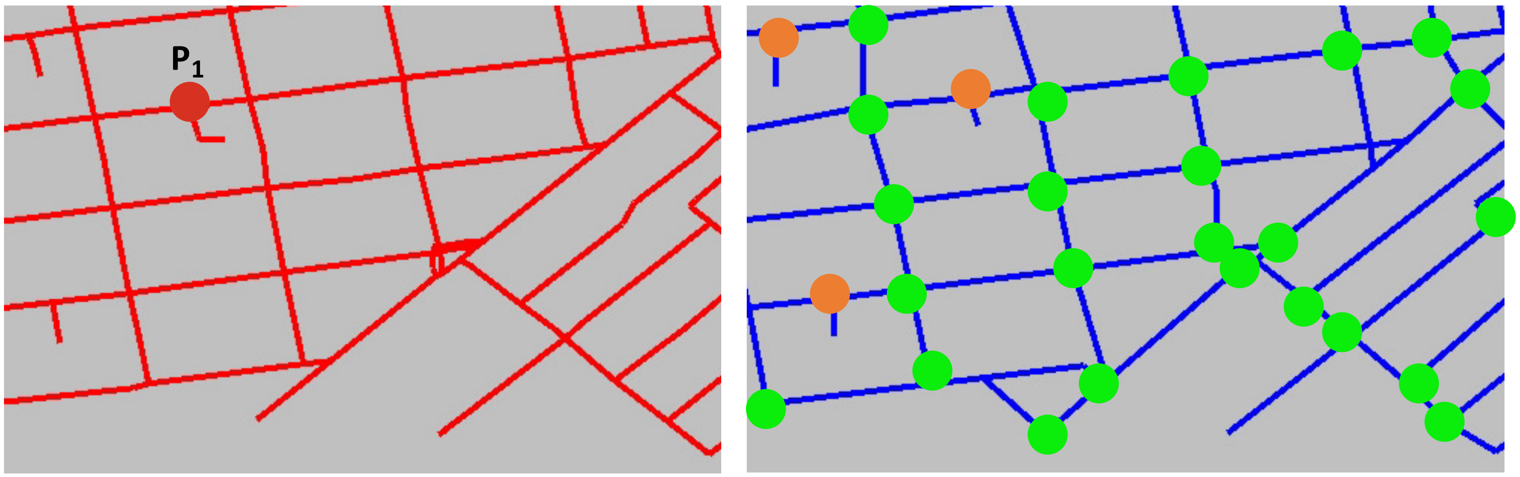
- Complexity is very high!

GeoPPM: Exploit Connectivity



Light Green: Impossible candidates for P_1
Orange: Possible candidates for P_1

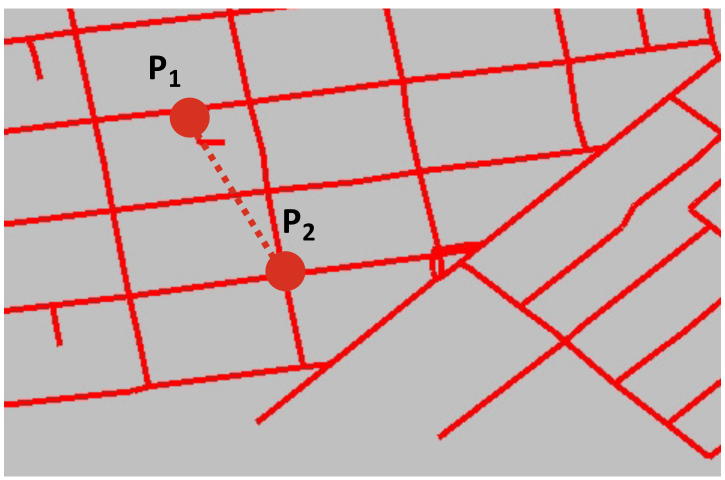
GeoPPM: Exploit Orientation

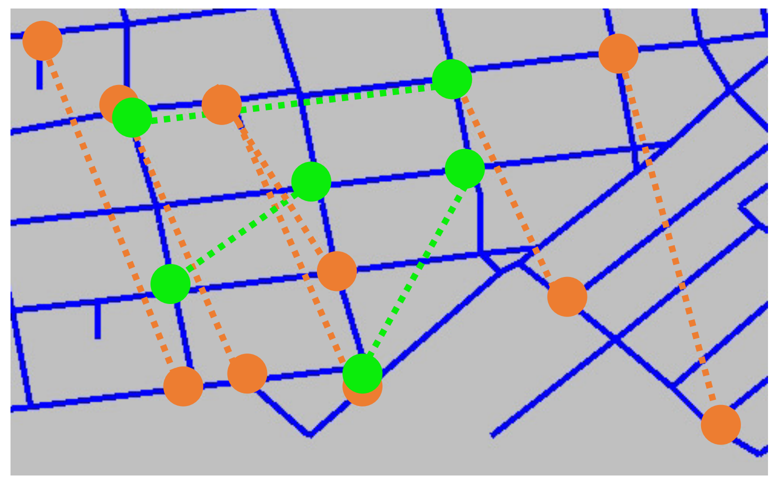


Orange: Possible candidates for P_1

Light Green: Impossible candidates for P_1

GeoPPM: Exploit Angles between Points

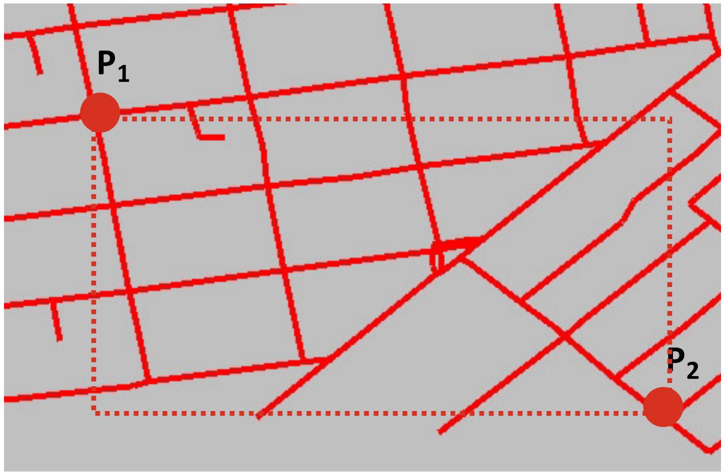


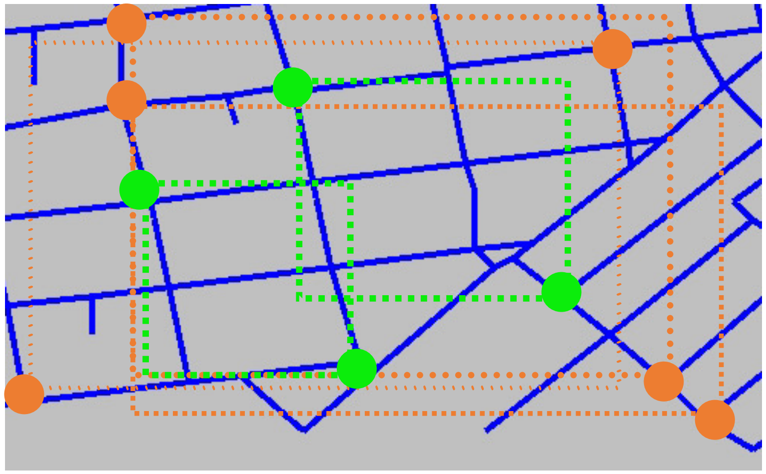


Some of the possible candidate pairs for P_1,P_2

Some of the impossible candidate pairs for P_1,P_2

GeoPPM: Exploit Density between Points



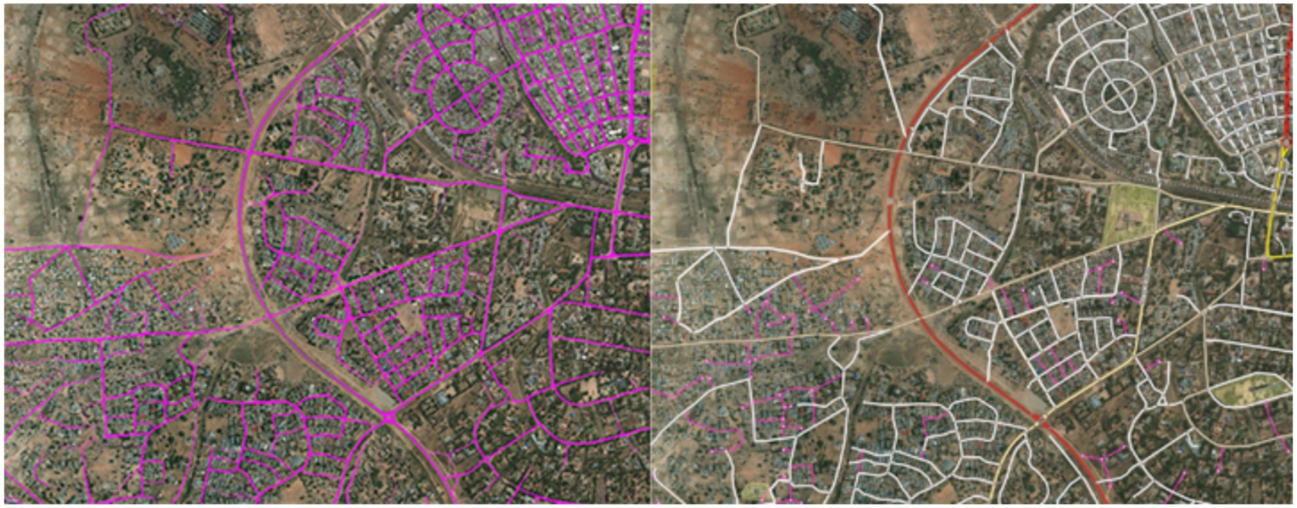


Some of the possible Candidate pairs for P_1,P_2

Some of the impossible Candidate pairs for P_1,P_2

Conflation Summery

- We can integrate geographic data from different sources by establishing correspondence between datasets
- Conflation helps
  - generate accurate training data for imagery understanding (and other machine learning tasks)
  - integrate the extracted data from imagery to existing data



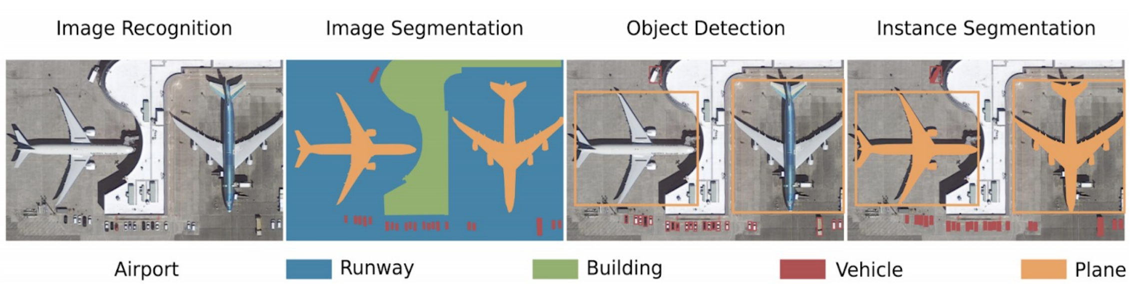
Left: results of the segmentation model per-pixel predictions; bright magenta means higher probability of the pixel belonging to a road. Right: Conflation of the vectorized roads data with the existing OSM roads (in white). (Satellite images provided by Maxar.)

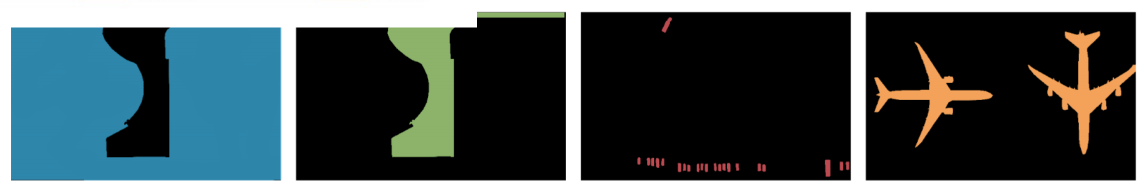
https://ai.facebook.com/blog/mapping-roads-through-deep-learning-and-weakly-supervised-training/

One more thing: EarthScan

EARTHSCAN
spatial ai powered earth x-ray

- How to effectively exploit prior knowledge of things in space for
  - Detecting objects from overhead imagery using reduced numbers and varieties of annotated visual samples, and
  - Parsing overhead imagery into complete geographic layers





Duan, et al. A Label Correction Algorithm Using Prior Information for Automatic and Accurate Geospatial Object Recognition. IEEE BigData
Duan, et al. Guided Generative Models using Weak Supervision for Detecting Object Spatial Arrangement in Overhead Images. IEEE BigData

Resources

- Datasets: https://github.com/chrieke/awesome-satellite-imagery-datasets
- Methods/Code: https://github.com/robmarkcole/satellite-image-deep-learning

Acknowledgements

- Deep learning slides adapted from https://m2dsupsdlclass.github.io/lectures-labs/ by Olivier Grisel and Charles Ollion (CC-By 4.0 license)
- Gil, Yolanda (Ed.) Introduction to Computational Thinking and Data Science. Available from http://www.datascience4all.org

We welcome your feedback and contributions.