Weapon Detection using Deep Learning Architecture

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Problem Statement

Detection of Guns using different Object Detection Deep Learning Techniques - Faster RCNN and Mask RCNN.

Motivation


TRUSTED. BALANCED. LOCAL.

Orlando Sentinel

Thursday, February 15, 2018

TOP STORY

AT LEAST 17 KILLED IN SCHOOL SHOOTING

House wants major expansion of scholarship program

OPD Chief Mina flies paperwork to run for Orange County mayor

Orlando activist looks to inspire kids with 'Black Panther' movie


Couples renew vows at beach ceremony

Naples Daily News

SCHOOL SHOOTING IN BROWARD COUNTY

'HORRIFIC DAY'

17 killed in high school attack; former student, 19, in custody

Donalds won't run for School Board again

MIROMAR OUTLETS

ROCK CLIMBING FUNWALLS GRAND OPENING

Saturday, February 17 at 11 a.m. in WORLD PLAYLAND


Thursday

The Palm Beach Post

POST IN-DEPTH BROWARD SCHOOL SHOOTING

17 SLAIN BY GUNMAN AT BROWARD SCHOOL

Cops: Expelled student had AR-15, extra ammo and smoke grenades.

Gov. Rick Scott, on the scene in Parkland: 'This is absolutely pure evil.'

Avossa: Expect police presence in Palm Beach County schools today.


Pathankot: Gunmen attack India air force base

Four attackers, 2 soldiers killed

Pakistan condemns attack


Find the right gift

Beat the stress with ideas from our holiday gift guide. It comes with its own bow, too. Weekend

Tampa Bay Times

FLORIDA'S BEST NEWSPAPER

tampabay.com

THURSDAY, DECEMBER 3, 2015 | $1

Mass attack kills 14; suspects die in gunfire

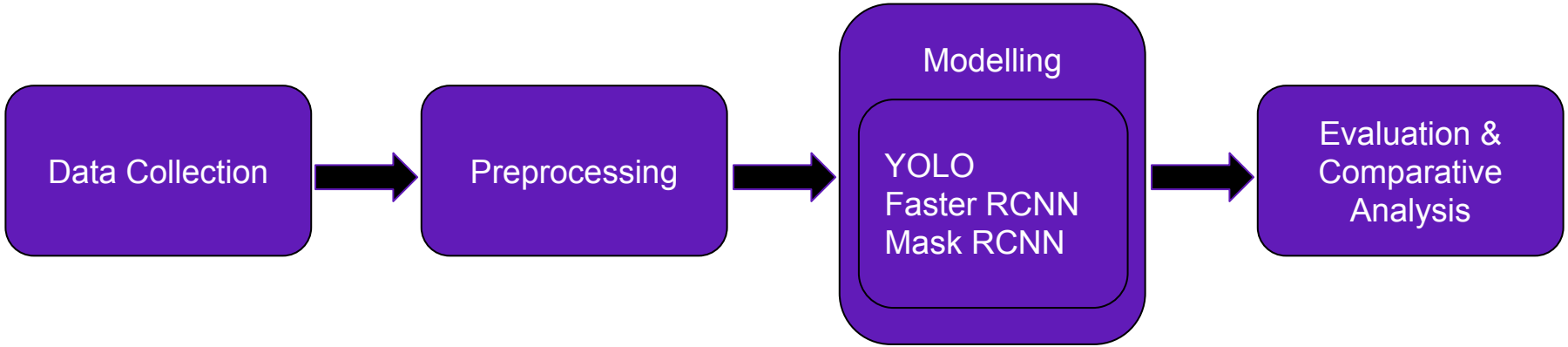
» It was the deadliest gun violence since Newtown, Conn., in 2012.

» California officials seek a motive for the assault on a social services center.

REUTERS/NBCLA.com

Rescue crews tend to the injured Wednesday in the intersection outside the Inland Regional Center in San Bernardino, Calif., in this image taken from video. Attackers burst into a social services center that helps people with disabilities. Two people armed with assault rifles and handguns were later killed in a gunbattle.

Methodology



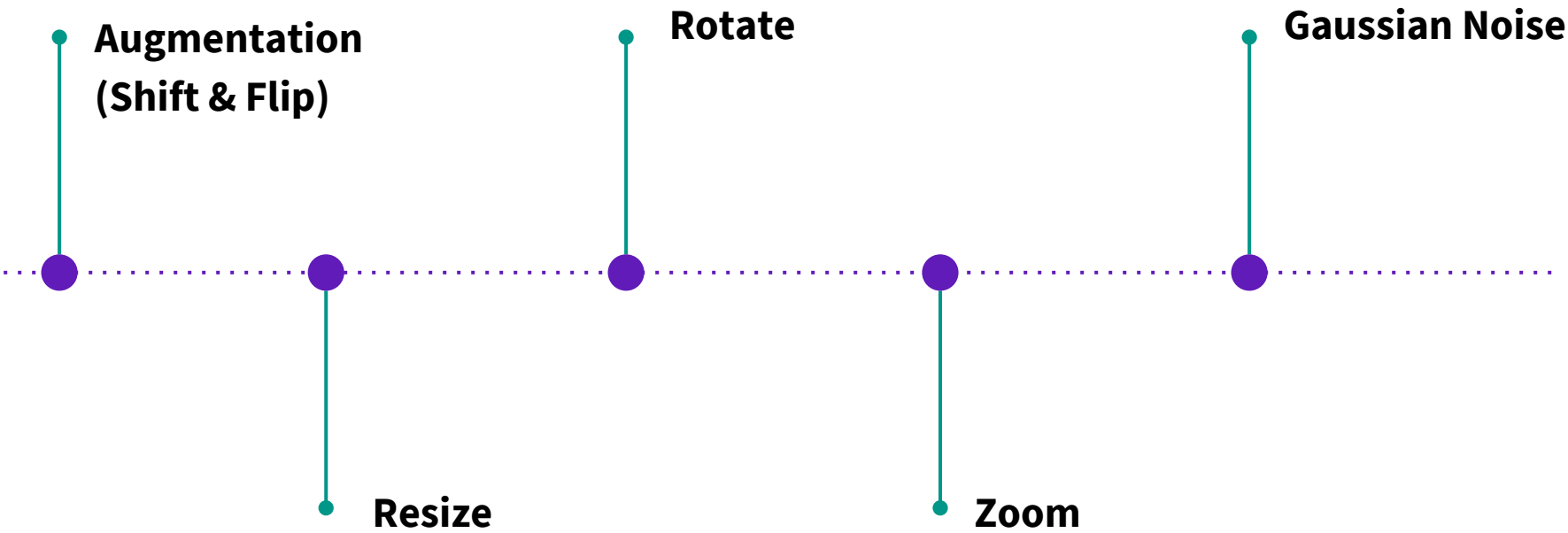
Data Collection

- Handgun Datasets from for all 3 approaches - https://sci2s.ugr.es/weapons-detection
    1) Collected 3000 images for object detection with YOLO and Faster RCNN
    2) Created 1751 annotated images for object detection in Mask RCNN
    3) 3405 images for classification task using Transfer learning to reduce false positives
- ImageNet Database
- COCO Dataset

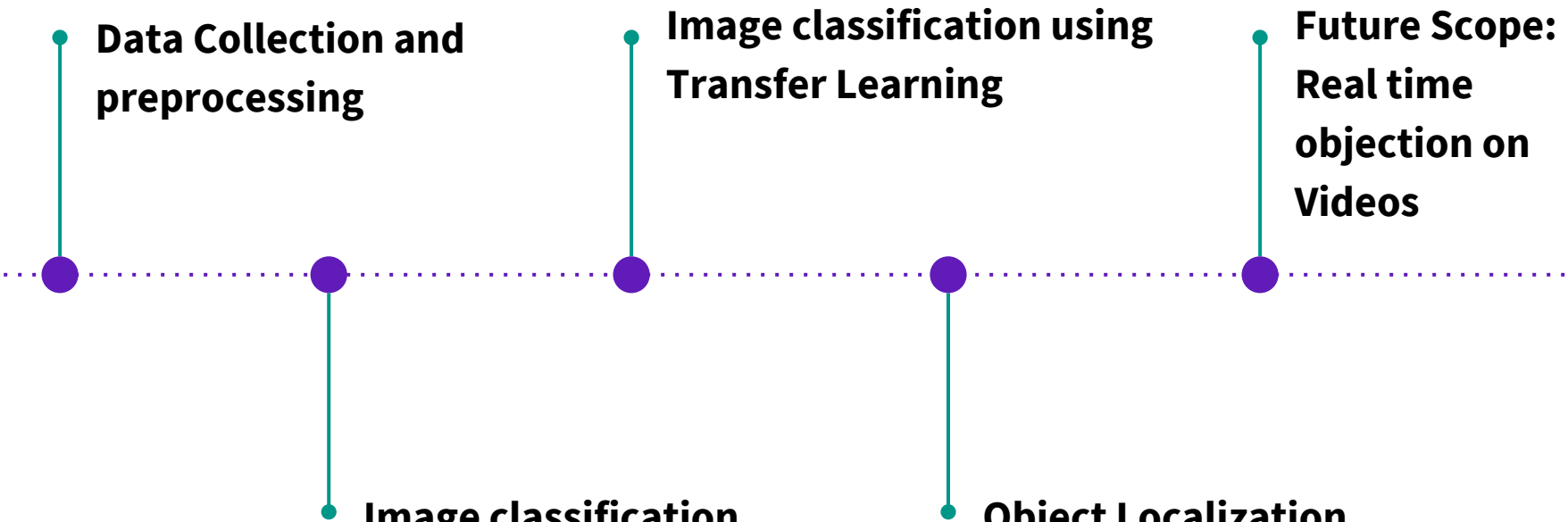
Annotation of Images for YOLO & Faster RCNN

Annotation of Images for Mask RCNN

Pre-processing Images



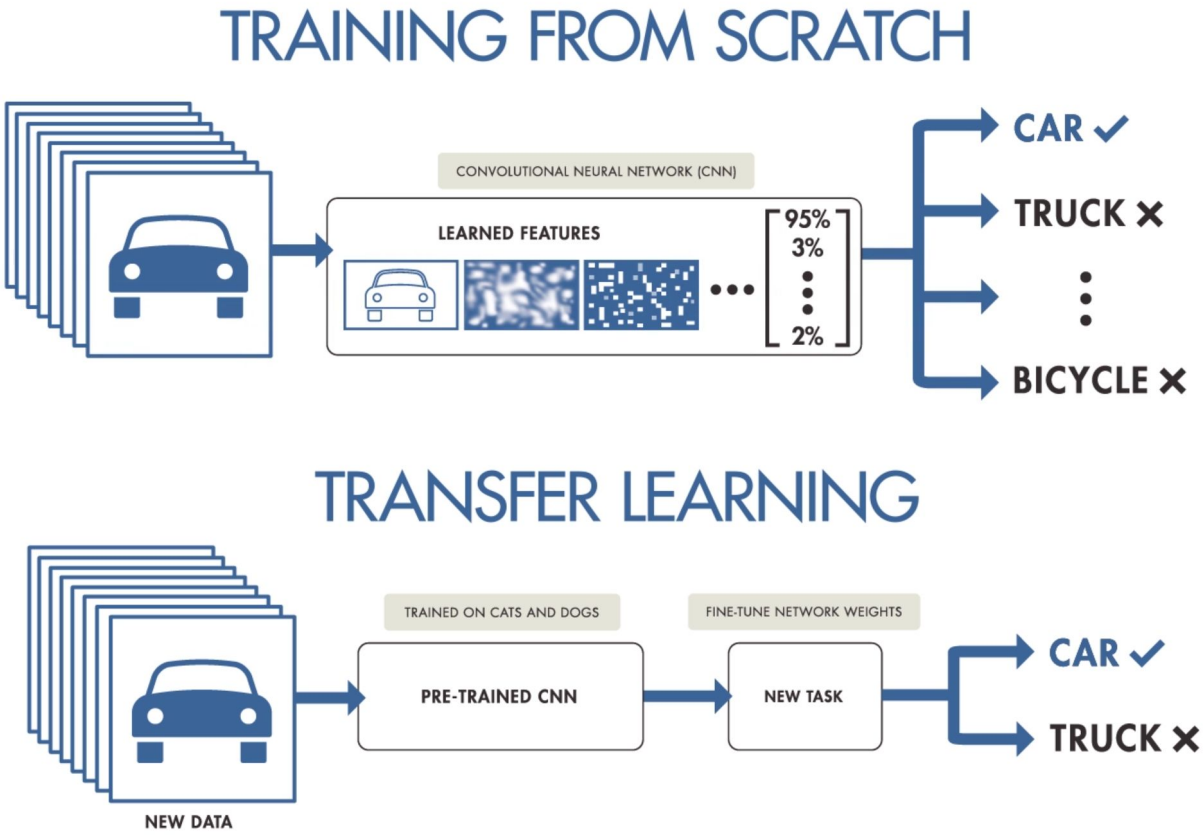
MODELLING ROADMAP



Transfer Learning

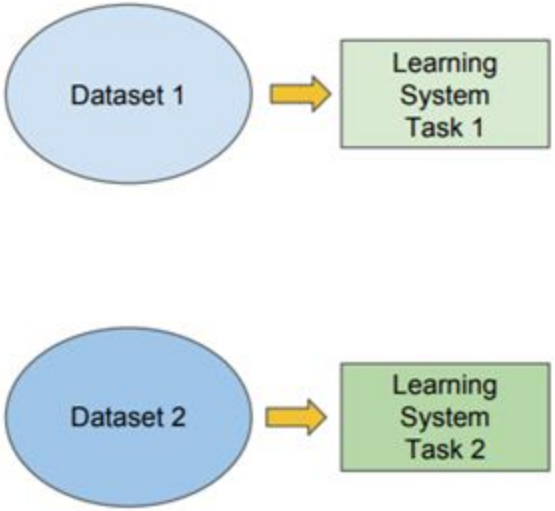
1. Transfer learning is a popular method in computer vision because it allows us to **build accurate models in a timesaving way** (Rawat & Wang 2017).
2. In computer vision, transfer learning is usually expressed through the use of **pre-trained models**.
3. Due to the high computational cost of training complex models, it is common practice to import and use models from published literature (e.g. VGG, Inception, MobileNet)

Concept of Transfer Learning

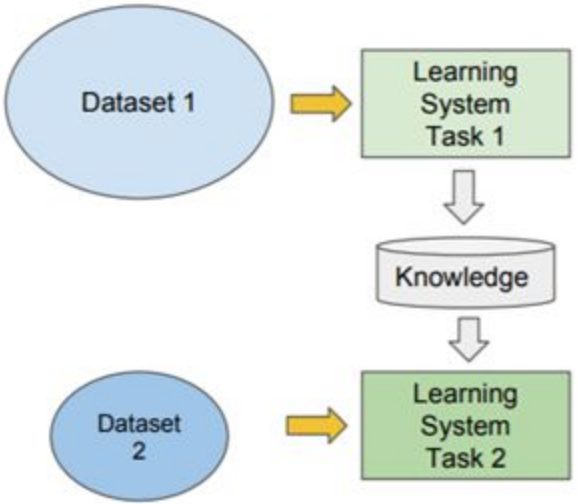


Traditional ML vs Transfer Learning

- Isolated, single task learning:
  - Knowledge is not retained or accumulated. Learning is performed w.o. considering past learned knowledge in other tasks



- Learning of a new tasks relies on the previous learned tasks:
  - Learning process can be faster, more accurate and/or need less training data



Repurposing a pre-trained model

We fine-tune our model according to one of these strategies:

1. Train the entire model with the pre-trained models architecture(Computationally expensive and data issues)
2. Train some layers and leave the others frozen.

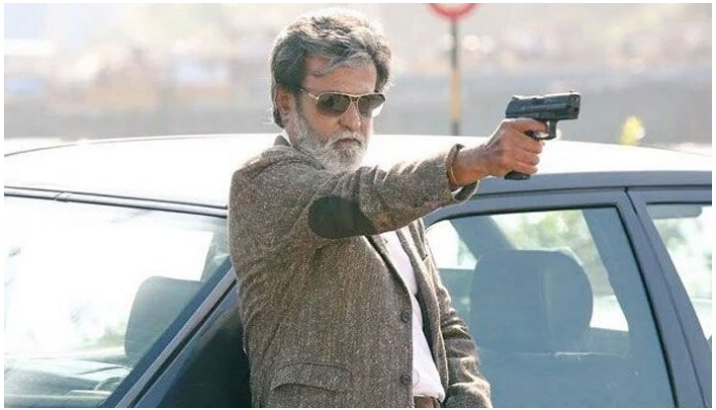
Image Classification Statistics

Model	Data Augmentation	Test Accuracy	Comments
CNN(Build from scratch)	No	0.66	
CNN(Build from scratch)	Yes	0.67	No significant boost
Pre-trained Model on Imagenet(Resnet,Inception V3, MobileNet)	No	0.87	
Pre-trained Model on Imagenet(Resnet,Inception V3, MobileNet) (With RMSprop and categorical_crossentropy as loss function)	Yes	0.91	Significant boost from original architecture

Image classification to object detection

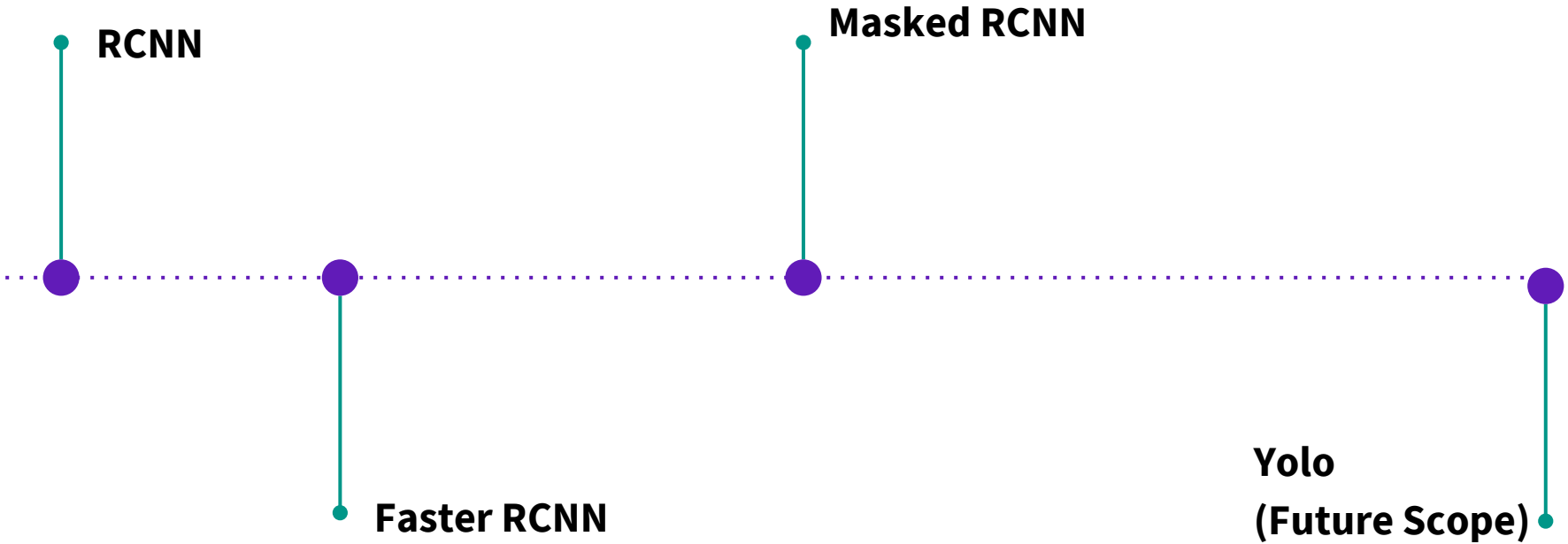
In Object detection, a bounding box is drawn around the object of interest to locate it within the image.

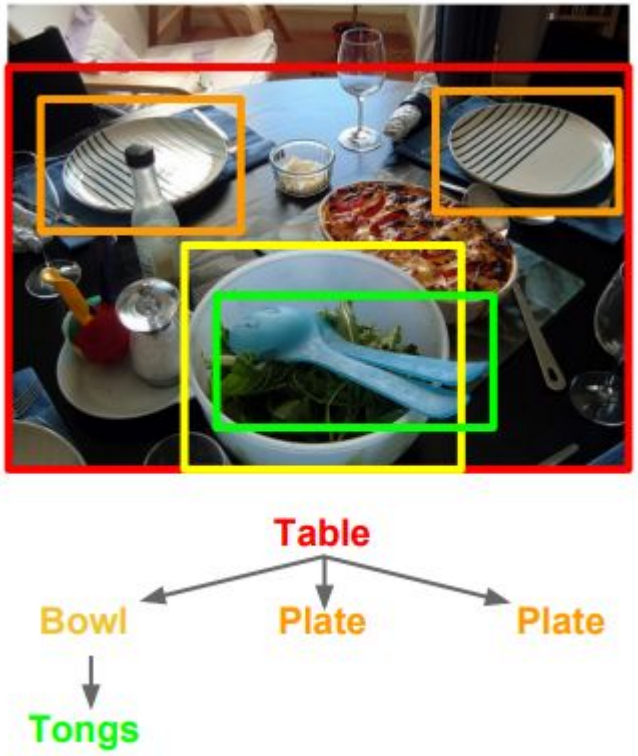
Why can’t we just use CNN?



Many bounding boxes representing different objects of interest within the image which may not be know beforehand i.e. length of output layer is variable.

Object Detection ROADMAP



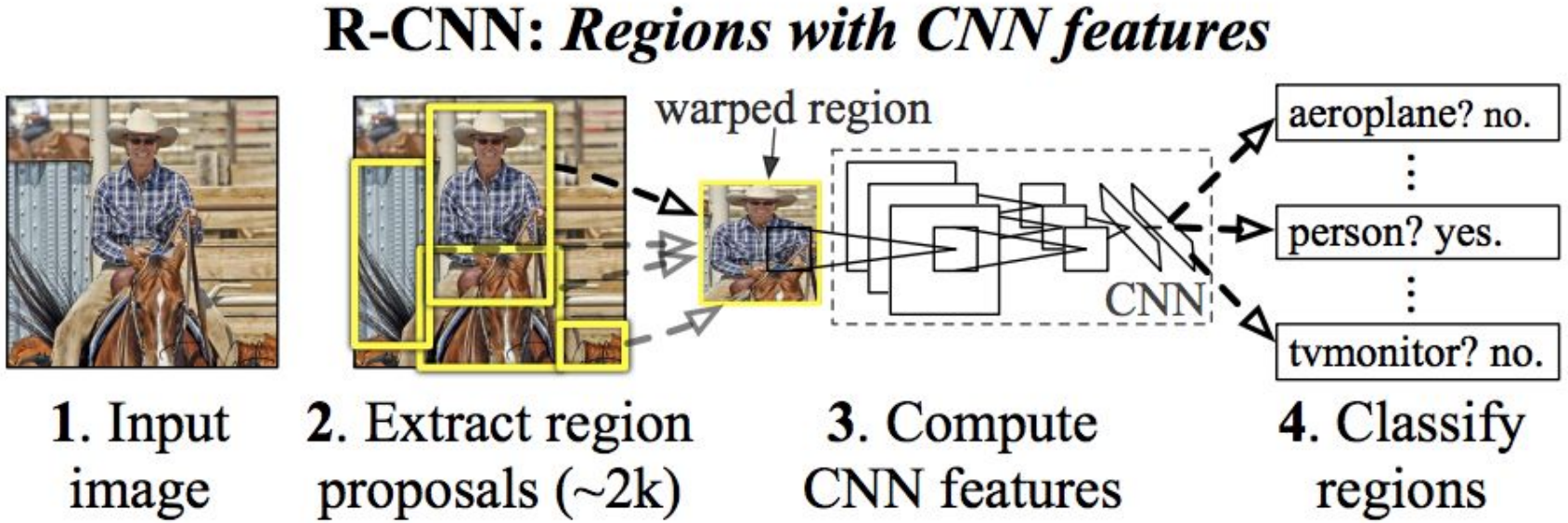


Sub-Segmentation maintaining Hierarchical Representation

1. Maintain Hierarchy
2. Generate many regions each of which belongs to at most one object.

Detect Multiple Overlapping Object

R-CNN


R-CNN: Regions with CNN features
warped region
CNN
aeroplane? no.
person? yes.
tvmonitor? no.
1. Input image
2. Extract region proposals (~2k)
3. Compute CNN features
4. Classify regions

Problems faced while building R-CNN

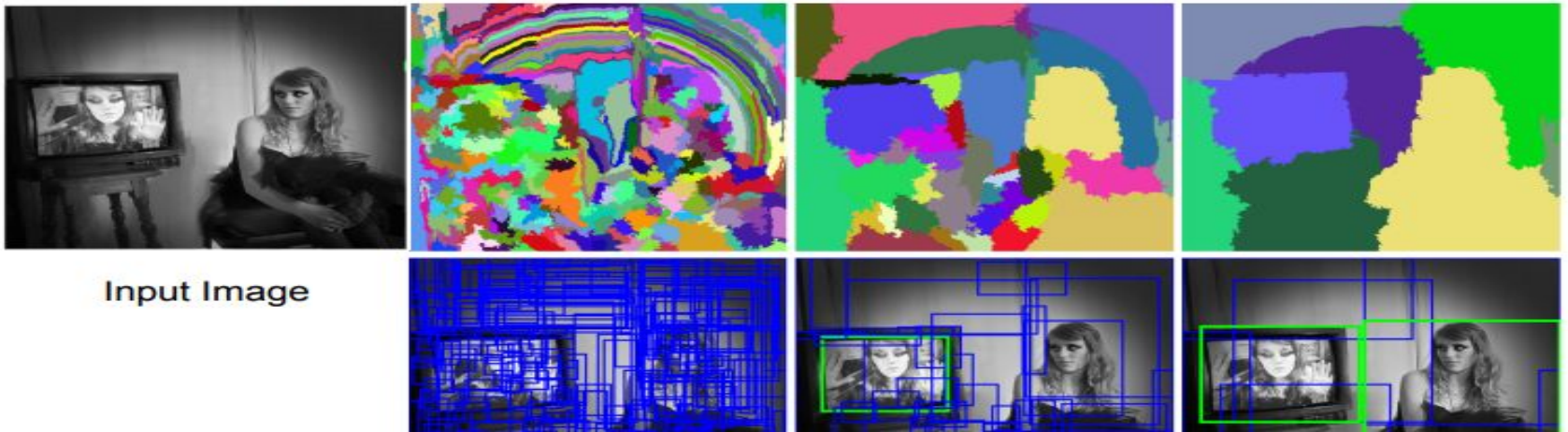
- It took a huge amount of time to train the network as it classified 2000 region proposals per image.
- Couldn’t be scaled as it took around 47 seconds for each test image.
- The selective search algorithm(Greedy Approach) is a fixed algorithm. Hence, no learning was happening at that stage and it lead to the generation of bad candidate region proposals and hence bas object detection.

Selective Search

1. Idea: Use bottom-up grouping of image regions to generate a hierarchy of small to large regions.
2. Recursively combine similar regions into larger ones. Greedy algorithm:

- From set of regions, choose two that are most similar.
- Combine them into a single, larger region.
- Repeat until only one region remains. This yields a hierarchy of successively larger regions.

Step 3: Use the generated regions to produce candidate object locations.



Input Image

Faster RCNN

Concept of Region Proposal Network(RPN) & fixing time complexity

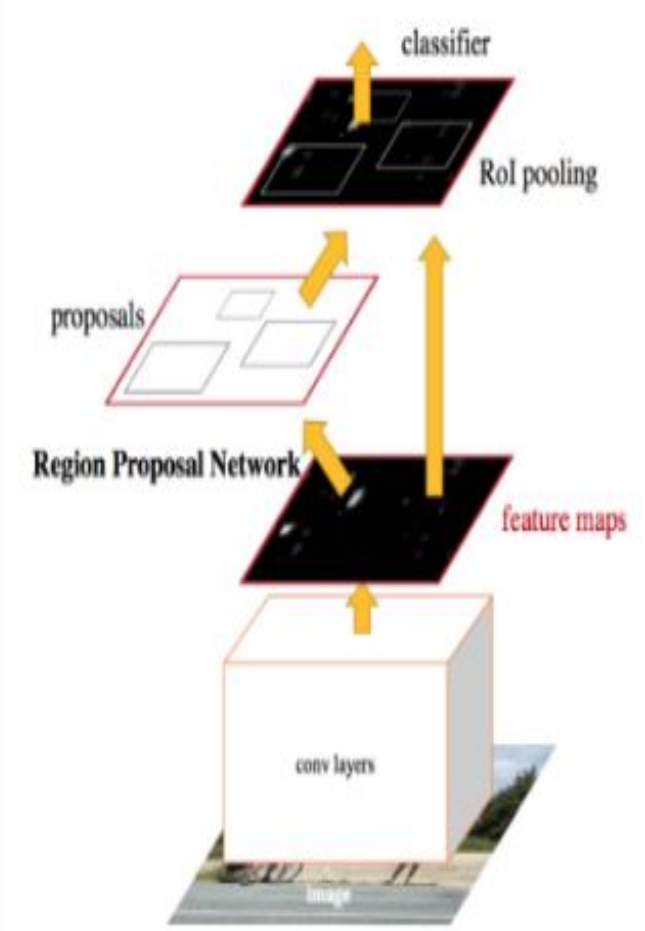


Fig. 7. An illustration of Faster R-CNN model. (Ima

- 3 things we have changed:

1. CNN at first
2. Instead of S.S use RPN
3. Then ROI pooling.

- Train RPN:

1. Each feature map creates anchors.
2. Anchors have 3X3 boxes of diff ratios(1:1, 1:2, 2:1)
3. Sampling, non-max-suppression used to reduce no of boxes.
4. ROI based cropping pooling.

Faster RCNN

Detail Architechture

1. Taken ResNet50 architecture at backend. With random initialization.
2. Train Samples: 2514. Val Sample: 486
3. Less amount of data on single class.
4. Optimised with Adam lr = exp(-5).
5. RPN Train: Positive sample IOU >0.7. Negative sample <0.3.
6. Threshold for bbox= 0.8
7. Regularizer prevented overfitting and false postive.
8. But less accuracy for different orientation of images.
9. Bounding box regression performance not well.
10. Time required for each image to read and write back to drive is 0.8 sec to 2.5 sec.

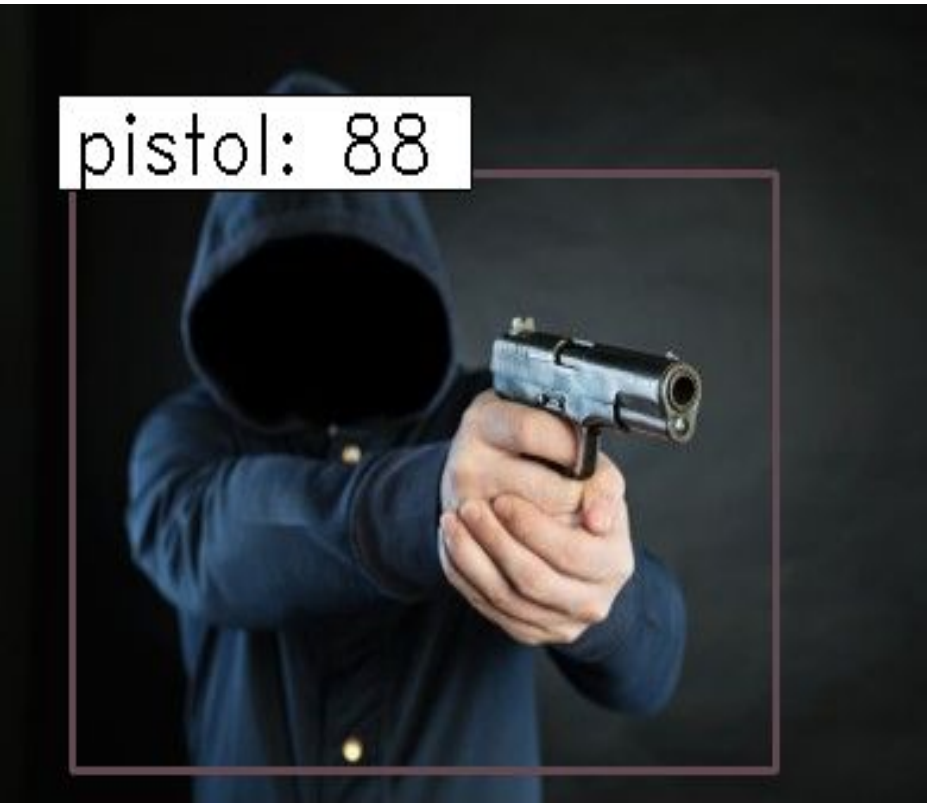

pistol: 97

Detecting gun along with hand posture.
Good or Bad??

Further can be worked on roi classification. And non max supression.

Adam exp(-4) to exp(-5). Thresold 0.7

Interference of background



Just can’t Hide


pistol: 92


pistol: 94

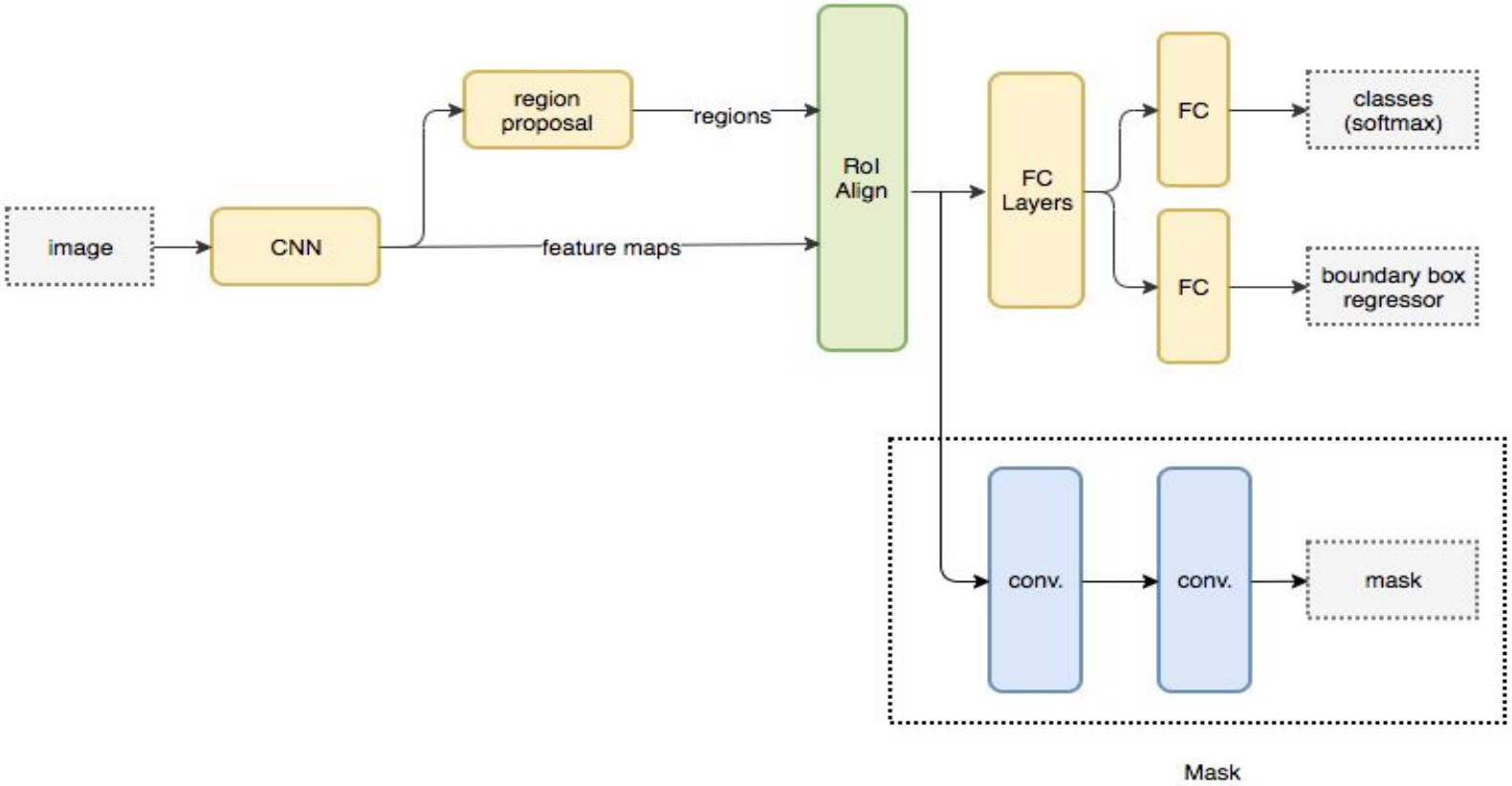
Mask RCNN

Official Paper published by Facebook AI Research(FAIR) on Jan 2018

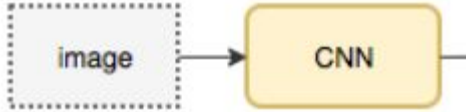
Best results till date on COCO object detection challenge

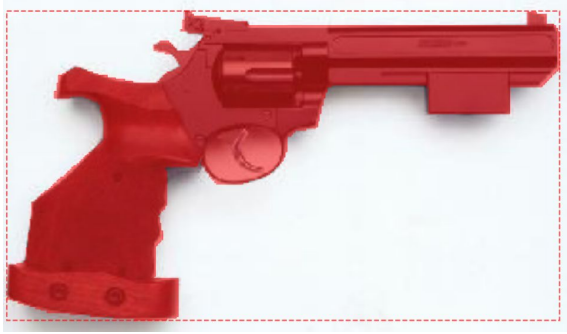
Combines object detection with image segmentation

Architecture of Mask RCNN



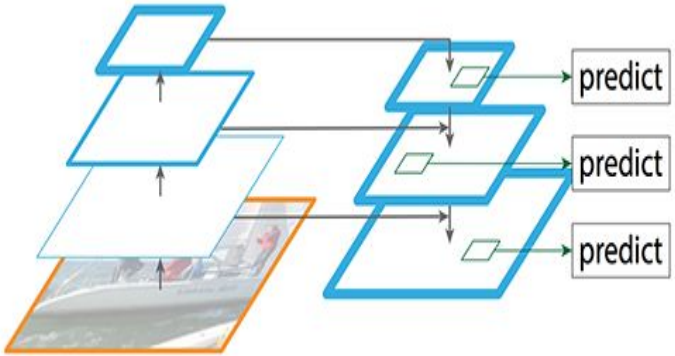
Inspecting Data for Mask RCNN

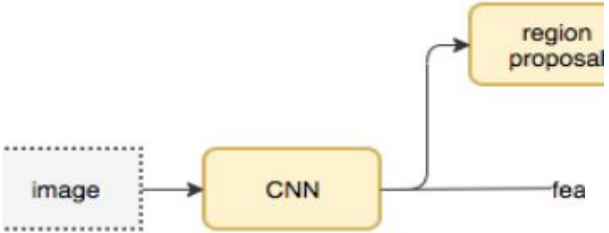


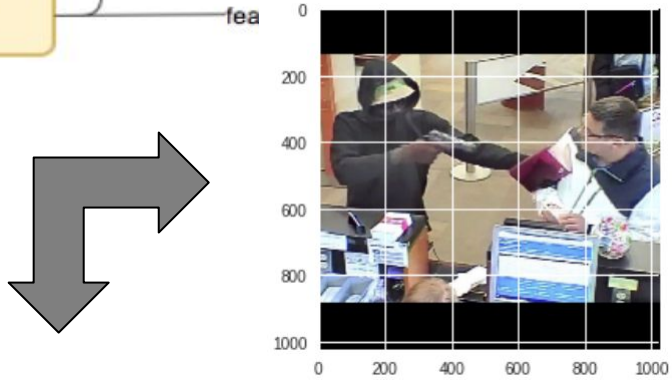


The ground truth for the Bounding Box and the Semantic Segmentation is created from annotated images.

The FPN network

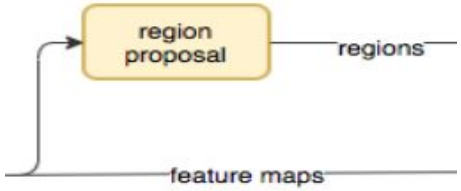


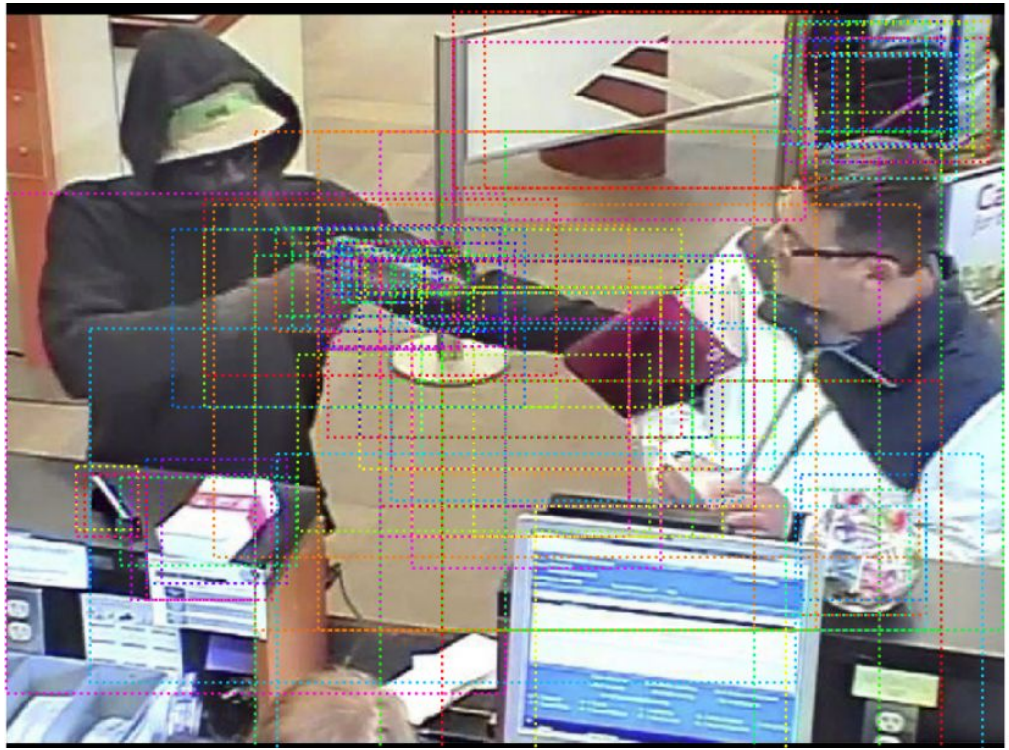




Feature Pyramid Network (**FPN**) is a feature extractor designed for such pyramid concept.It generates multiple feature map layers (**multi-scale feature maps**) with better quality information for **small** object detection.

Region Proposals Generation



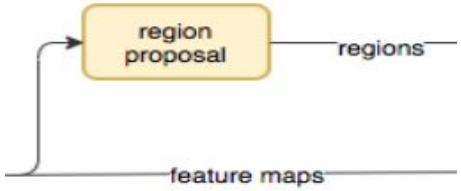


Step 1:

We create randomly 2000 region proposals or anchors for the image.

Only the top 100 have been shown here.

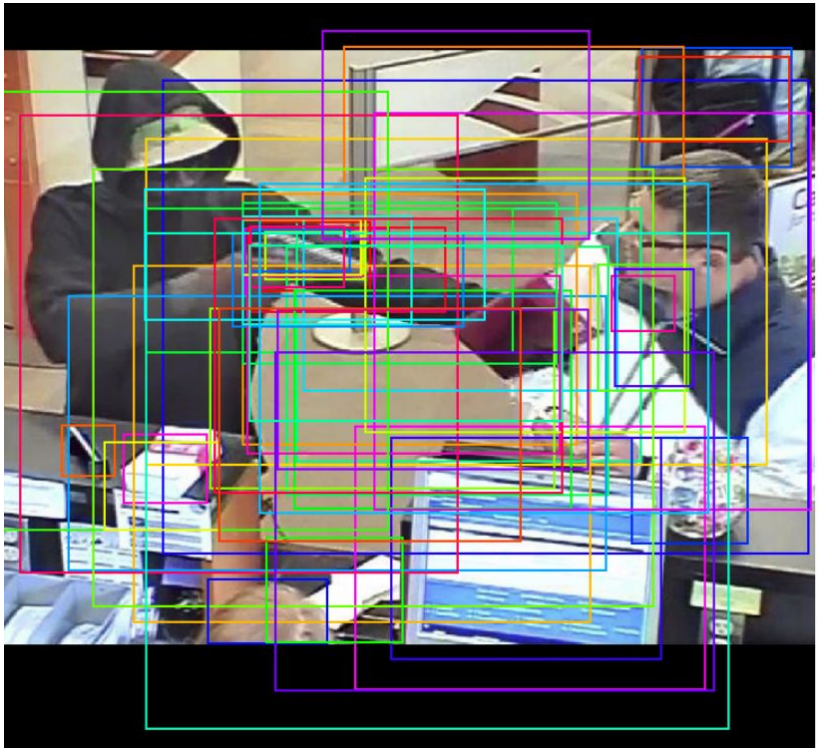
Anchor Box Refinement

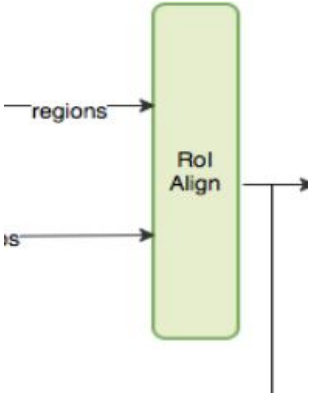


Step 2

Anchor Box Refinement: A anchor might not be centered perfectly over the object. So the RPN refines the anchor box to fit the object better.

Final ROIs

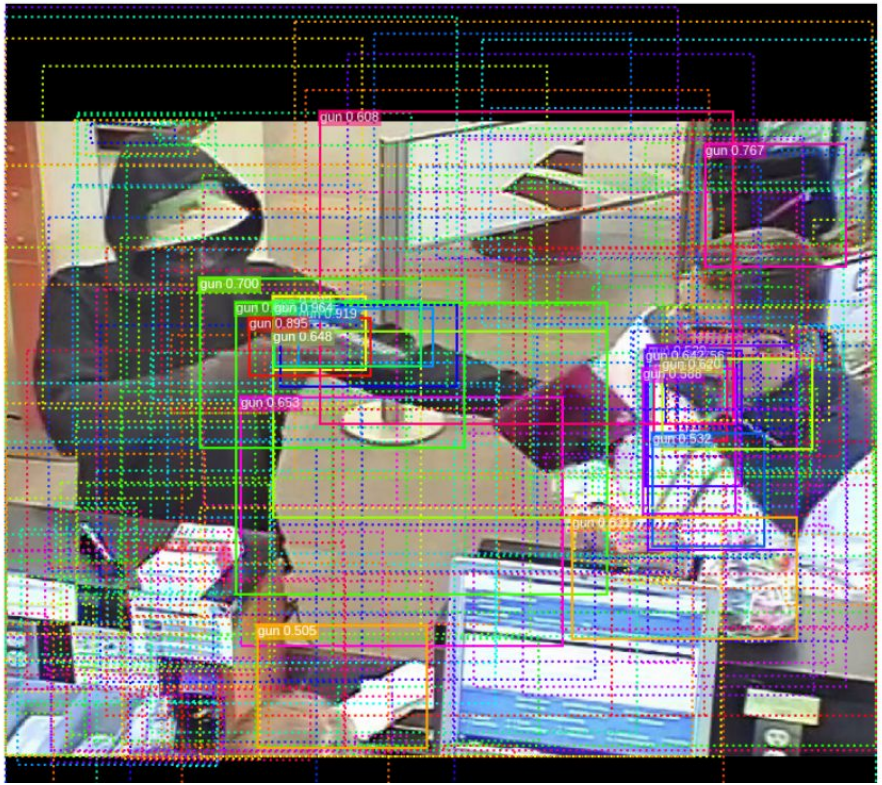


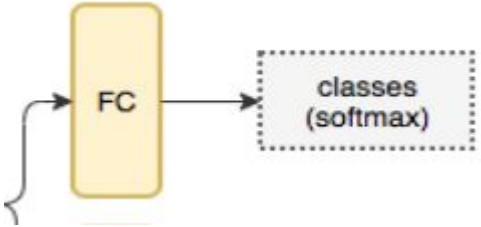


Step 3:

The final top 50 ROIs after non max suppression are shown here.

Proposal Classification



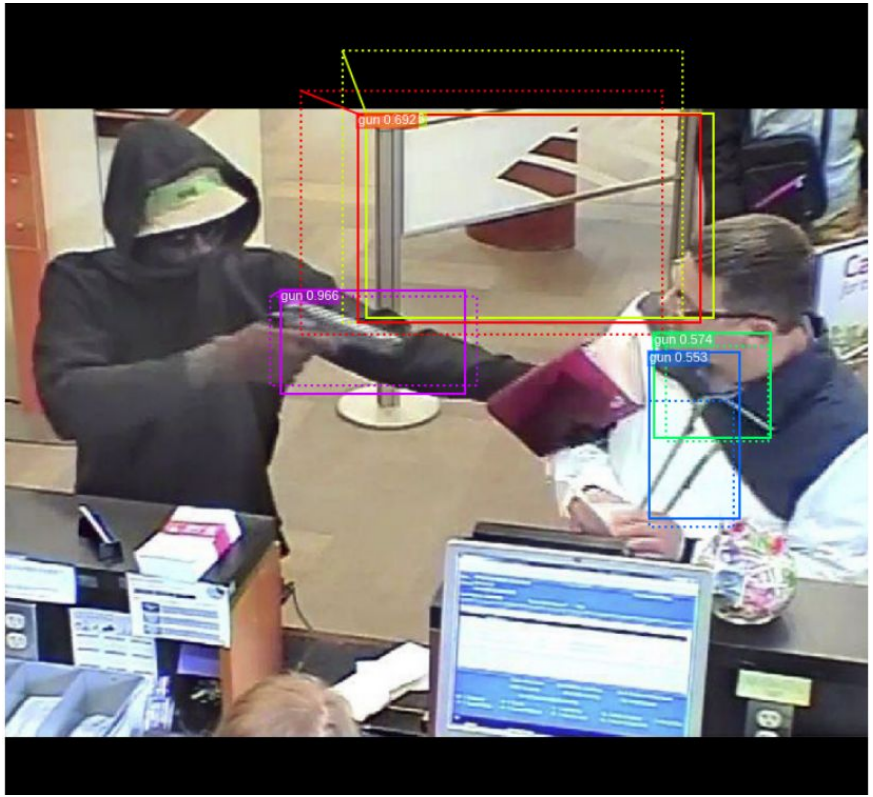


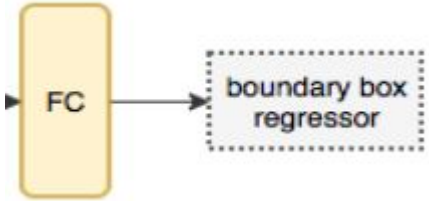
Step 4:

Proposal Classification running a pretrained ResNet 101 with COCO weights for classification

The solid lines shows detected guns with accuracies

Bounding Box Regressor

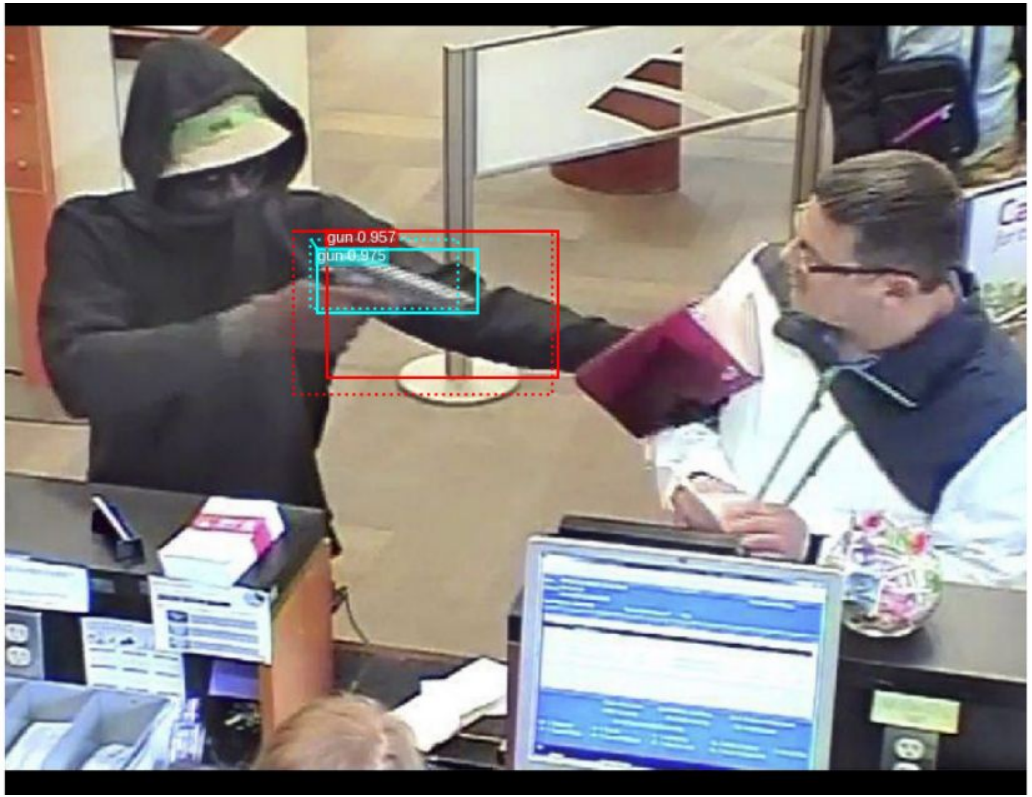


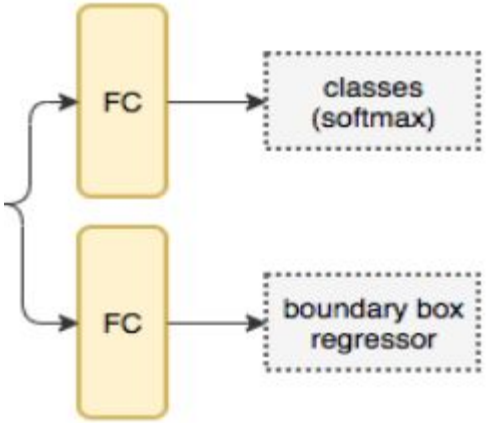


Step 5:

Applying Bounding Box Refinement using bilinear interpolation

Filtering Low Confidence Detections

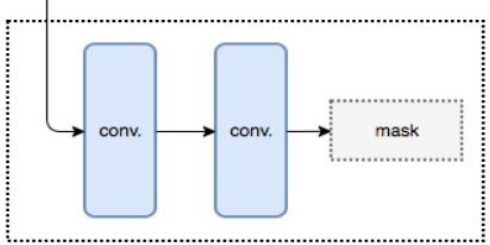


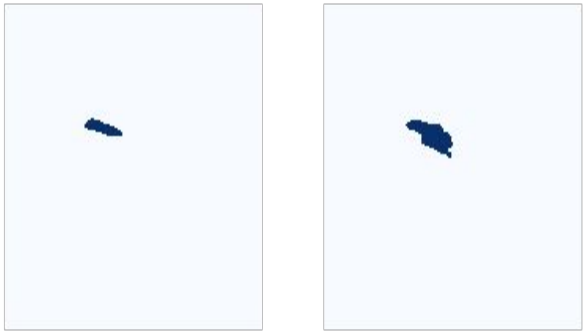


Step 6:

We filter out images with accuracies lesser than 93 % percent

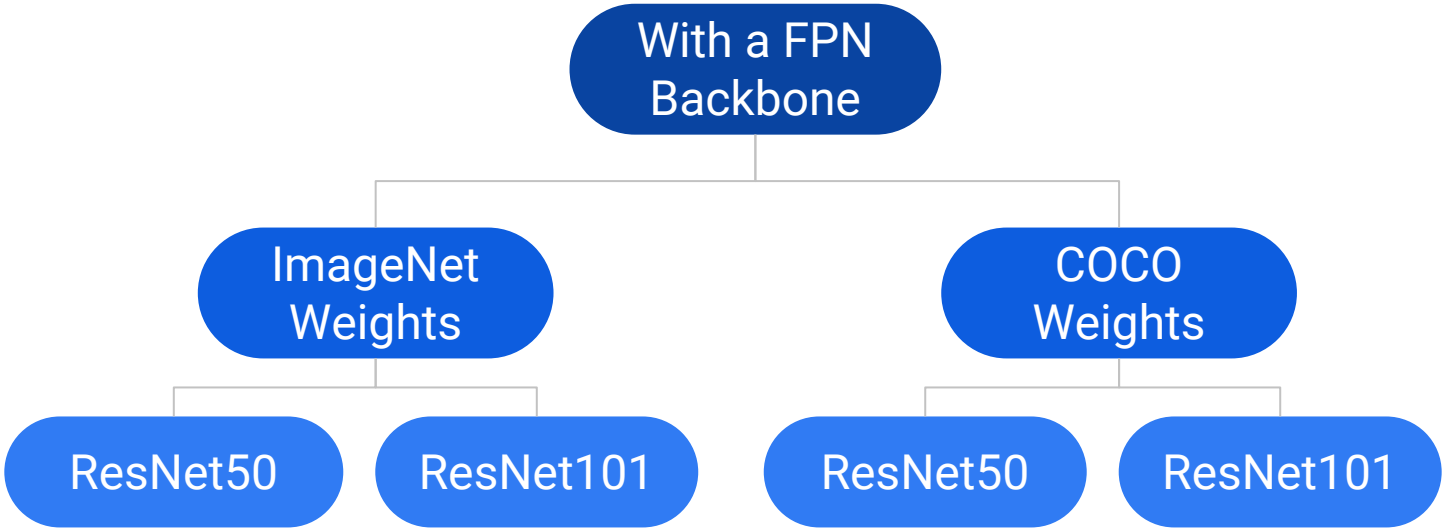
Appyling Mask





Step 7:
The masks are generated by connecting two convolution layers back to back and getting the output of the convolution layer as a feature map

4 Approaches under Mask RCNN



Comparative Analysis under Mask RCNN

Approaches under MASK RCNN	Validation mask_loss	Validation class_loss
ResNet50 (ImageNet)	0.5927	0.0597
ResNet101 (ImageNet)	0.5885	**0.0403**
ResNet50 (COCO)	0.2532	0.0536
ResNet101 (COCO)	**0.2294**	0.0527

Comparative Analysis:

Faster RCNN v/s Mask RCNN

But we did have some False Positives!

Misclassification errors due to - Overfitting & Inability of training more blurry images

Fine Tuning the Network

Transfer learning to reduce FPs

Classification Task:

3405 (800 guns/ 2605 not guns) images trained on ResNet101 (ImageNet Weights) improved the scores of ResNet101 ImageNet Mask RCNN Model.
Using Transfer learning we reduced false positives with metrics -
Validation Mask_loss = 0.475 Validation Class_loss = 0.0383

Another Challenge with Exploding Gradients

Review Weight Stats

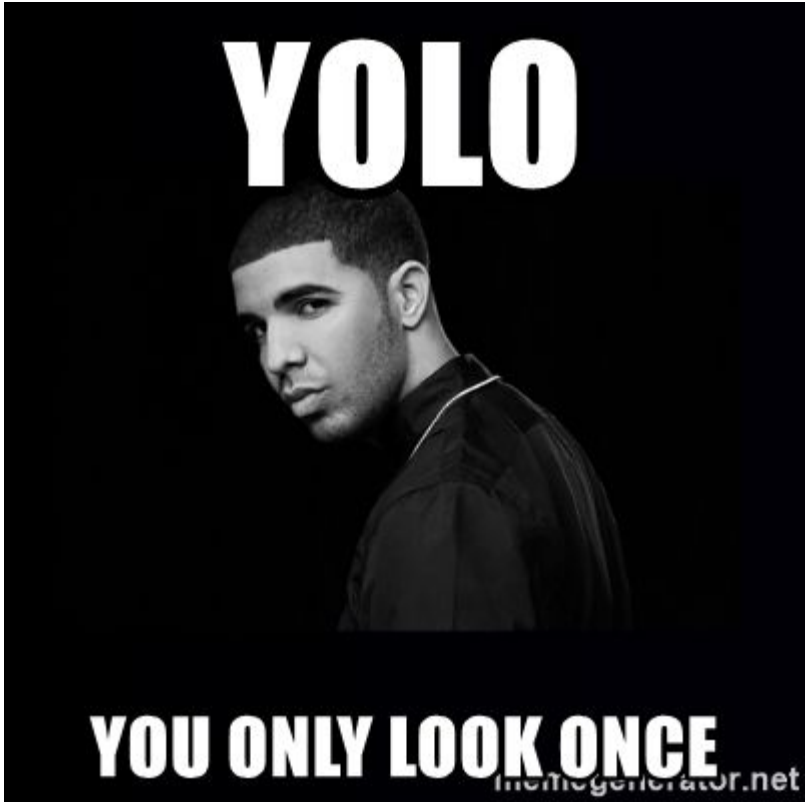
[11]:
```
# Show stats of all trainable weights
visualize.display_weight_stats(model)
```

WEIGHT NAME	SHAPE	MIN	MAX	STD
conv1/kernel:0	(7, 7, 3, 64)	-0.8616	+0.8451	+0.1315
conv1/bias:0	(64,)	-0.0002	+0.0004	+0.0001
bn_conv1/gamma:0	(64,)	+0.0835	+2.6411	+0.5091
bn_conv1/beta:0	(64,)	-2.3931	+5.3610	+1.9781
bn_conv1/moving_mean:0	(64,)	-173.0470	+116.3013	+44.5654
bn_conv1/moving_variance:0*** Overflow?	(64,)	+0.0000	+146335.3594	+21847.9668
res2a_branch2a/kernel:0	(1, 1, 64, 64)	-0.6574	+0.3179	+0.0764
res2a_branch2a/bias:0	(64,)	-0.0022	+0.0082	+0.0018

EXCEPTIONAL RESULTs with MASK RCNN

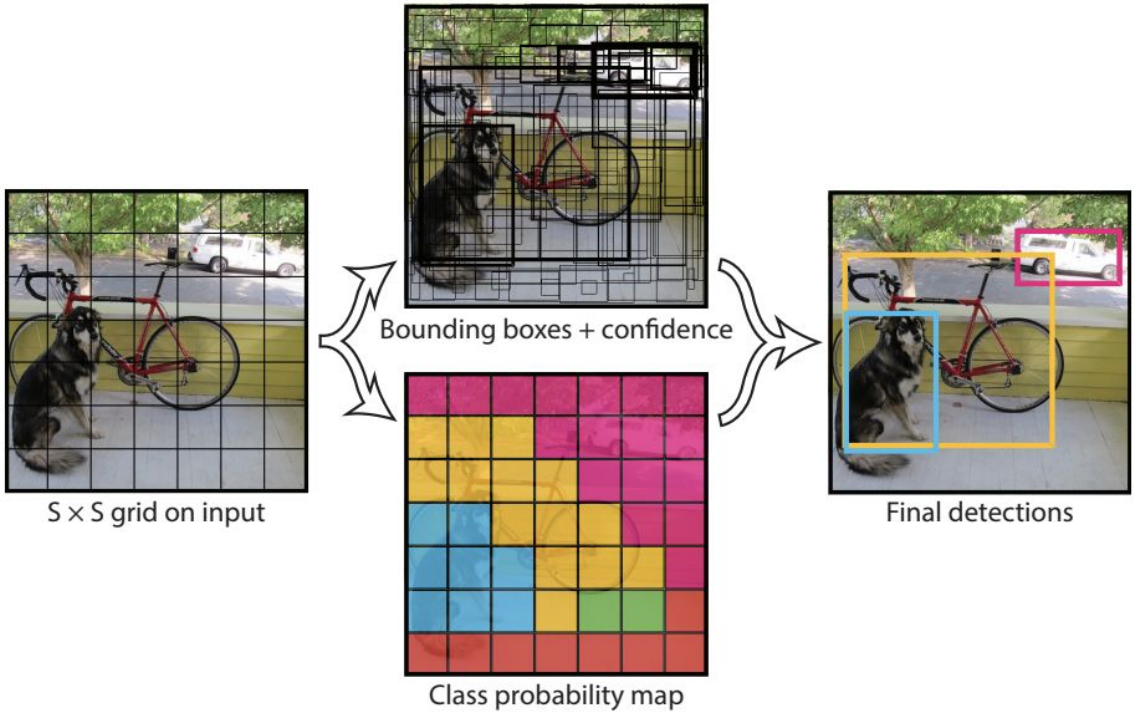
Wait..What about Speed?

- You only look once (YOLO) is a state-of-the-art, real-time object detection system.
- Mobile App Demo.(Reference: https://github.com/gauravsawant/Weapon-Detector)
- **How?** The network does not look at the complete image. Instead, parts of the image which have high probabilities of containing the object.



~ YOLO is out of scope for this implementation.

Grid to Bounding Boxes to Detections with Classification



Speed Vs Accuracy ?

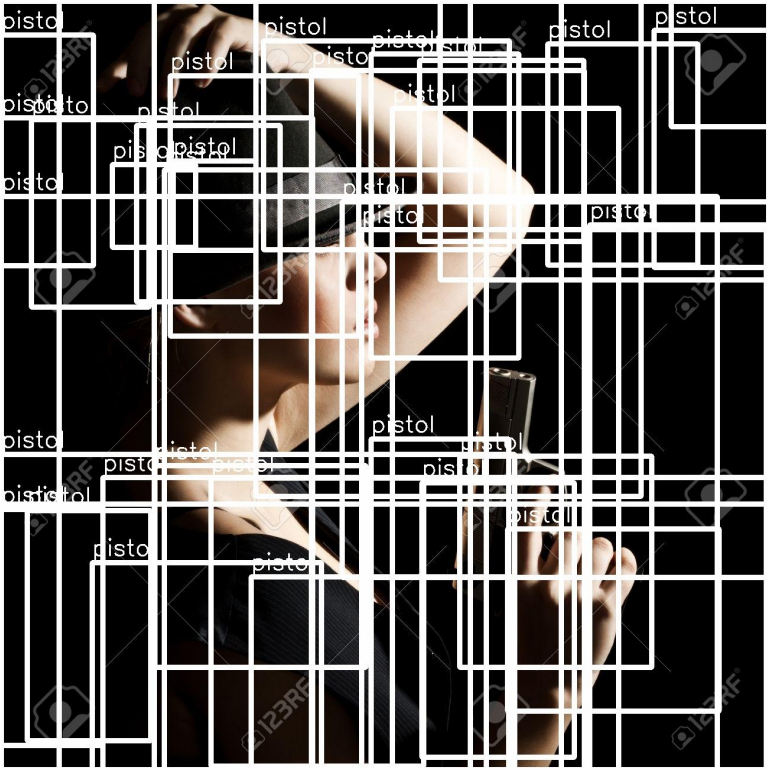
YOLO makes predictions with a single network evaluation due to which it is much faster than other object detection algorithm.

Limitation - YOLO algorithm struggles a lot with small objects within the image.

Model	Speed of Detection(On a single frame)
Faster RCNN	300 ms
Masked RCNN	350 ms
YOLO	10 ms

Note: Speed will vary with different CPU architectures. These figures are from GPU used on Google Colab

Glimpse of our bad predictions using YOLO



Overall Challenges we faced...

1. Data and time constraints for YOLO.
2. Annotating images manually for masked and faster RCNN.
3. Shortage of Hardware Requirements for video and real time analysis.
4. Couldn’t try experimentations with training due to GPU limitation on Google colab and CC Labs.
5. Steep Learning curve while studying for the project.

Future Scope >>>

1. Real-Time implementation with YOLO.
2. Unified loss metric(like Mean Average Precision) for all the three approaches
3. Detecting categories of weapons and identifying fake from real ones
4. Detecting handheld guns using Pose and Human Key point Estimation.
5. Ensemble techniques for detection combining Instance segmentation with Human Keypoint estimation
6. Creating a model API and pushing it to realtime deployment in a drone or CCTV using a Raspberry PI
7. Trying out more faster algorithms like MXNet or MobileNet for gun detection.
8. Trying out RNN based approach for creating automated annotations(DEXTR and PolygonRNN++)

THANK YOU!

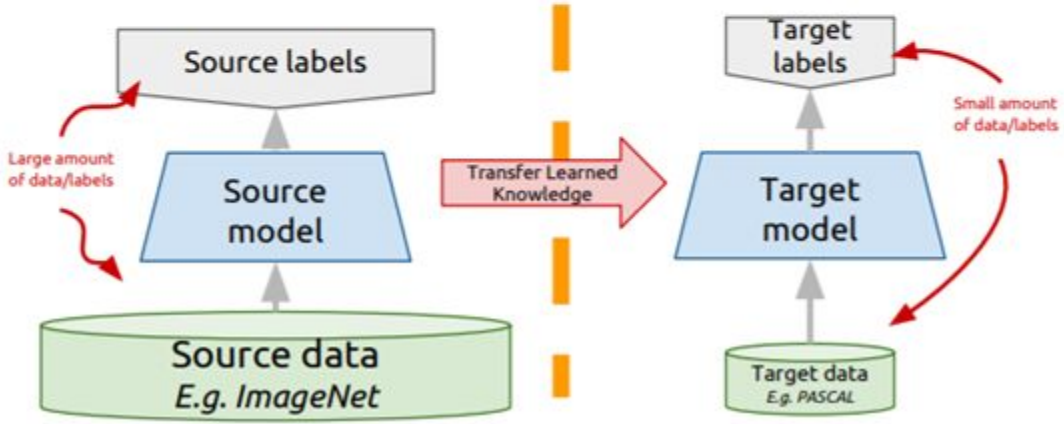
EXTRA REFERENCE SLIDES BELOW DONT DELETE

Instead of training a deep network from scratch for your task:

- Take a network trained on a different domain for a different **source task**
- Adapt it for your domain and your **target task**

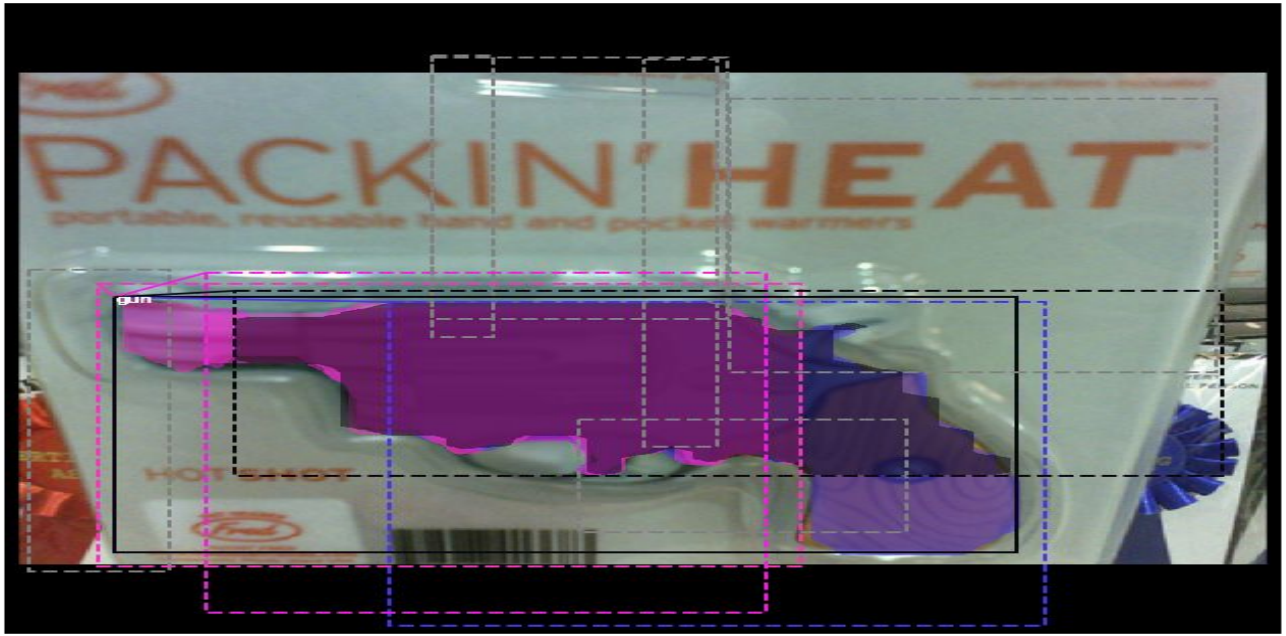
Variations:

- Same domain, different task
- Different domain, same task

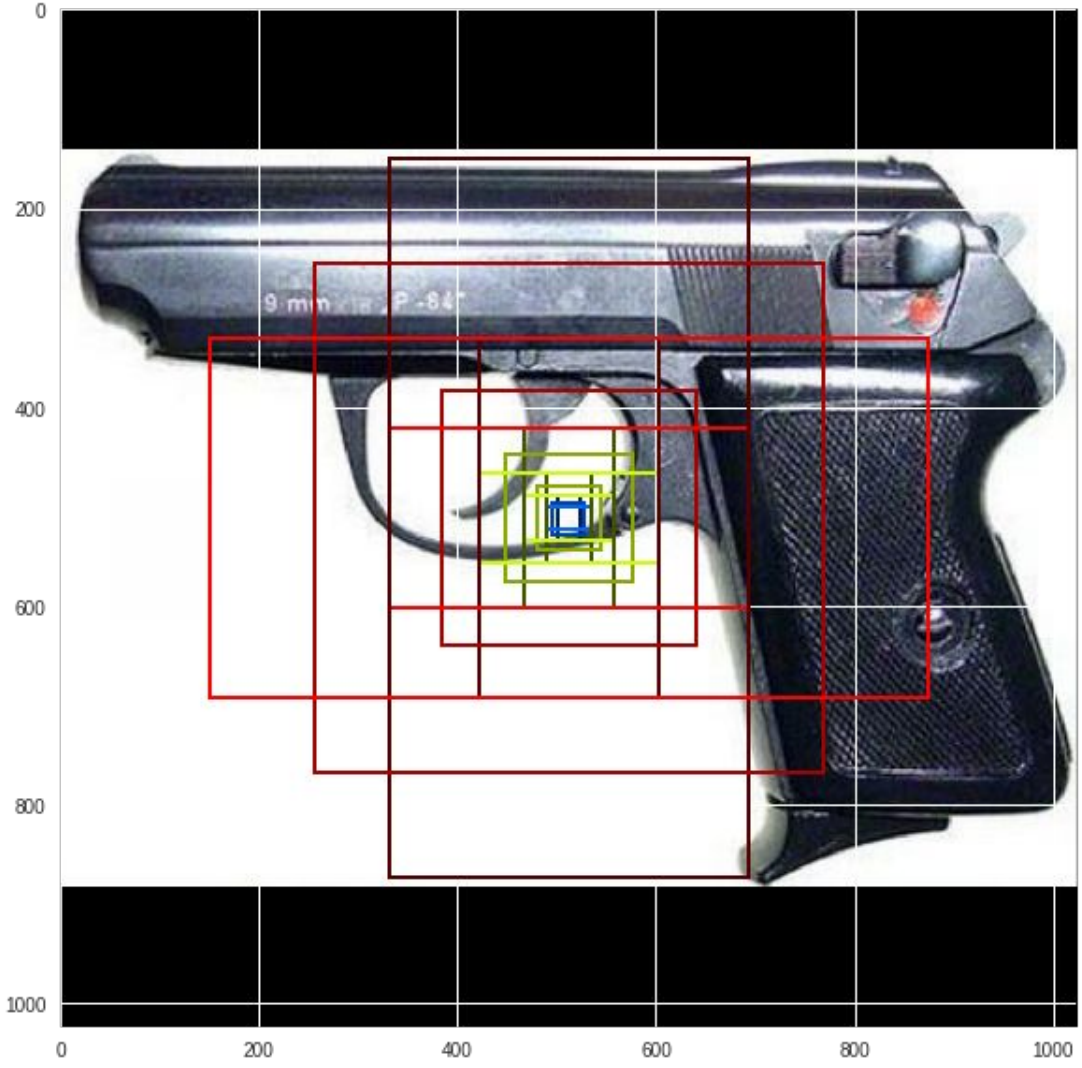



PACKIN' HEAT
HOT SHOT

Showing 10 random ROIs out of 200




PACKIN'HEAT
portable, reusable hand and pocket warmers
HOT SHOT


0
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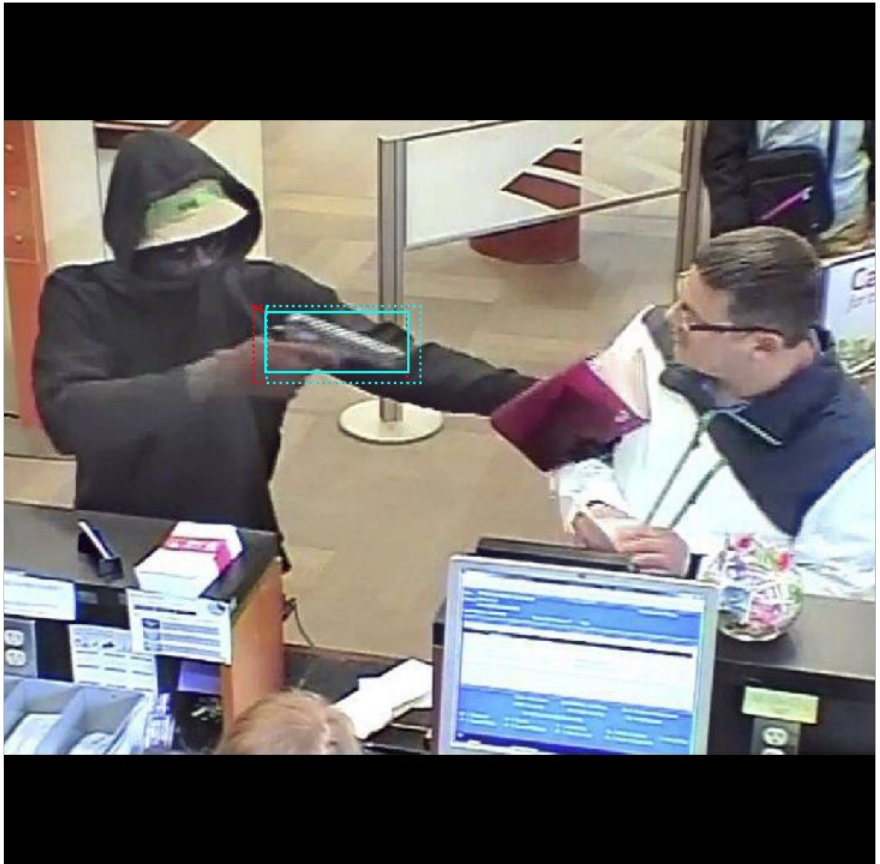
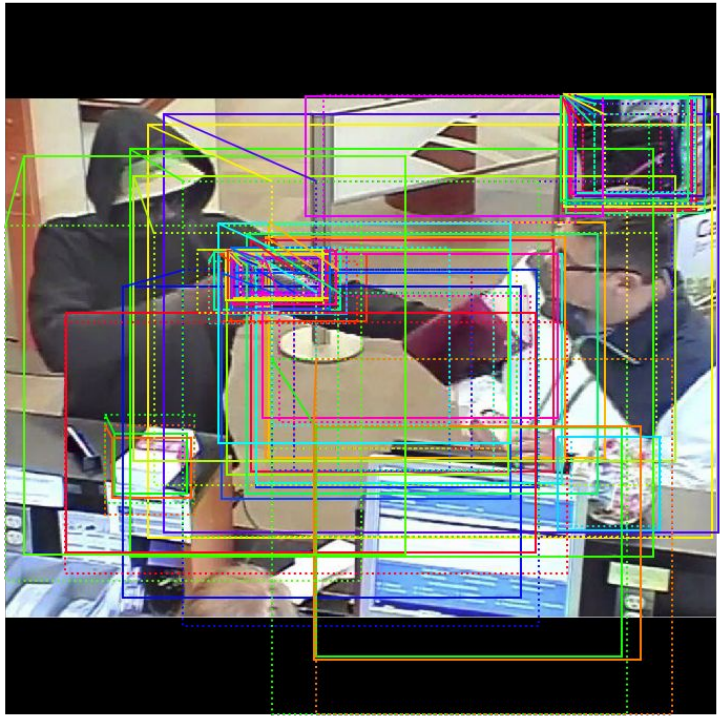
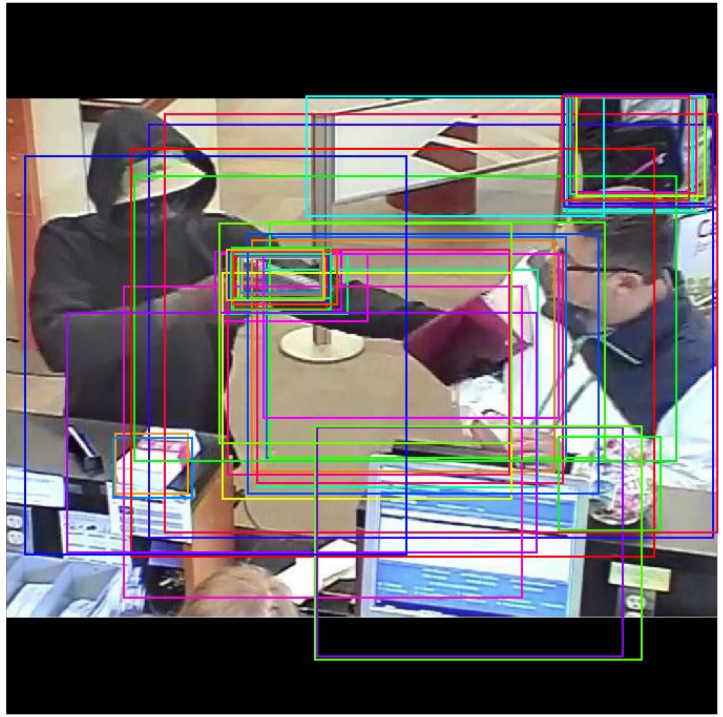
gun

Positiv anchors before and after refinement

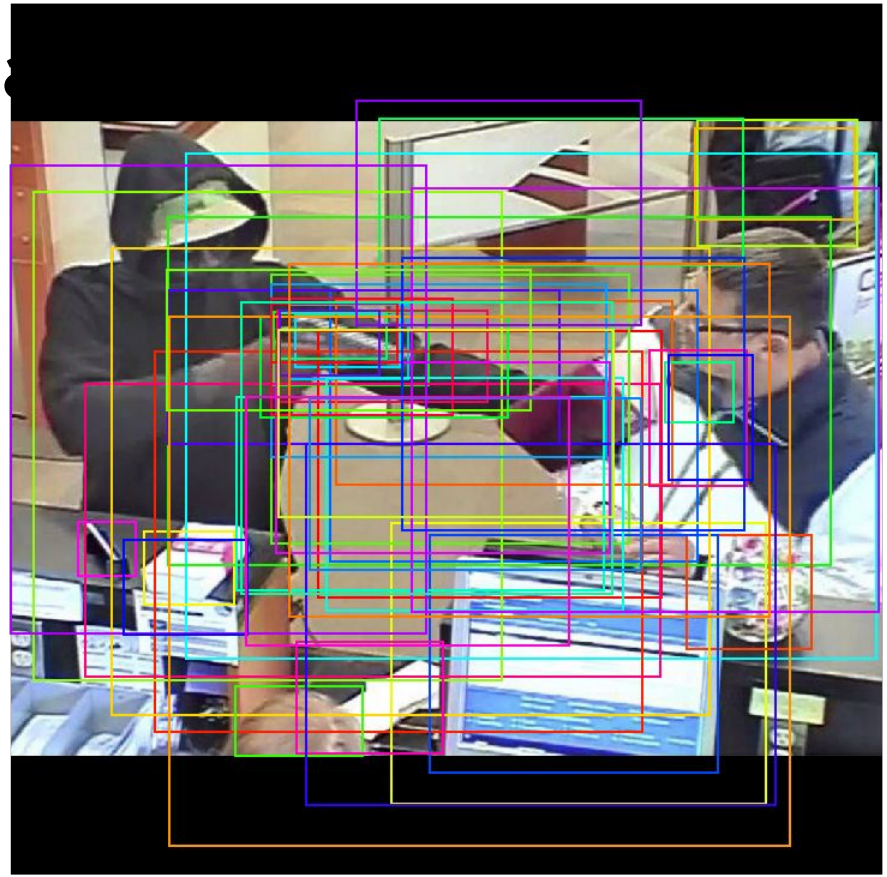


Top 50 anchors after refining

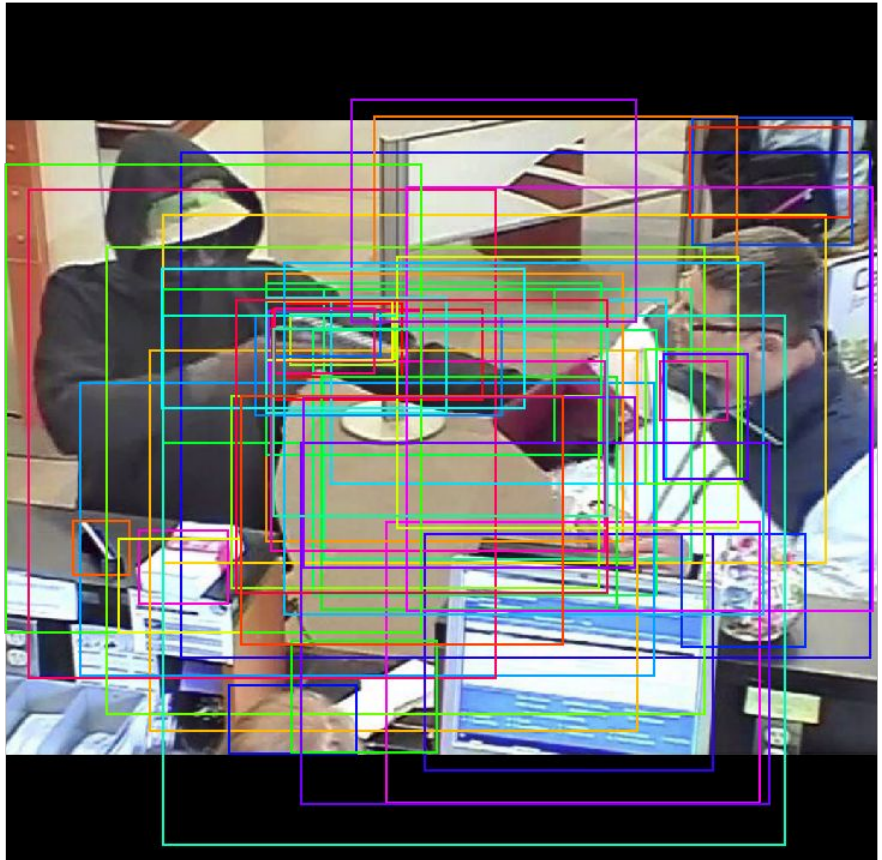




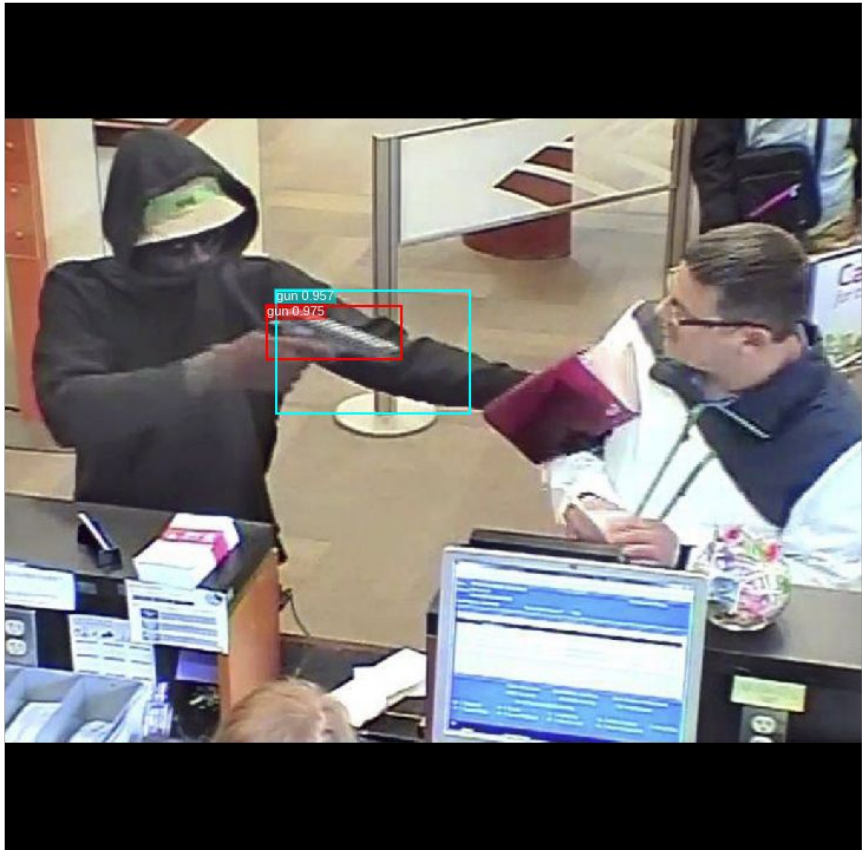
After non ma



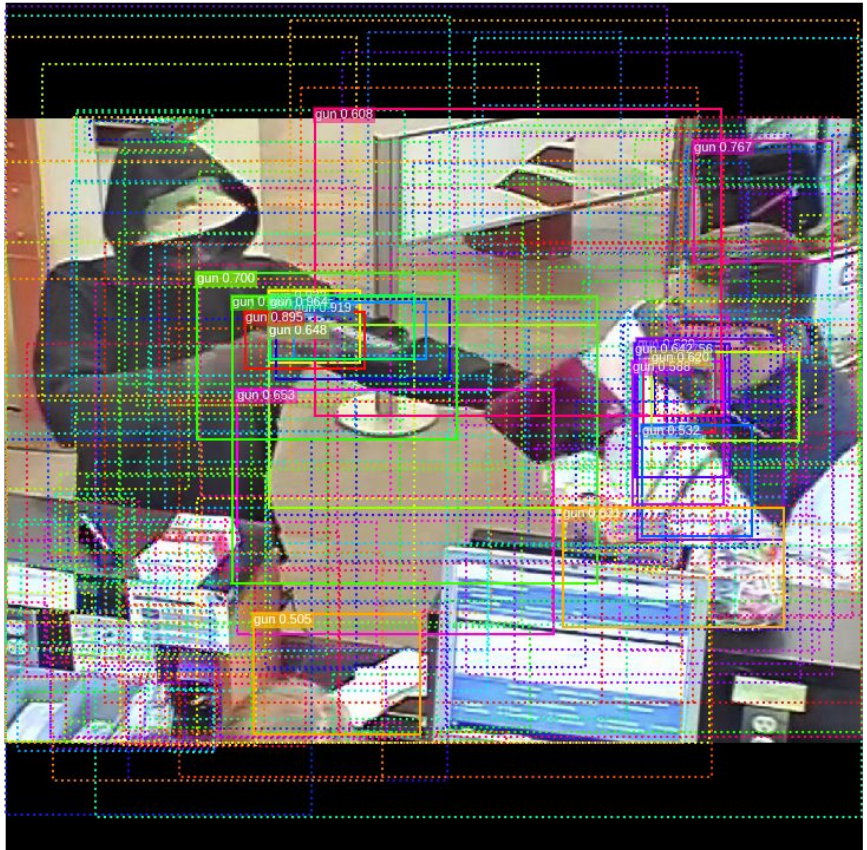
Coordinate Normalisation

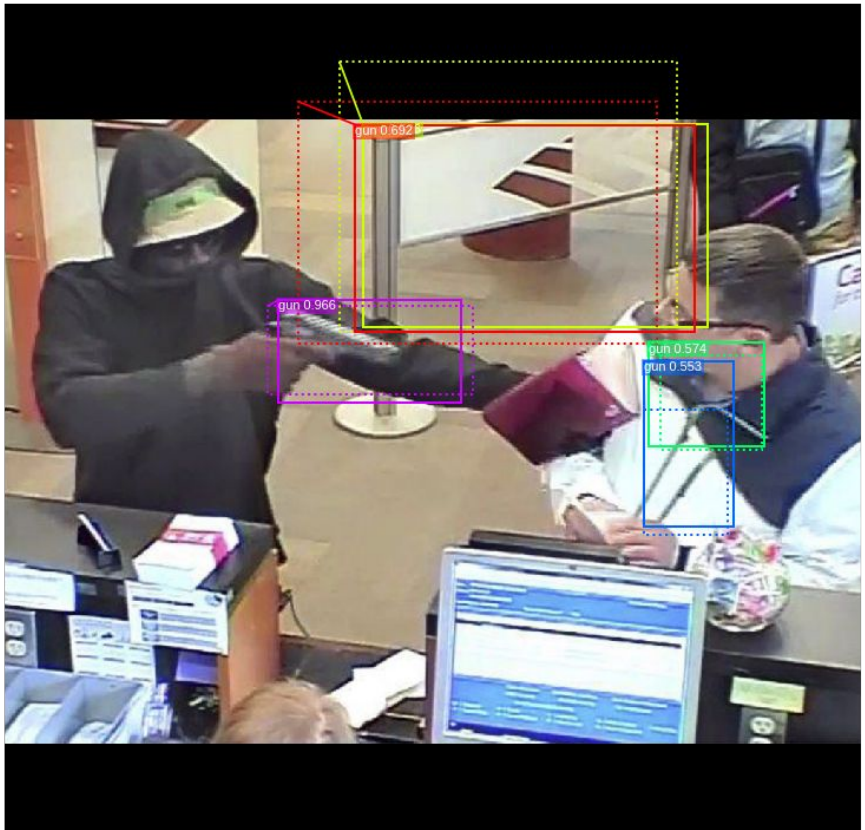


Proposal Classification



ROI before and after refinement

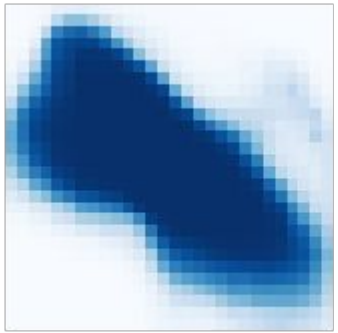


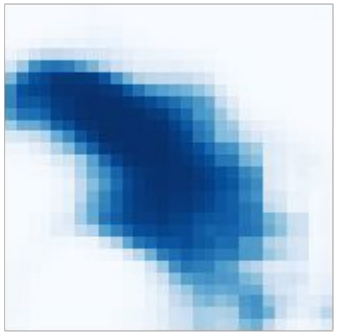


Detection after Non Max suppression

Detections after NMS

Creating Masks





De

Predictions