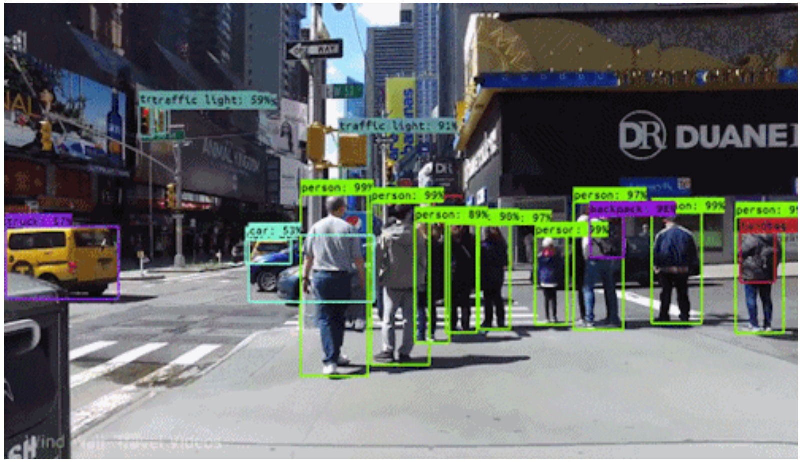
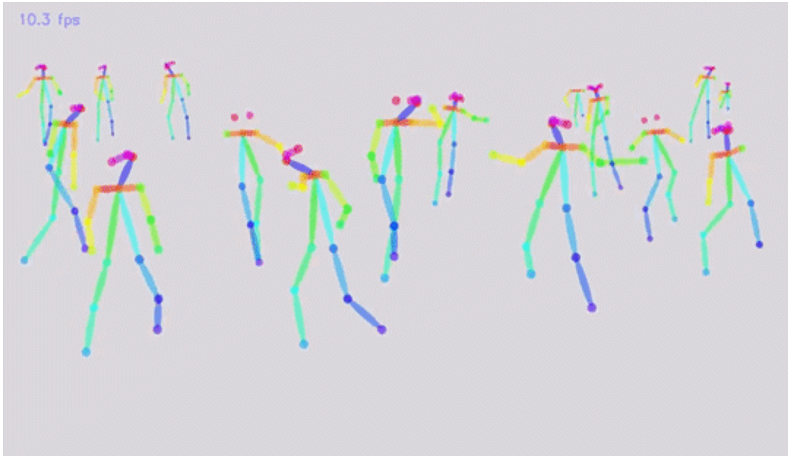
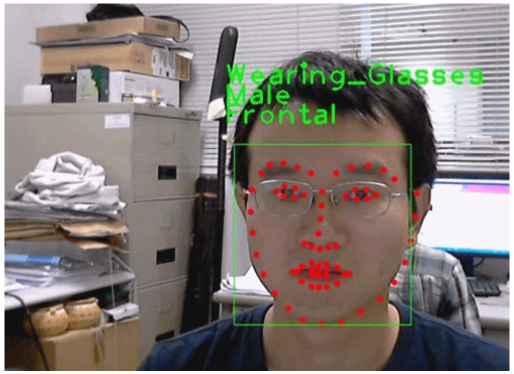
Computer Vision Applications

Computer Vision Applications

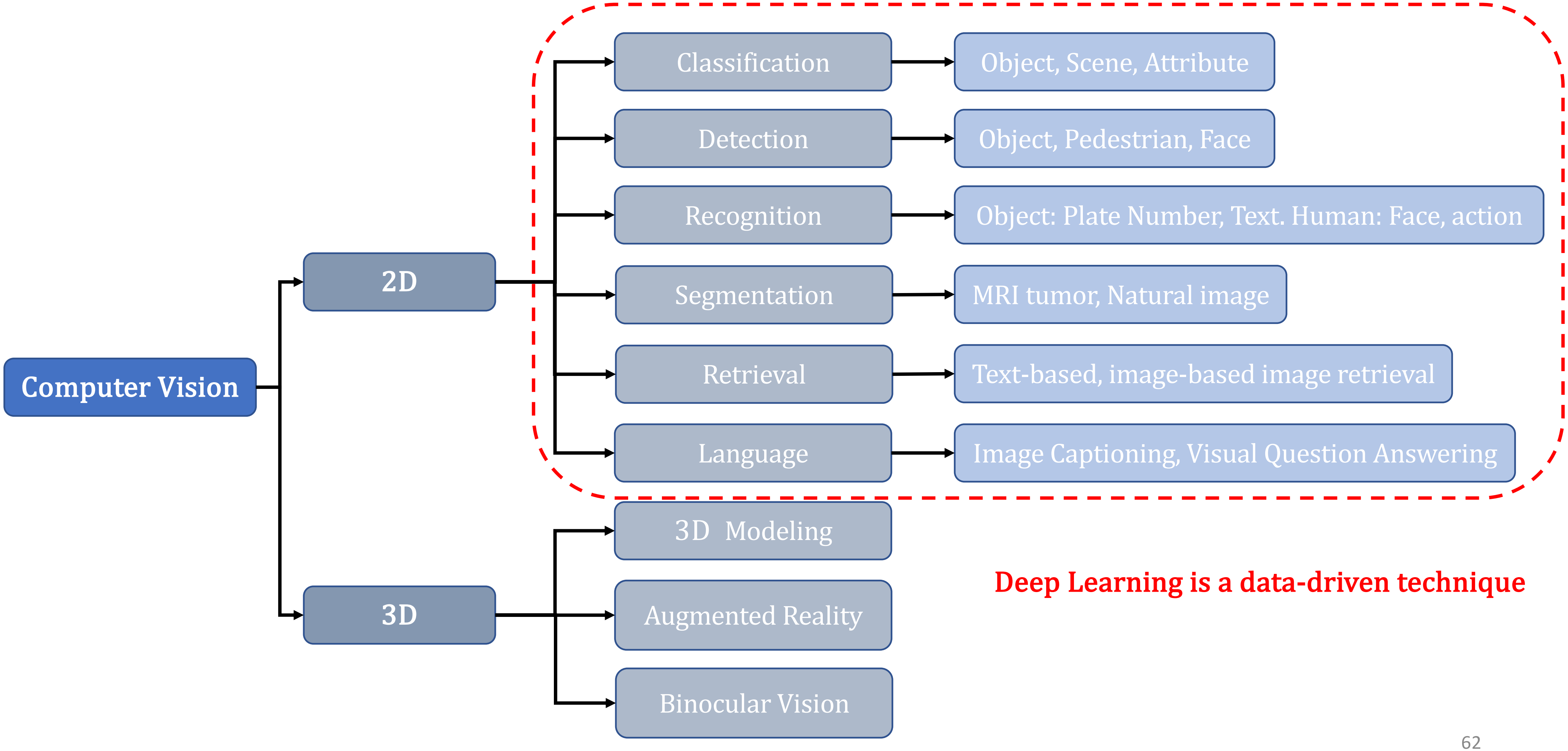




RGB



Computer Vision Applications



Deep Learning is a data-driven technique

Computer Vision Applications

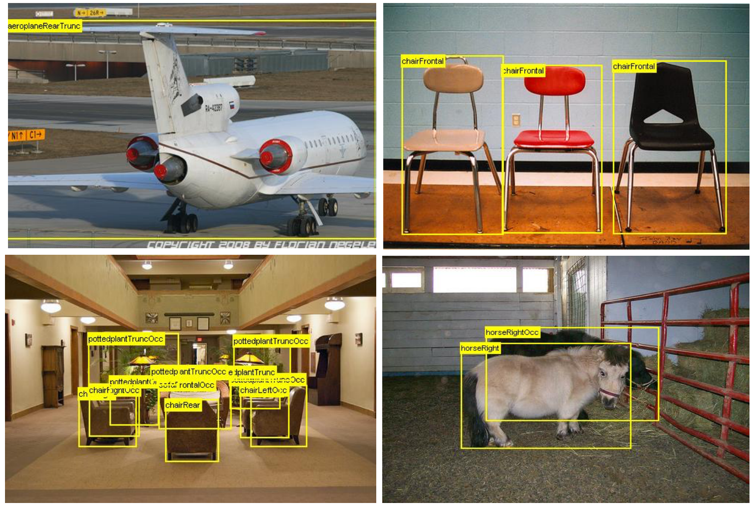
- Object Detection: Dataset

Oxford Pascal VOC

- VOC 2007 and 2012

- 20 Classes：
    - Person
    - Animal: Bird, Cat, Cow, Dog, Horse, Sheep
    - Vehicle: Aeroplane, Bicycle, Boat, Bus,
      Car, Motorbike, Train
    - Indoor: Bottle, Chair, Dining Table, Potted Plant,
      Sofa, TV/Monitor

- VOC 2012: 11,530 images (train/val). 27,450 bounding boxes



http://host.robots.ox.ac.uk/pascal/VOC/voc2012/

PEKING UNIVERSITY

Computer Vision Applications

- Object Detection: Dataset

COCO
Common Objects in Context

Microsoft COCO

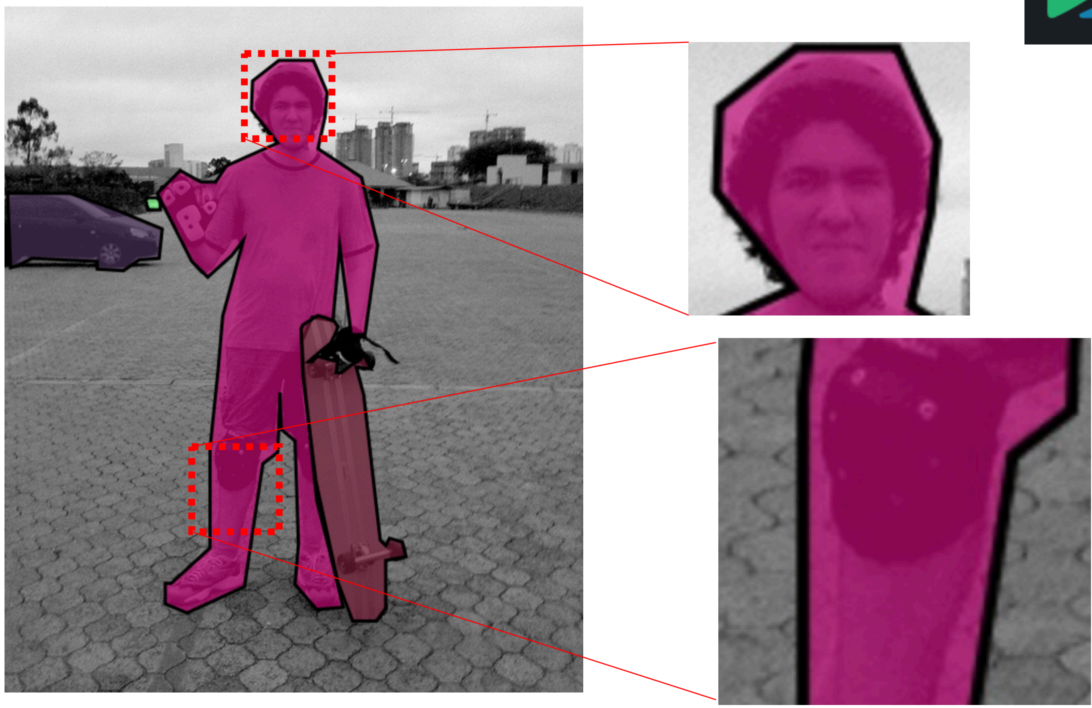
- 80 classes
- COCO 2014, 82,783 training images, 40,504 validating images, and 40,775 testing images
- Apart from object detection, it also have the annotations of:
    - Image captioning
    - Pose estimation
    - Image segmentation

http://cocodataset.org/#explore

Computer Vision Applications

- Object Detection: Dataset

COCO
Common Objects in Context



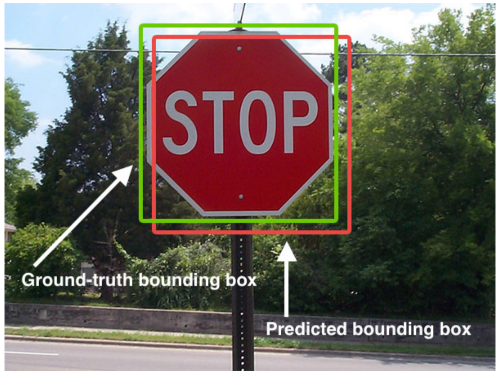
Sometime the dataset is “bad”

Computer Vision Applications

- Object Detection: Evaluation

Intersection over Union (IoU)

$$IoU = \frac{Area\ of\ Intersection}{Area\ of\ Union} =$$



- IoU is a scalar between 0 ~ 1
- If IoU==1, the predicted and GT boxes are fully matched.
- If IoU==0, the predicted and GT boxes are fully mismatched.
- If IoU>threshold, object detected.

Computer Vision Applications

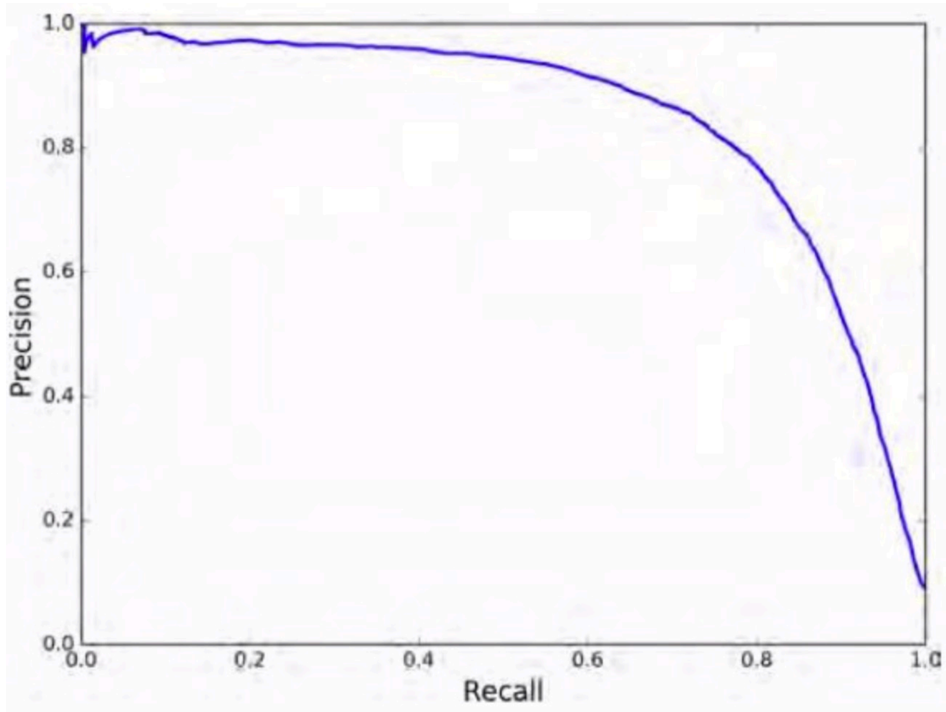
- Object Detection: Evaluation

Average Precision (AP)

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

- The area under P-R curve is the Average Precision (AP)



Computer Vision Applications

- Object Detection: Evaluation

- The mAP is the averaged AP for each class
- To further evaluate the algorithm, we would compute AP using different settings, such as the IoU threshold and the size of object.

Average Precision (AP):

AP	% AP at IoU=.50:.05:.95 **(primary challenge metric)**
$AP^{IoU=.50}$	% AP at IoU=.50 (PASCAL VOC metric)
$AP^{IoU=.75}$	% AP at IoU=.75 (strict metric)

AP Across Scales:

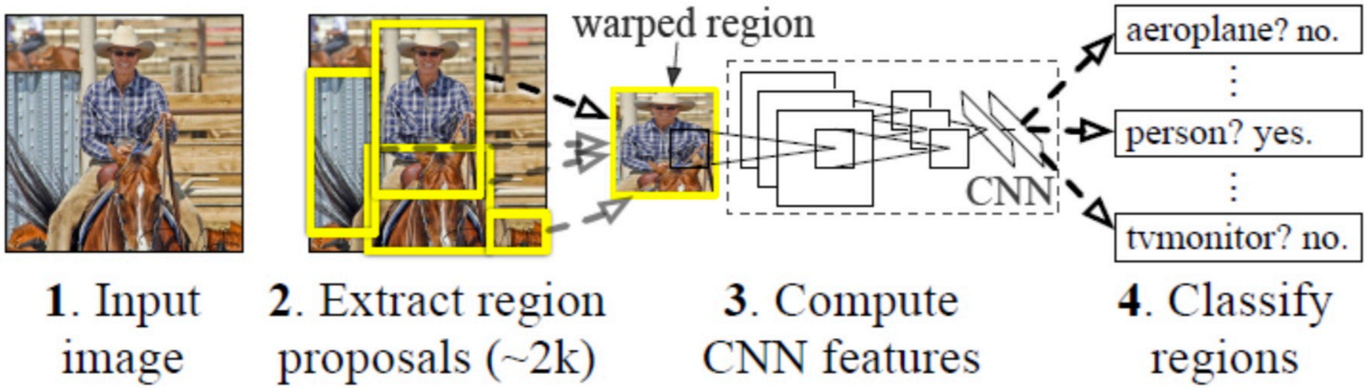
AP^{small}	% AP for small objects: area < 32^2
AP^{medium}	% AP for medium objects: 32^2 < area < 96^2
AP^{large}	% AP for large objects: area > 96^2

Average Recall (AR):

$AR^{max=1}$	% AR given 1 detection per image
$AR^{max=10}$	% AR given 10 detections per image
$AR^{max=100}$	% AR given 100 detections per image

Computer Vision Applications

- Object Detection: R-CNN

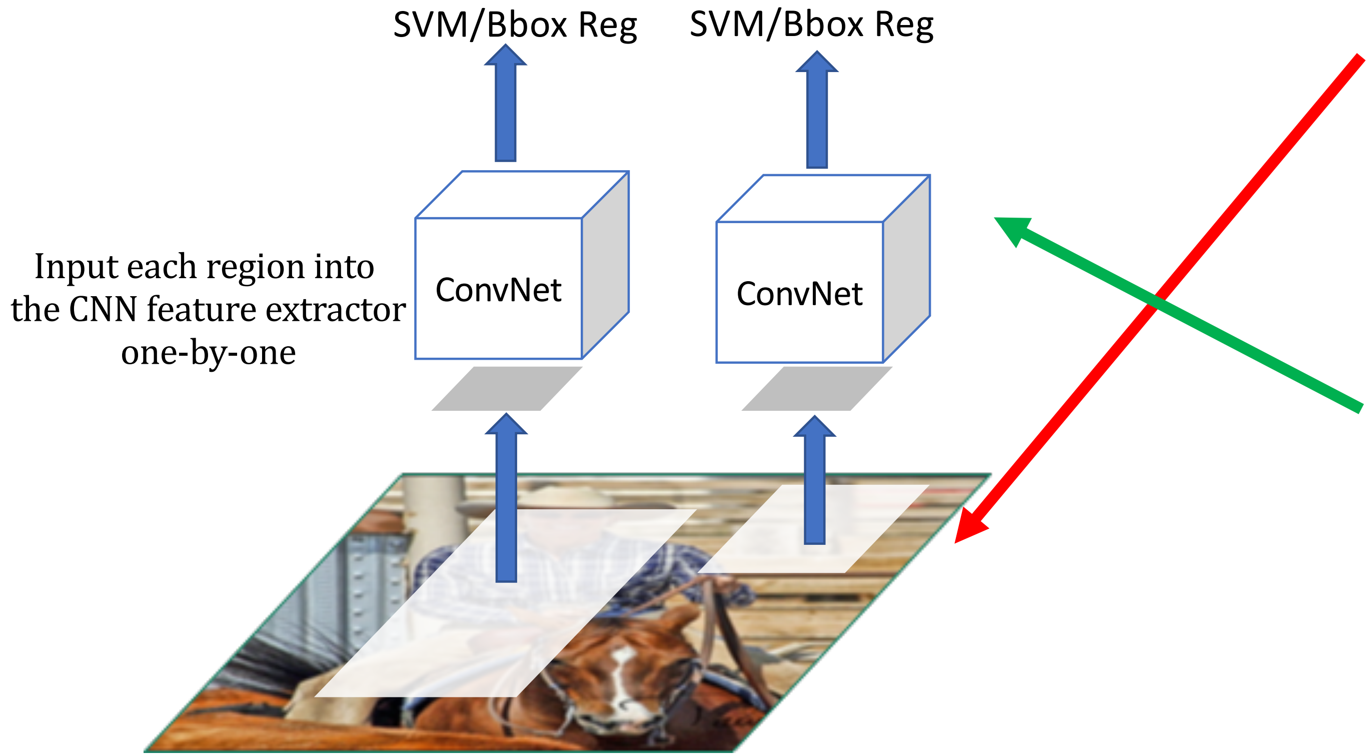


- Step 1: Use Selective Search algorithm to obtain 2,000 proposal regions from an image.
- Step 2: Resize all regions to a given fixed size.
- Step 3: Feed each regions to the VGG to extract image features, and classify the image via the features.
- Step 4: Obtain the bounding box location via regression.

Rich feature hierarchies for accurate object detection and semantic segmentation. *Girshick, Ross etal. CVPR. 2014.*

Computer Vision Applications

- Object Detection: R-CNN



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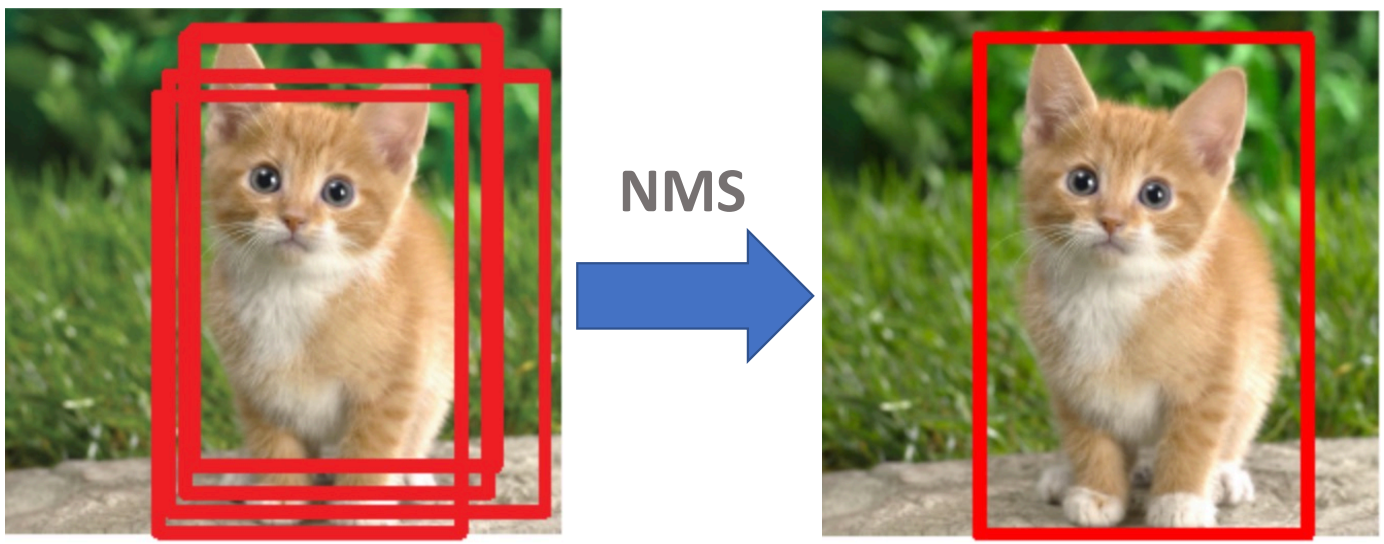
Rich feature hierarchies for accurate object detection and semantic segmentation. *Girshick, Ross etal. CVPR. 2014.*

Computer Vision Applications

- Object Detection: Non-Maximum Suppression, NMS



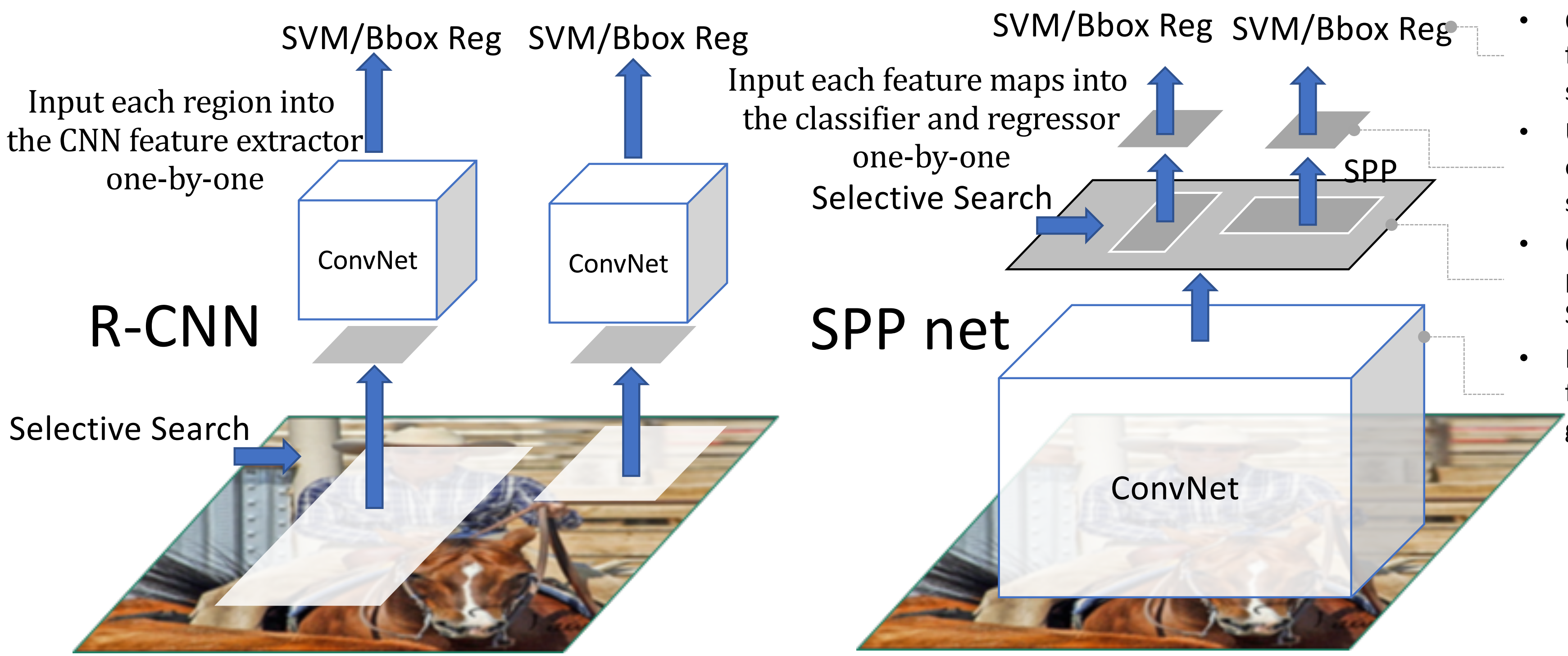
An object can have many potential output bounding boxes, NMS helps to remove the overlap boxes and keep the best one.

Computer Vision Applications

- Object Detection: SPP Net
  - R-CNN Limitations:
    - 1. Selective Search is slow.
    - 2. Resizing the proposal region leads to scale change of width and height, which affect the classification accuracy.
    - 3. Feed each region into the VGG individually, which is very slow.
    - 4. Not end-to-end training.
  - SPP Net Contribution:
    - 1. Solve the 2^{nd} and 3^{rd} limitations of R-CNN.
    - 2. Propose Spatial Pyramid Pooling, SPP, which resize the features into the same size.
    - 3. Feed entire image into CNN to obtain global features, and obtain the features of each region on the global features.

Computer Vision Applications

- Object Detection: SPP Net



- Obtain the class labels and bboxes from the feature maps with the same size
- Use SPP to resize the feature maps of all proposal regions into the same size
- Obtain the feature maps of all proposal regions based on Selective Search.
- Input the entire image into the feature extractor to obtain the global feature maps.

Spatial pyramid pooling in deep convolutional networks for visual recognition. *Kaiming He etal. ECCV. 2014.*

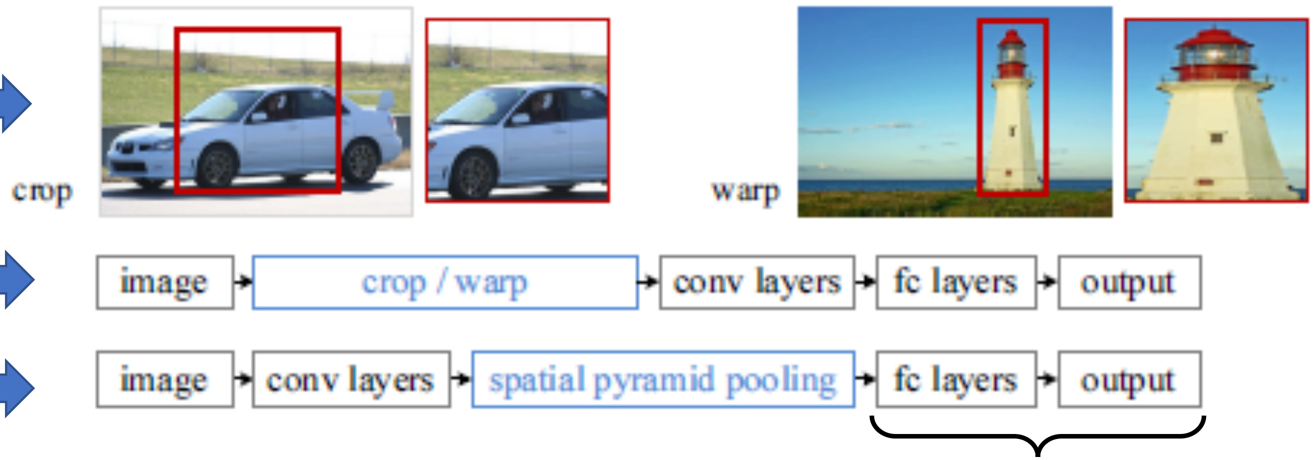
Computer Vision Applications

- Object Detection: SPP Net

R-CNN changes the image scale

R-CNN

SPP net



SVM

- Compared to R-CNN, SPP Net have the following advantages.
  - Use global features instead of feeding images into VGG one-by-one.
  - Do not change the image scale.

Spatial pyramid pooling in deep convolutional networks for visual recognition. *Kaiming He etal. ECCV. 2014.* （图片来自）

Computer Vision Applications

- Object Detection: Fast R-CNN

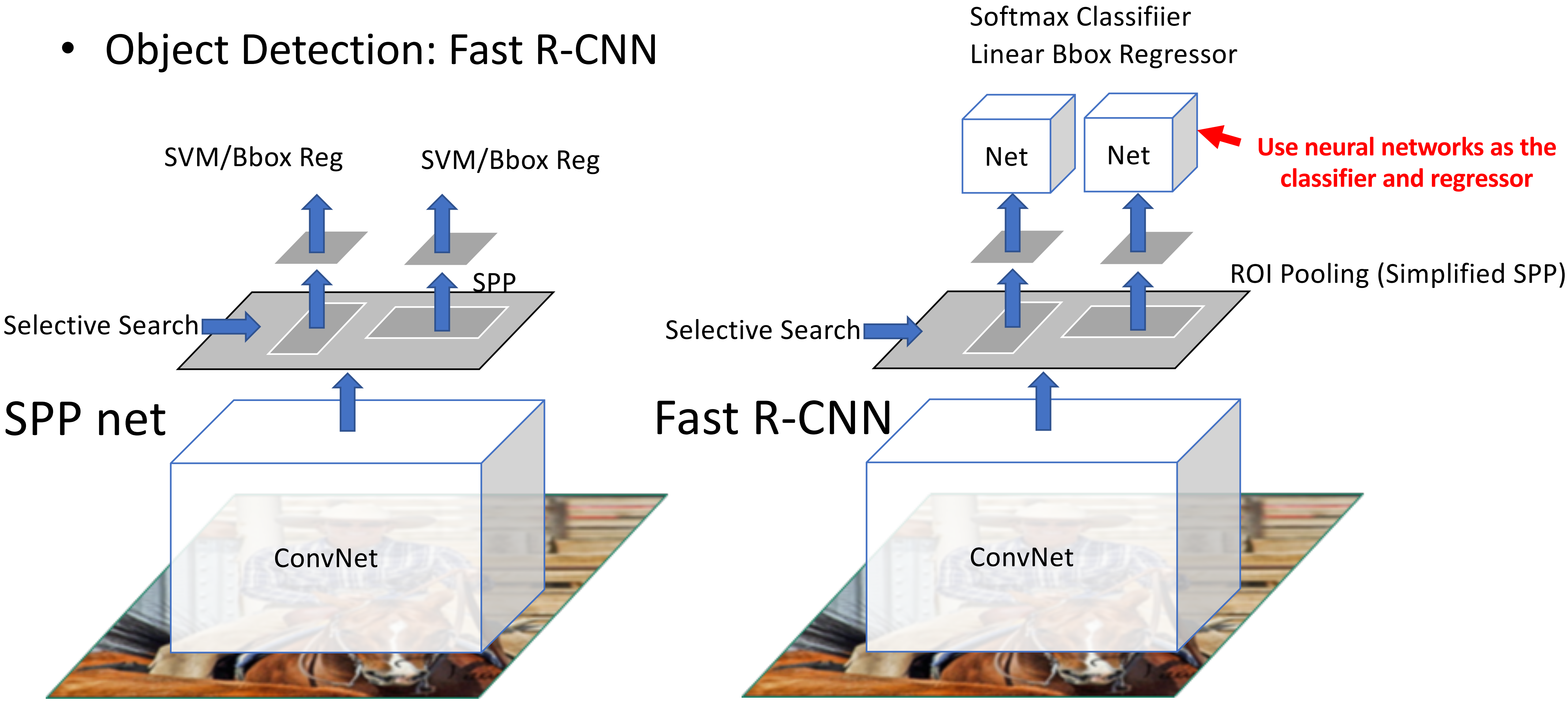
  - SPP Net Limitations:
    - 1. Still use Selective Search, which is very slow.
    - 2. Still not end-to-end training.

  - Fast R-CNN Contributions:
    - 1. Propose ROI (Region of Interest) Pooling layer, which is a simplified Spatial Pyramid Pooling that uses one pooling size only.
    - 2. End-to-end training, the classifier and bbox regressor are trained together with the CNN feature extractor.

Fast R-CNN. *Girshick, Ross etal. ICCV. 2015.*

Computer Vision Applications

- Object Detection: Fast R-CNN



Fast R-CNN. *Girshick, Ross etal. ICCV. 2015.*

Computer Vision Applications

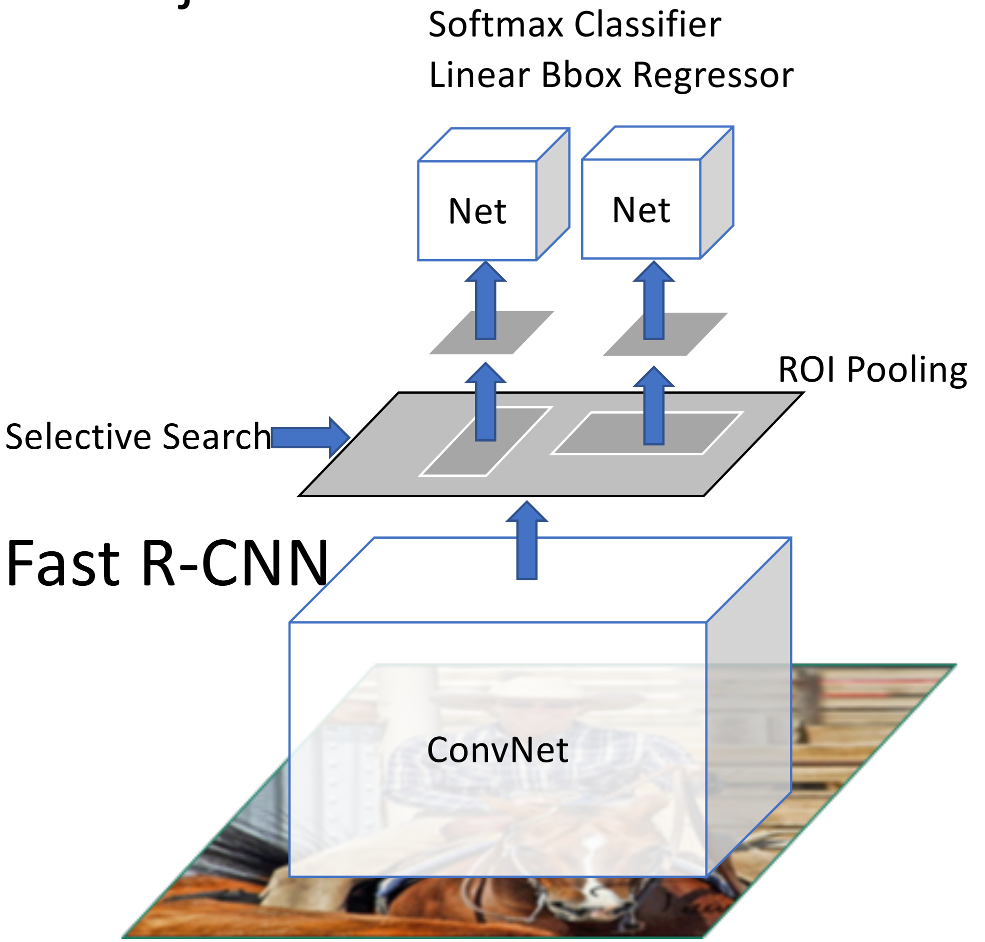
- Object Detection: Faster R-CNN

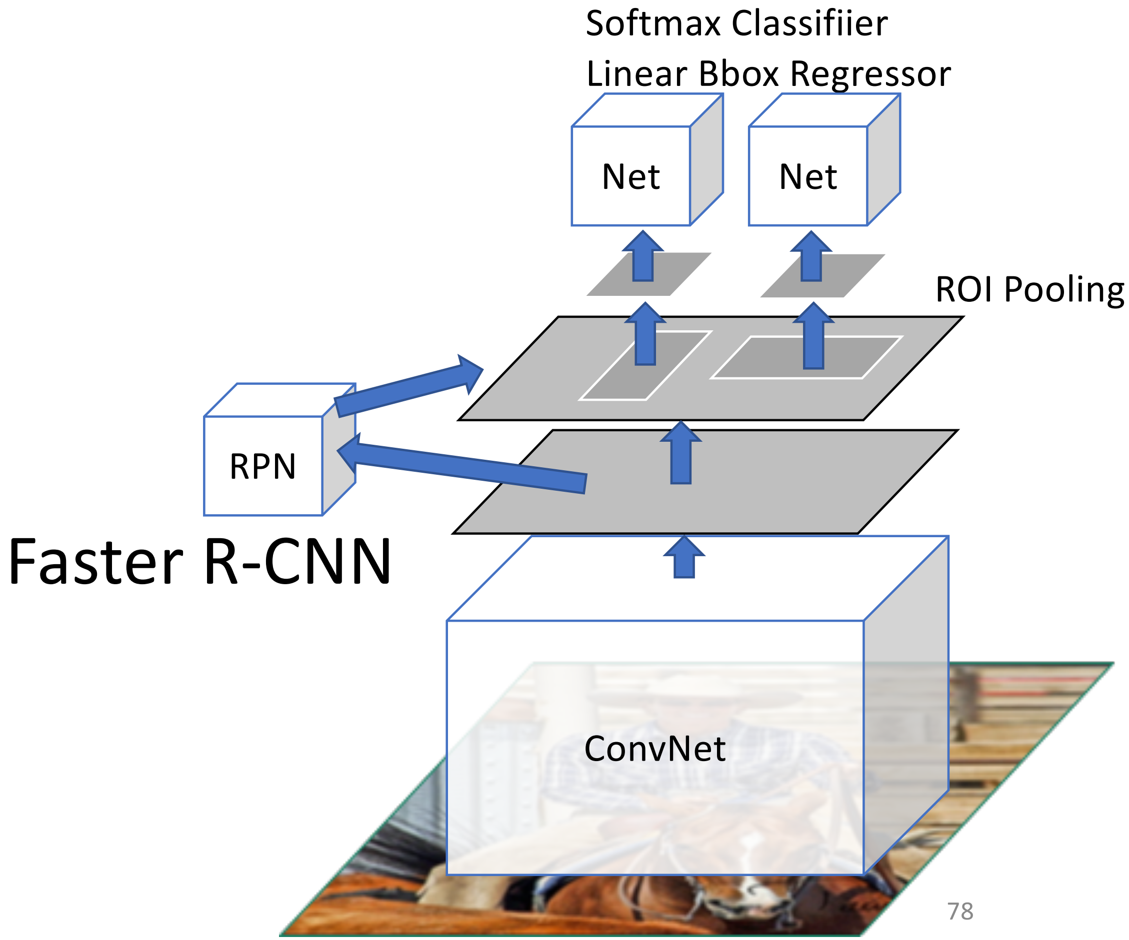
  - Fast R-CNN Limitation:
    - 1. Still use Selective Search, which is very slow.

  - Faster R-CNN Contribution:
    - 1. Use Region Proposal Networks (RPN) to replace Selective Search, enable neural networks to search the proposal regions, which is very faster.
    - 2. Achieve end-to-end training, accuracy increased.

Computer Vision Applications

- Object Detection: Faster R-CNN





Faster R-CNN. *Shaoqing Ren, Kaiming He, Ross Girshick, Jian Sun. NIPS. 2015.*

Computer Vision Applications

- Object Detection: Timeline of Proposal-based Methods

Time →

	R-CNN	SPP net	Fast R-CNN	Faster R-CNN
Region Proposal	Selective Search	Selective Search	Selective Search	Region Proposal Network
Feature Extraction	Deep Network	Deep Network	Deep Network	Deep Network
Classification & Regression	SVM	SVM	Deep Network	Deep Network

- Object Detection: Rethinking

    - The above algorithms all need region proposal, but it is necessary?
    - To know the locations of different objects in an image, the human would not manually select many proposal regions and classify them one-by-one, instead, human can find all objects in an image by just one glance.

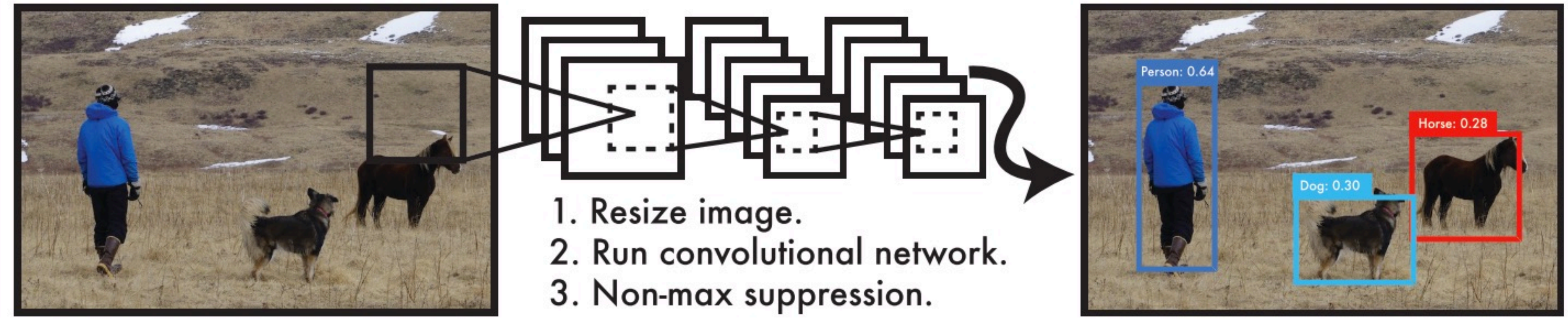
YOLO

You Only Look Once

Computer Vision Applications

- Object Detection: YOLO

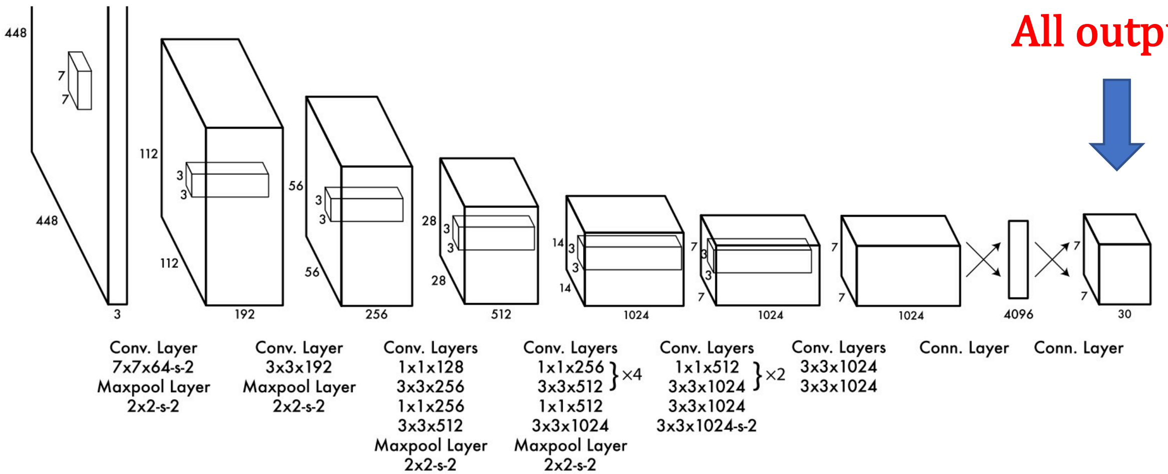
  - Object detection problem → Regression problem.
  - No Region Proposal, a fully convolutional networks output the class labels and location information directly.
  - Very fast.

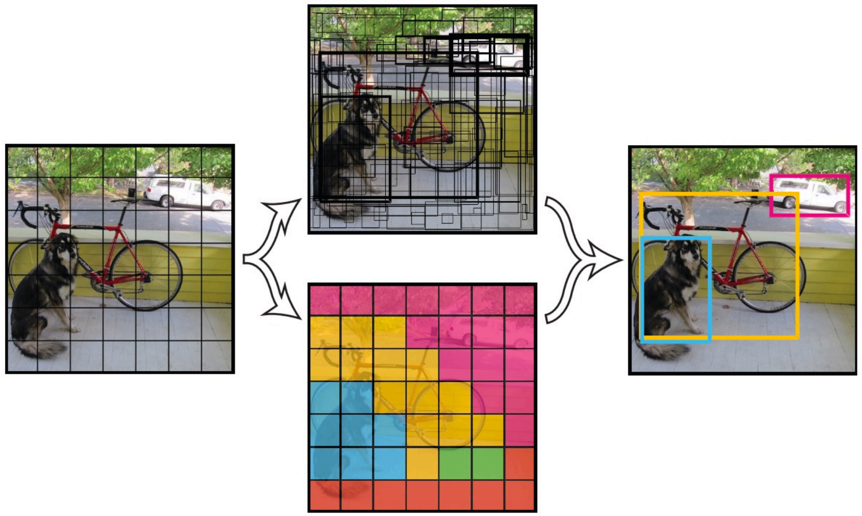


Computer Vision Applications

- Object Detection: YOLO

An image is separated into a 7x7 grid, each cell in the grid predicts the class label, object width and height, and object confidence of the corresponding image location.

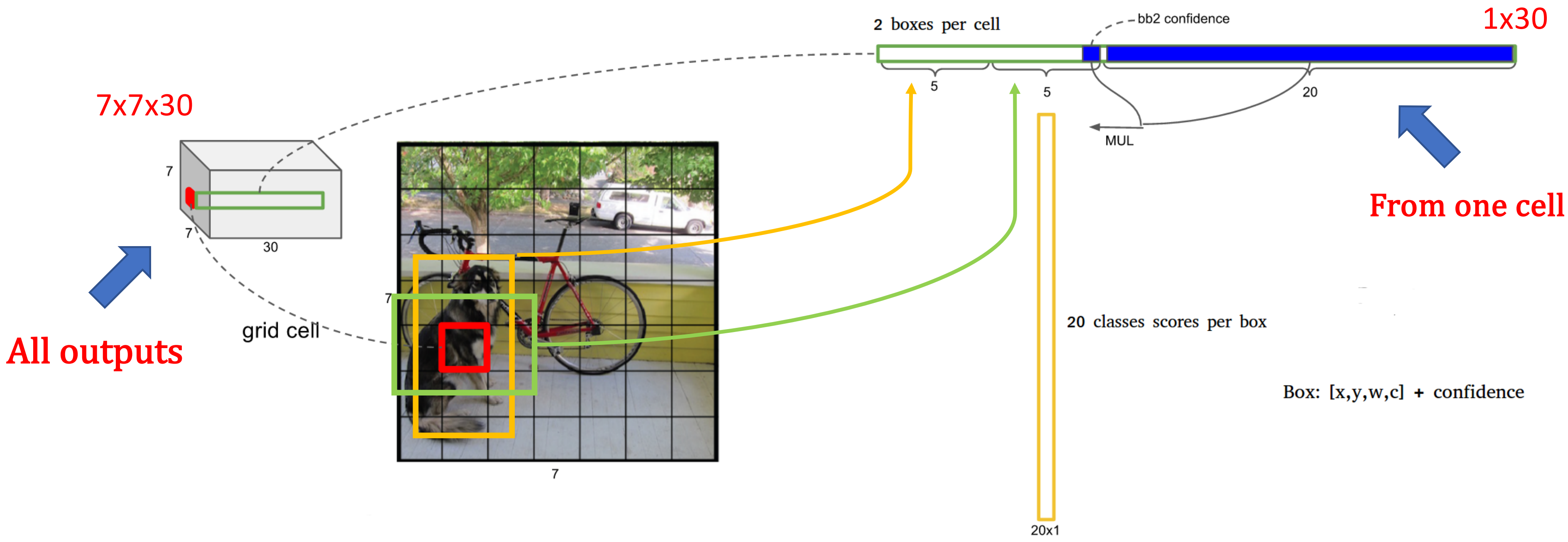




Computer Vision Applications

- Object Detection: YOLO

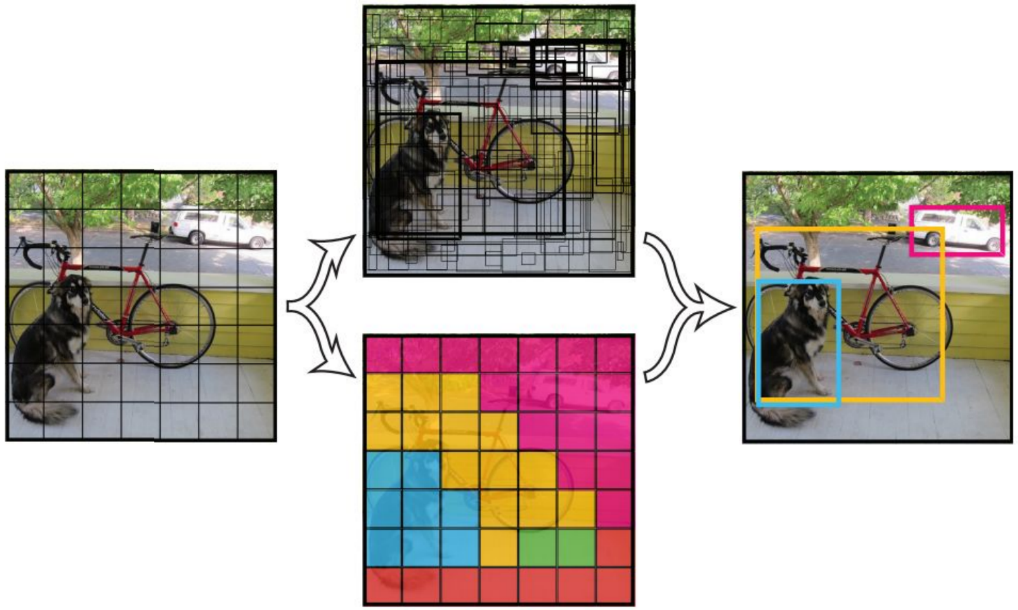
  - Each cell has 30 outputs, 10 for the information of 2 bboxes (x, y, w, h, confidence), 20 for 20 class probabilities of VOC dataset.
  - Therefore, each cell has 2 potential bboxes, but can only have one kind of object.



Computer Vision Applications

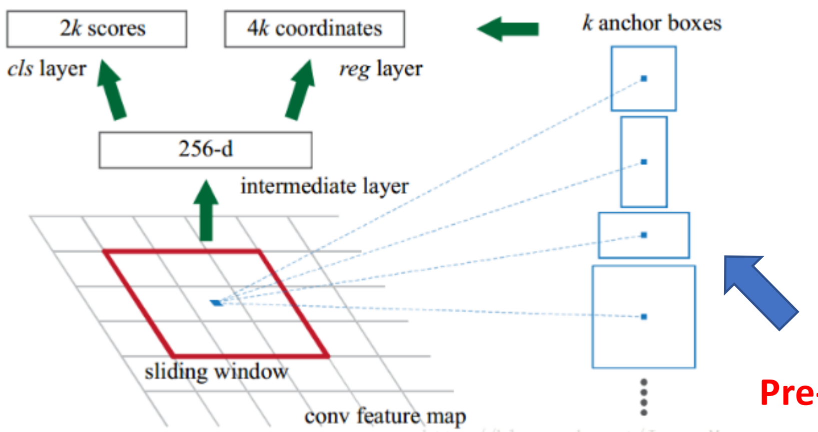
- Object Detection: YOLO

Remove the bboxes with low confidence and perform NMS to obtain the final result.

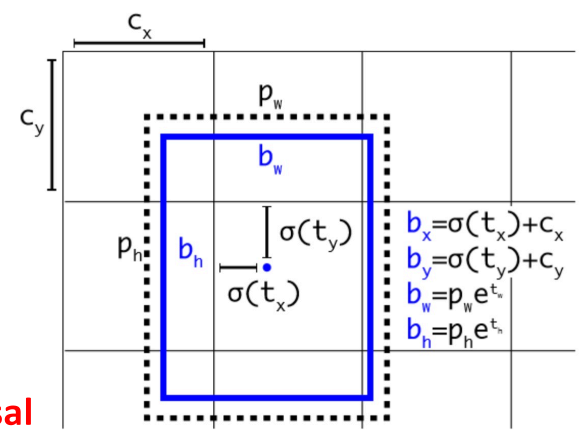


Computer Vision Applications

- Object Detection: YOLO2
  - YOLO Limitation:
    - Difficult to detect small objects.
  - YOLO2：
    - Pre-define multiple proposal regions for each cell i.e., pre-defined anchor.

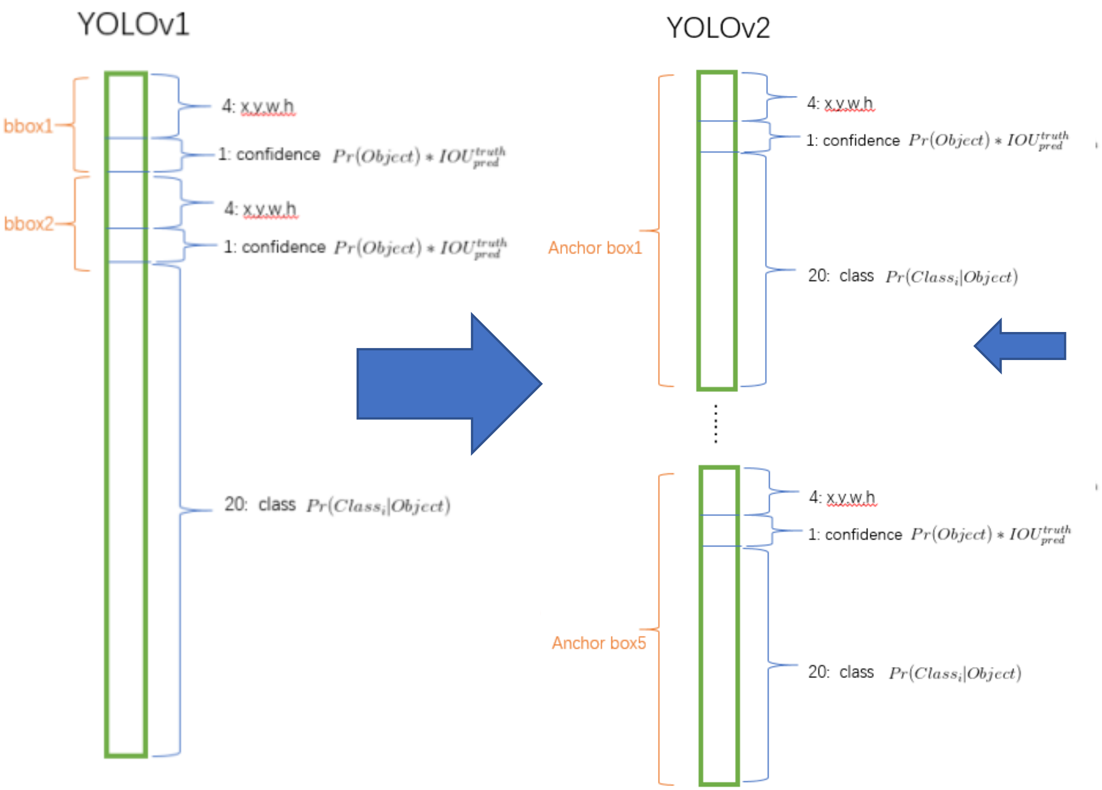


Pre-defined Region Proposal



Computer Vision Applications

- Object Detection: YOLO2

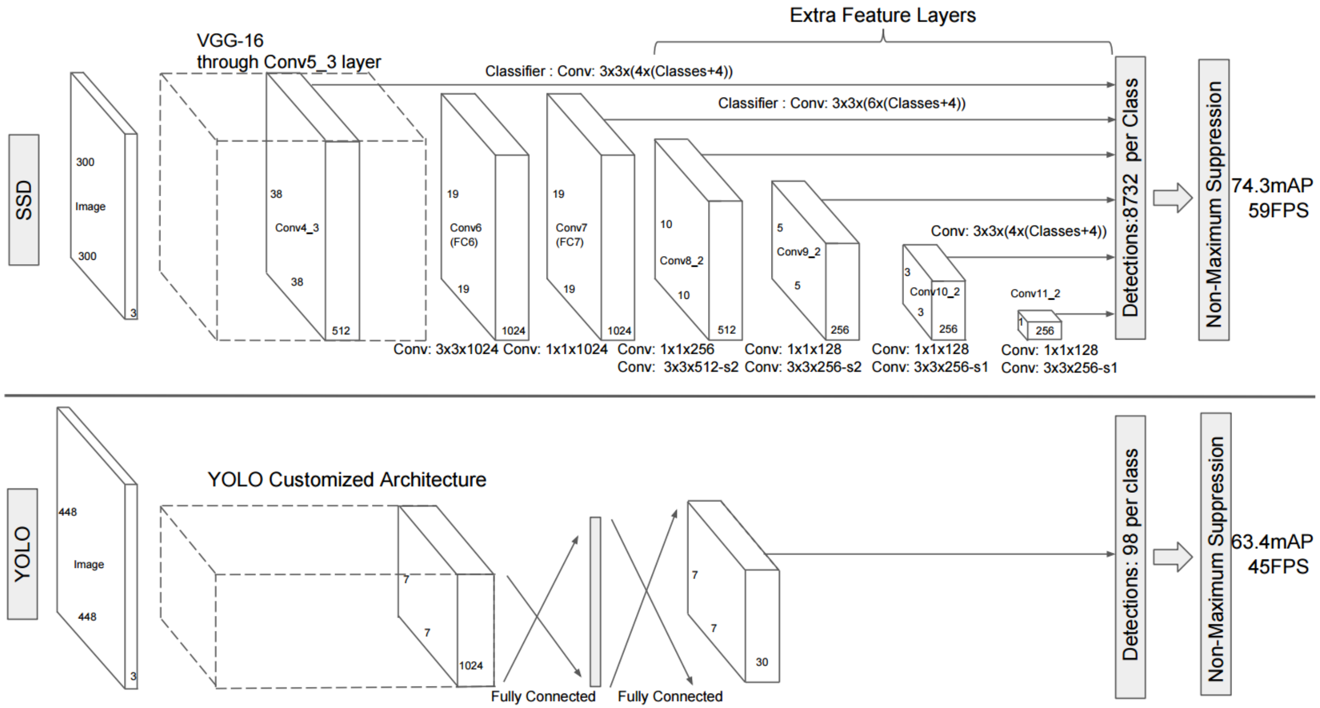


- Increase the grid resolution from 7x7 to 13x13.
- Pre-define 6 anchors for each cell, YOLO2 can predict 13x13x6=1014 potential bboxes, while YOLO1 only have 7x7x2=98 bboxes.
- Each cell has multiple class probabilities vectors i.e., each cell can detect different types of object. (each cell in YOLO1 can only be one class)

Computer Vision Applications

- Object Detection: SSD

SSD is another "Only Look Once" algorithm from Google.



Computer Vision Applications

- Object Detection: More and more …

R-CNN (2013.11) → OverFeat (ICLR' 14) → MultiBox (CVPR' 14) → SPP-Net (ECCV' 14) → MR-CNN (ICCV' 15) → DeepBox (ICCV' 15) → AttentionNet (ICCV' 15) →

Fast R-CNN (ICCV' 15) → DeepProposal (ICCV' 15) → RPN (NIPS' 15) → Faster R-CNN (NIPS' 15) → YOLO v1 (CVPR' 16) → G-CNN (CVPR' 16) → AZNet (CVPR' 16) →

Inside-OutsideNet(ION) (CVPR' 16) → HyperNet (CVPR' 16) → OHEM (CVPR' 16) → CRAFT (CVPR' 16) → MultiPathNet(MPN) (BMVC' 16) → SSD (ECCV' 16) →

GBDNet (ECCV' 16) → CPF (ECCV' 16) → MS-CNN (ECCV' 16) → R-FCN (NIPS' 16) → PVANET (NIPSW' 16) → DeepID-Net (PAMI' 16) → NoC (TPAMI' 16) → DSSD (Arxiv' 17) → TDM (CVPR' 17) →

Feature Pyramid Net(FPN) (CVPR' 17) → YOLO v2 (CVPR' 17) → RON (CVPR' 17) → DCN (ICCV' 17) → DeNet (ICCV' 17) → CoupleNet (ICCV' 17) → RetinaNet (ICCV' 17) →

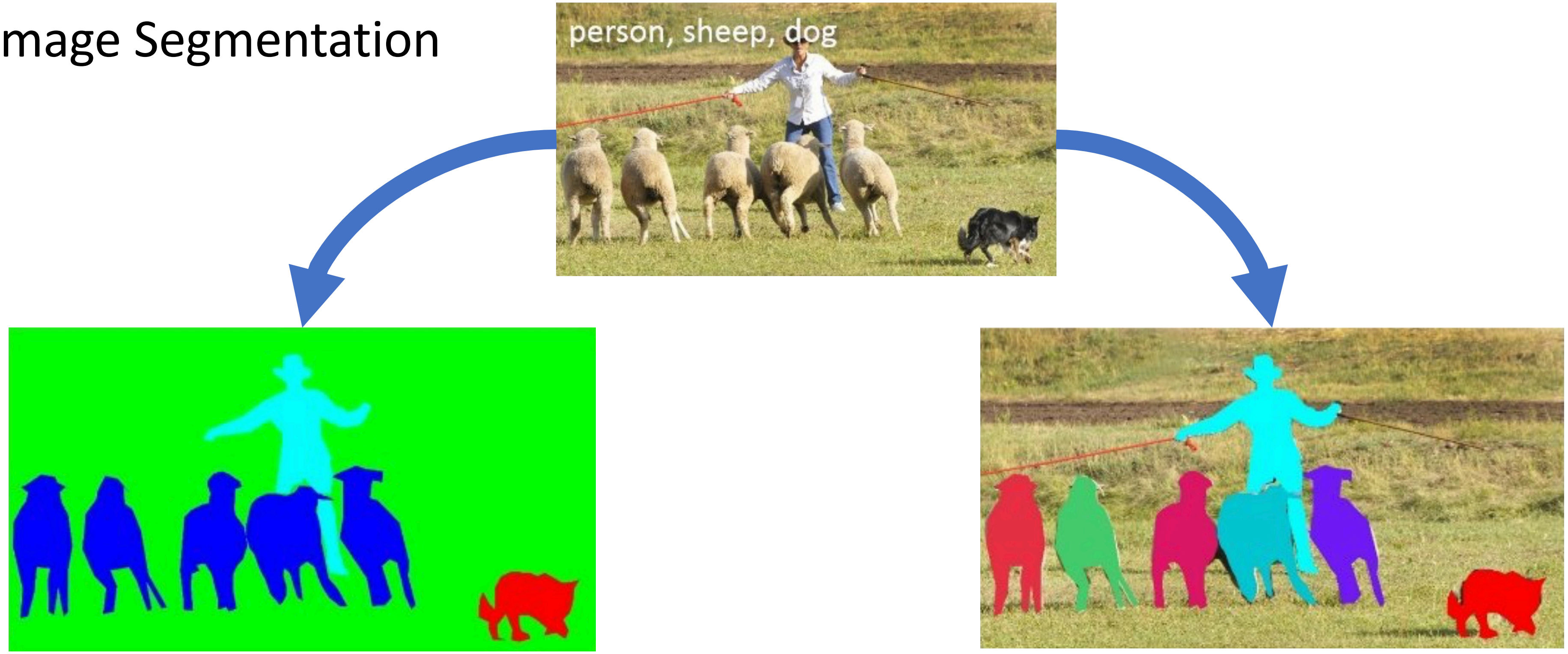
Mask R-CNN (ICCV' 17) → DSOD (ICCV' 17) → SMN (ICCV' 17) → YOLO v3 (Arxiv' 18) → SIN (CVPR' 18) → STDN (CVPR' 18) → RefineDet (CVPR' 18) → RFBNet (ECCV' 18) → …

Challenge：

- Speed
- Accuracy
- Weakly-supervised
- 3D detection
- Small object
- Object overlapping
- Multi-task learning
- …..

Computer Vision Applications

- Image Segmentation



Semantic Segmentation **Instance Segmentation**

Computer Vision Applications

- Image Segmentation: Pixel-wise Classification

Input

segmented

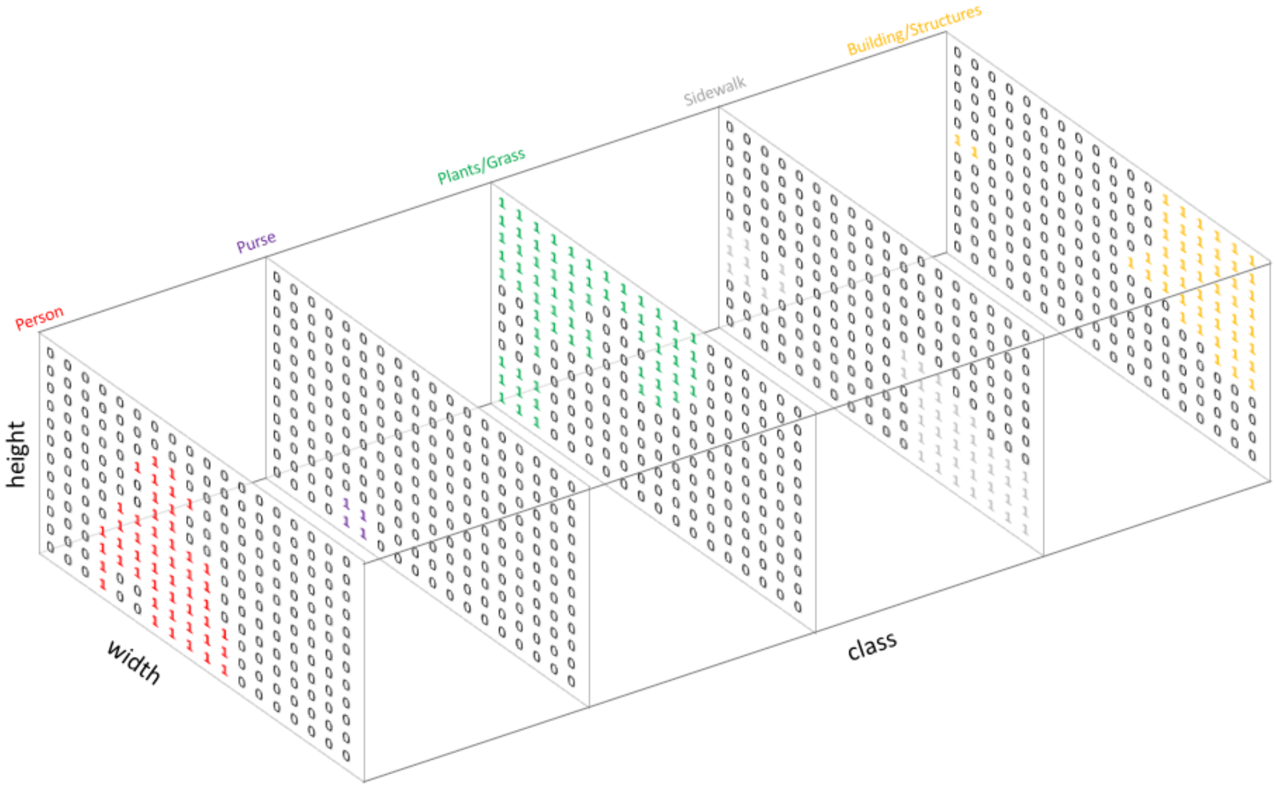
1: Person
2: Purse
3: Plants/Grass
4: Sidewalk
5: Building/Structures

3	3	3	3	3	3	3	3	3	3	3	3	5	5	5	5	5	5
3	3	3	3	3	3	3	3	3	3	3	3	5	5	5	5	5	5
3	3	3	3	3	3	1	1	3	3	3	3	5	5	5	5	5	5
3	3	3	3	3	1	1	1	1	3	3	3	5	5	5	5	5	5
3	3	3	3	3	3	1	1	3	3	3	5	5	5	5	5	5	5
5	5	3	3	3	3	1	1	3	3	5	5	5	5	5	5	5	5
4	4	3	4	1	1	1	1	1	1	4	4	4	5	5	5	5	5
4	4	3	4	1	1	1	1	1	1	4	4	4	4	4	5	5	5
4	4	4	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4
3	3	3	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4
3	3	3	1	2	2	1	1	1	1	1	4	4	4	4	4	4	4
3	3	3	1	2	2	1	1	1	1	1	4	4	4	4	4	4	4

Semantic Labels

Computer Vision Applications

- Image Segmentation: Pixel-wise Classification

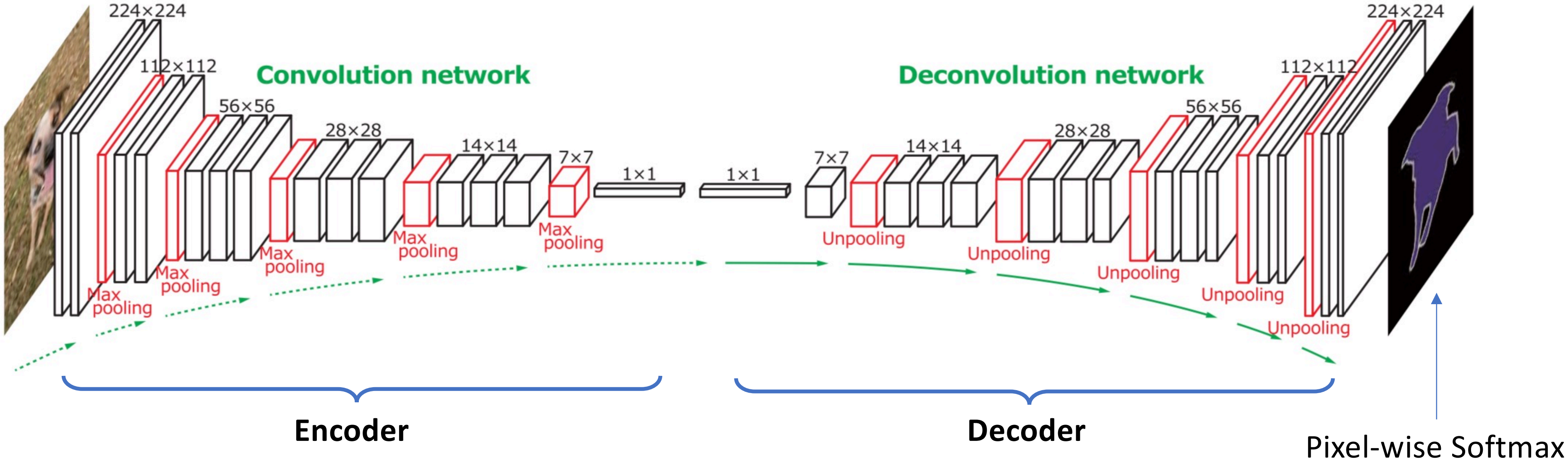


Computer Vision Applications

- Image Segmentation: Fully Convolutional Networks, FCN

FCN uses convolution and pooling only, which allows to input images with arbitrary size.

- Encoder uses pooling, strided convolution for “downsampling”.
- Decoder uses transposed convolution for “upsampling”.



Fully Convolutional Networks for Semantic Segmentation. *Long, Shelhamer, and Darrel. CVPR. 2015.*

Learning Deconvolution Network for Semantic Segmentation. *Noh et al. ICCV. 2015.* (Image is from here)

Computer Vision Applications

- Image Segmentation: Skip-connection

In the encoding process, as the number of layers increased, we can have higher level features, but lost the low-level features.

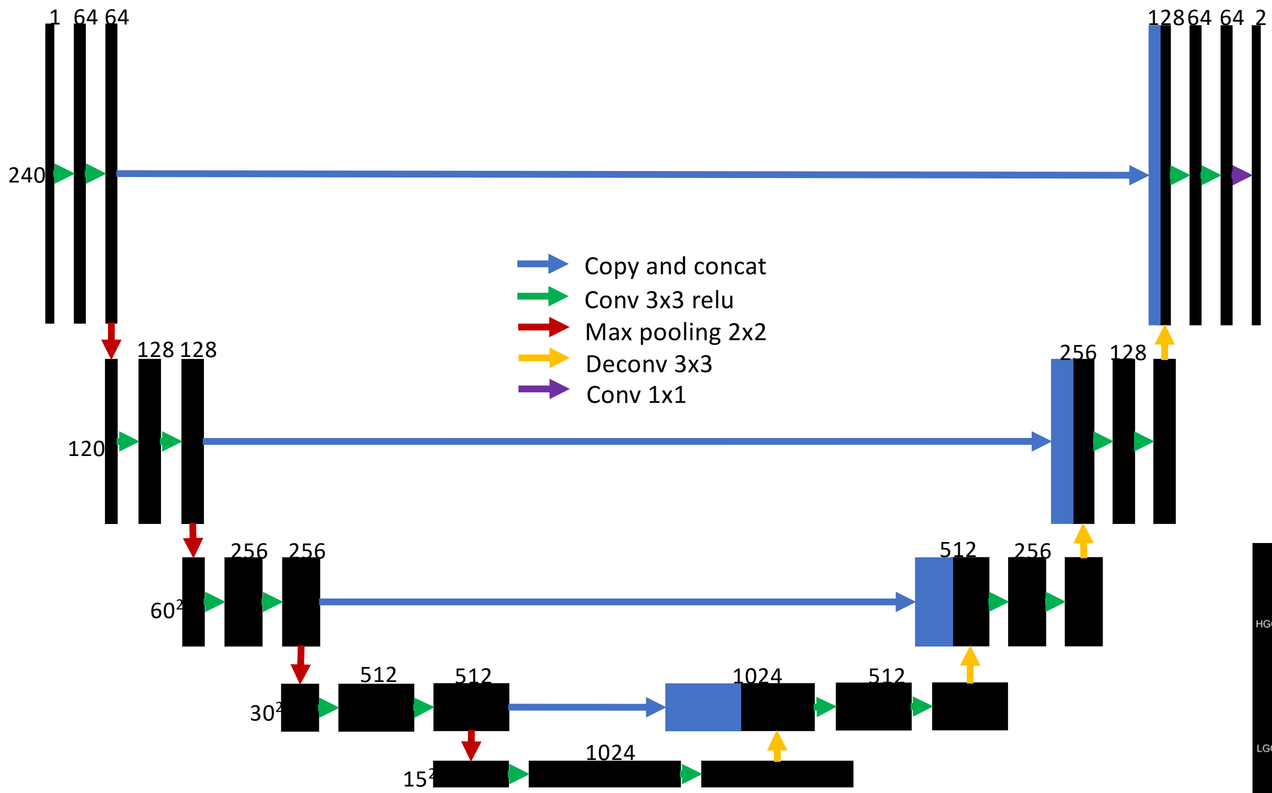
Ground truth target

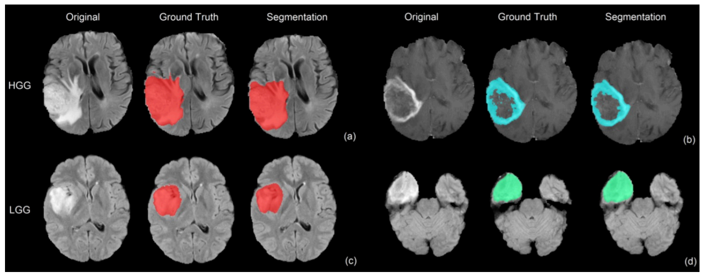
Predicted segmentation

Lost low-level details

Computer Vision Applications

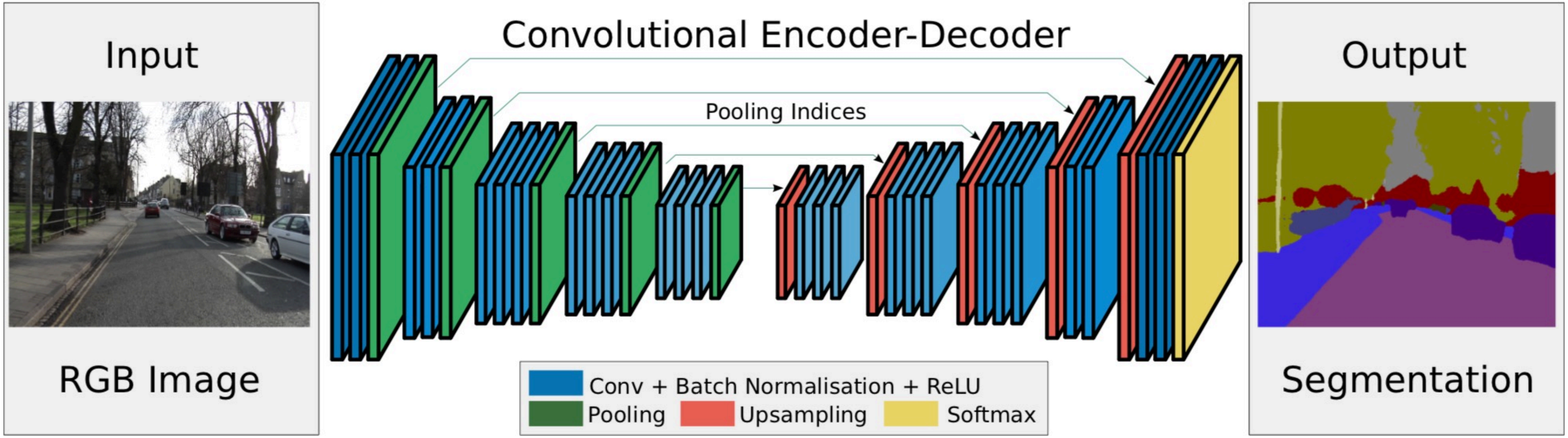
- Image Segmentation: Skip-connection





Computer Vision Applications

- Image Segmentation: Skip-connection

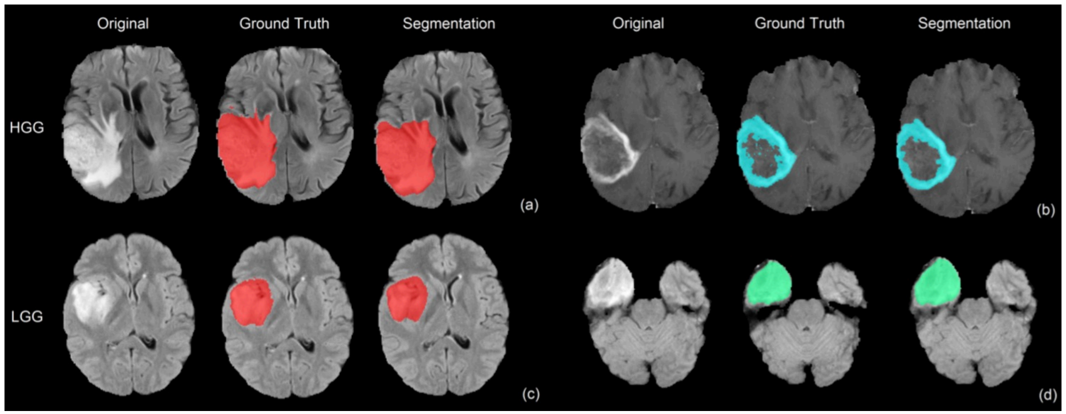


SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. *Vijay, Badrinarayanan etal. PAMI. 2015*

Computer Vision Applications

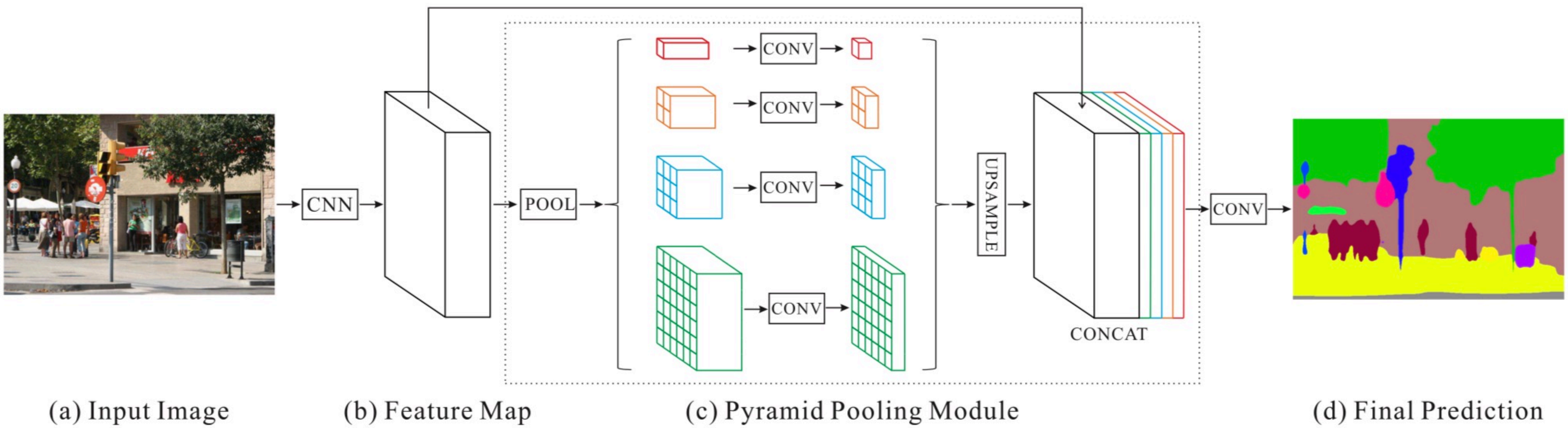
- Image Segmentation: Skip-connection

Skip-connection sends low-level features to the decoding process, which improves the performance for segmenting the detailed pattern.



Computer Vision Applications

- Image Segmentation: PSPnet (Pyramid Scene Parsing Network)



PSPnet: Pyramid Scene Parsing Network. *Hengshuang. Zhao, Jianping. Shi etal. CVPR. 2017.*

Computer Vision Applications

- Image Segmentation

Pixel-wise cross entropy:

- Considering each pixel as an individual label for classification
- Drawback: objects will larger area have larger weights on the loss, which lead to low performance for segmenting small objects.

Dice coefficient:

- Address the imbalance problem of pixel-wise cross entropy.
- $Dice = \frac{2|A \cap B|}{|A|+|B|}$, where A and B are two vectors with values of 0 and1,
  - $|A \cap B|$ is the intersection area.
  - If A and B are fully overlapped, Dice=1.
  - If A and B are fully separated, Dice=0,

$$Dice = \frac{2|A \cap B|}{|A| + |B|} = \frac{2TP}{2TP + FP + FN} = \frac{2|A \cdot B|}{|A|^2 + |B|^2}$$

when values are all 0 and 1

Computer Vision Applications

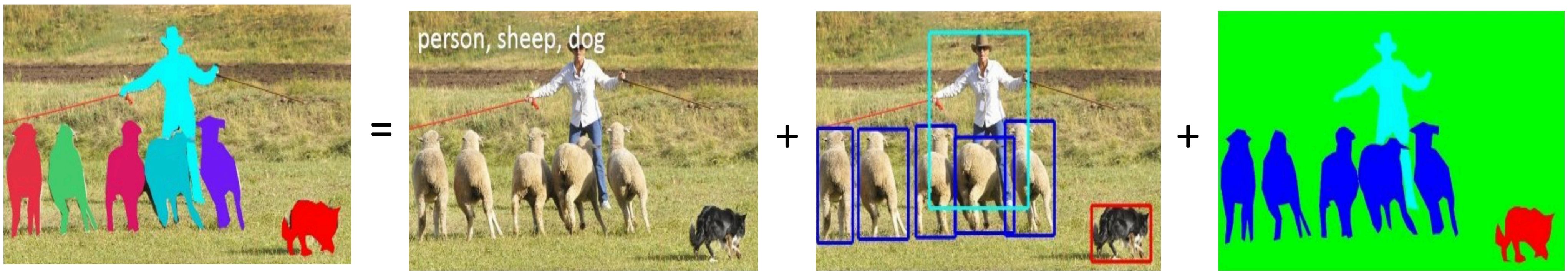
- Image Segmentation

  - DeepLab series
  - Discriminative Feature Network, DFN. CVPR 2018
  - ExFuse. ECCV 2018
  - …

Computer Vision Applications

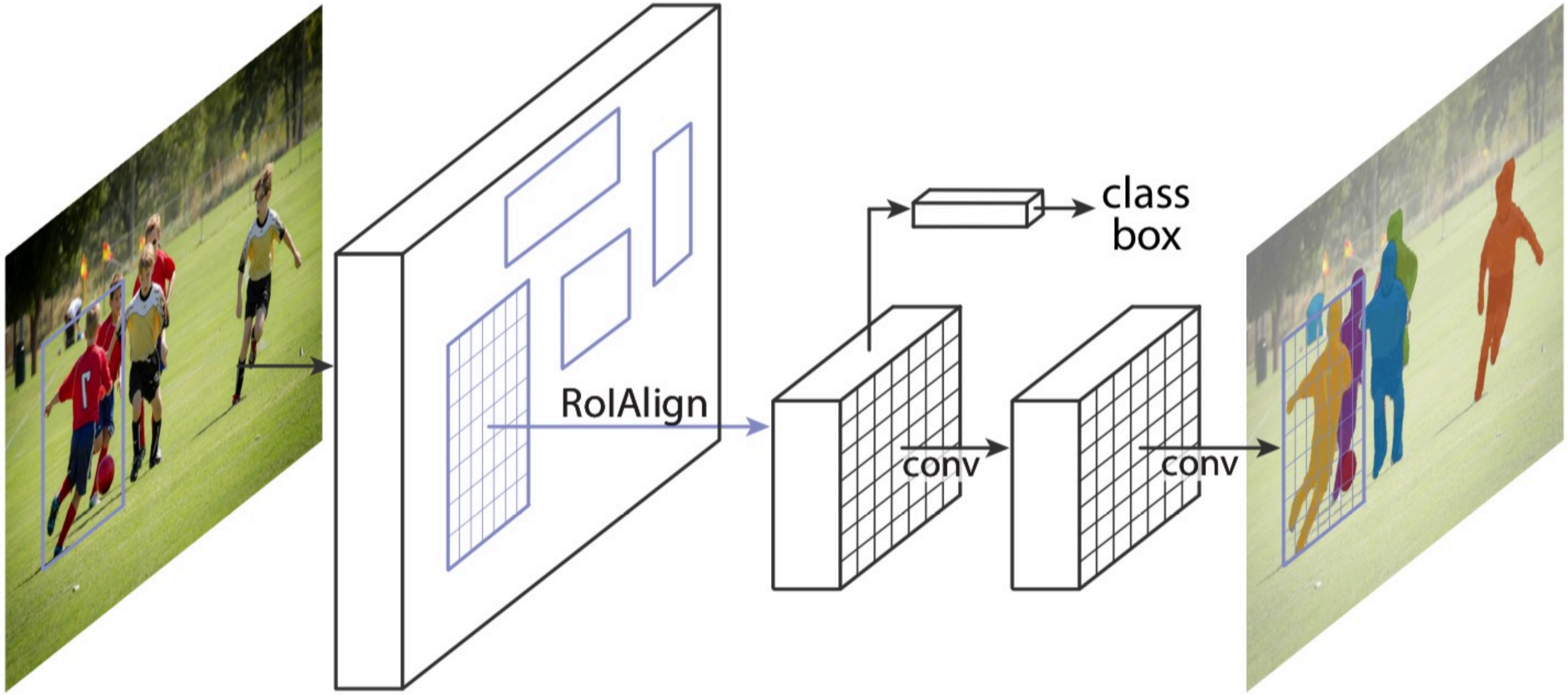
- Image Segmentation: Instance Segmentation

Instance Segmentation = Object Classification + Object Detection + Semantic Segmentation



Computer Vision Applications

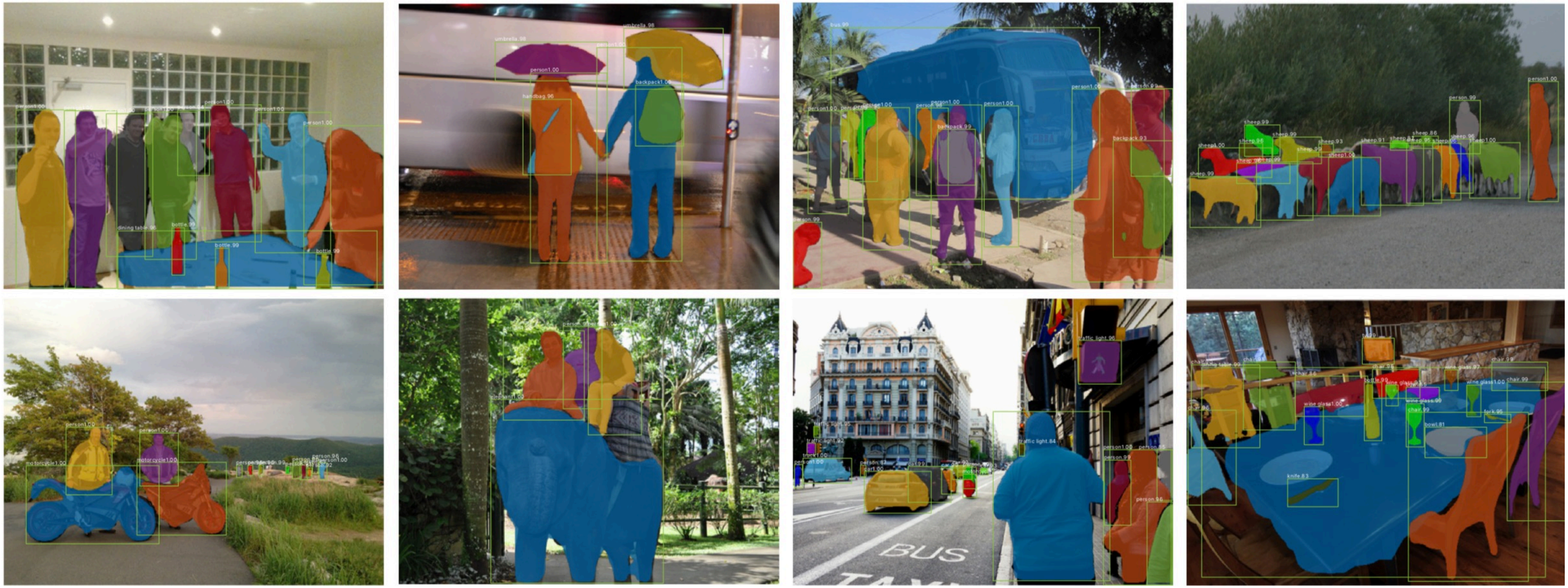
- Image Segmentation: Instance Segmentation



Mask R-CNN. *Long, Kaiming He, Georgia Gkioxari etal. ICCV. 2017.*

Computer Vision Applications

- Image Segmentation: Instance Segmentation



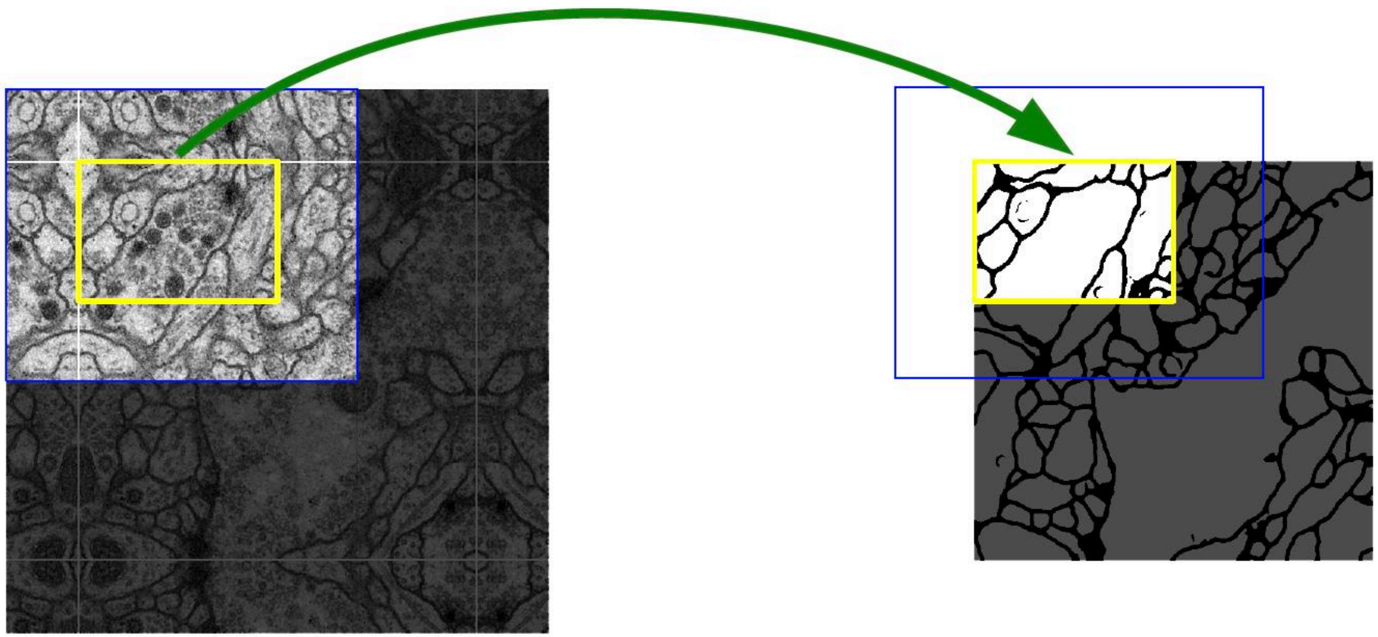
Mask R-CNN. *Long, Kaiming He, Georgia Gkioxari etal. ICCV. 2017.*

Computer Vision Applications

- Image Segmentation: Tricks

Mirror Padding

- Avoid to lost information on the boundary.

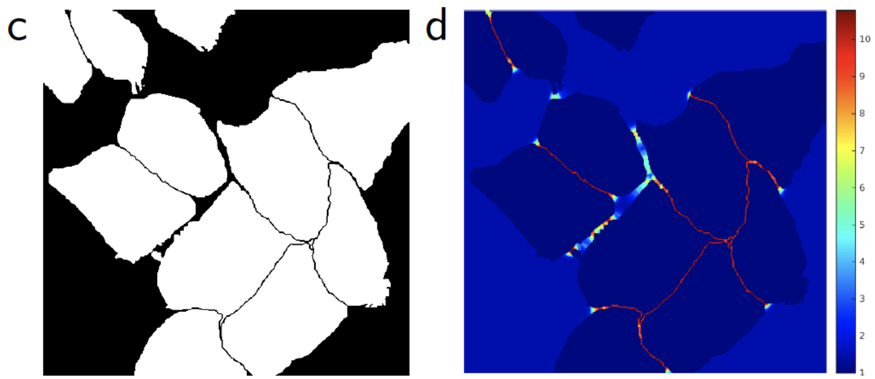


Computer Vision Applications

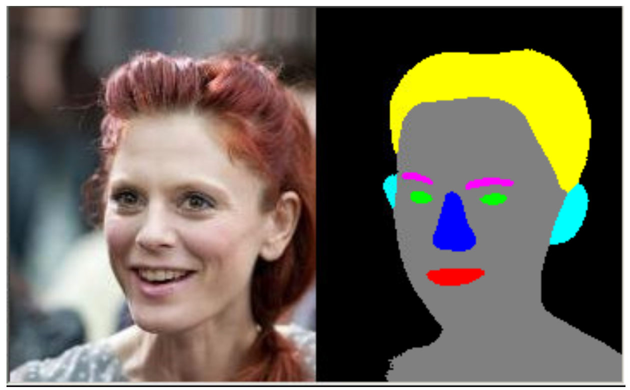
- Image Segmentation: Tricks

Loss weighting：

- Edge weighting: increase the weight of edge, which make the loss more sensitive to the edges.
- Balance weighting: increase the weight of small objects according to their size.



Increase the weight of edges

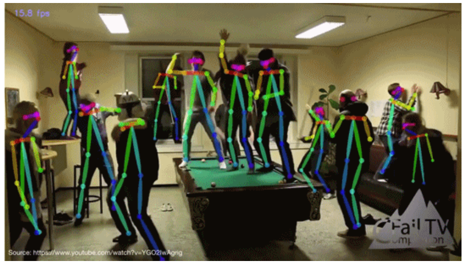


Increase the weight of small objects e.g., eyes

Computer Vision Applications

- Pose Estimation

	Pipeline	Advantage	Disadvantage
Top-down approach	Detect each person and then estimate their pose one-by-one.	If object detection works well, the accuracy is high.	If object detection fails to detect the person, we cannot estimate the pose. Inferencing time relate to the number of people.
Bottom-up approach	Detect all keypoints and then assign the keypoints to different person.	Fixed inferencing time.	Difficult to assign the keypoints to different person.

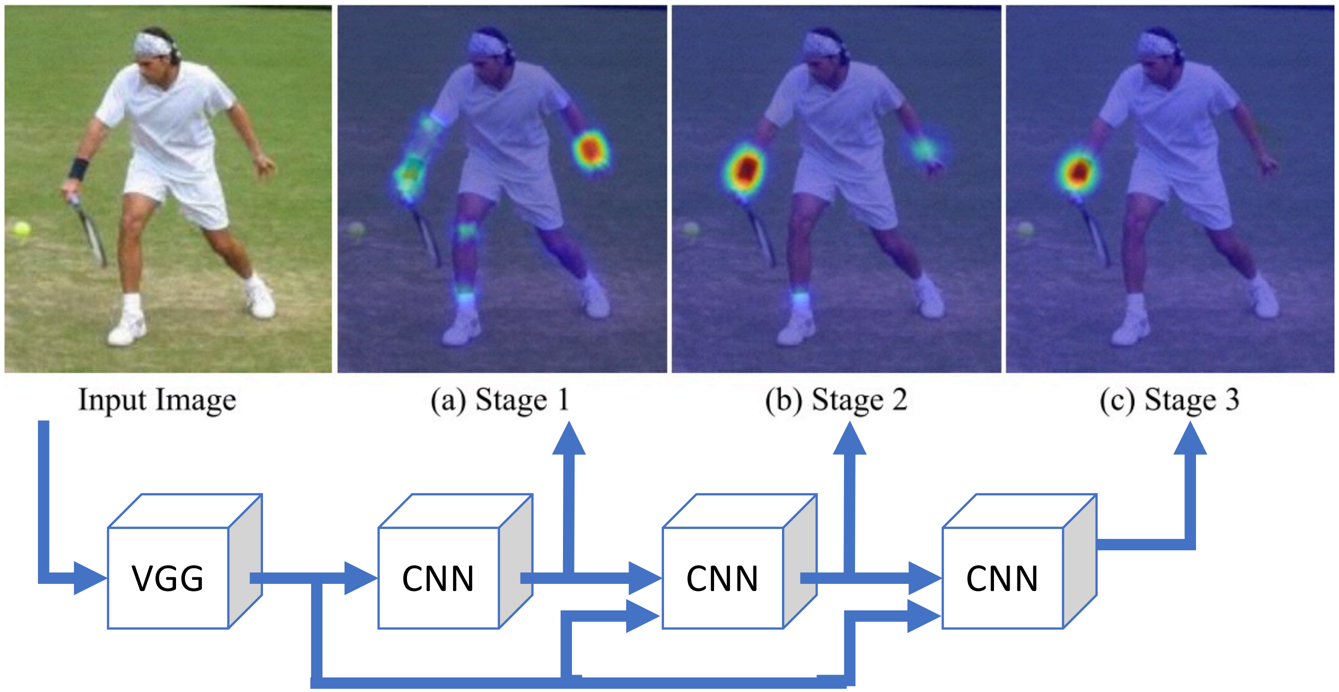


Computer Vision Applications

- Pose Estimation: Convolutional Pose Machine, CPM

Heat map of the right hand

Top-down

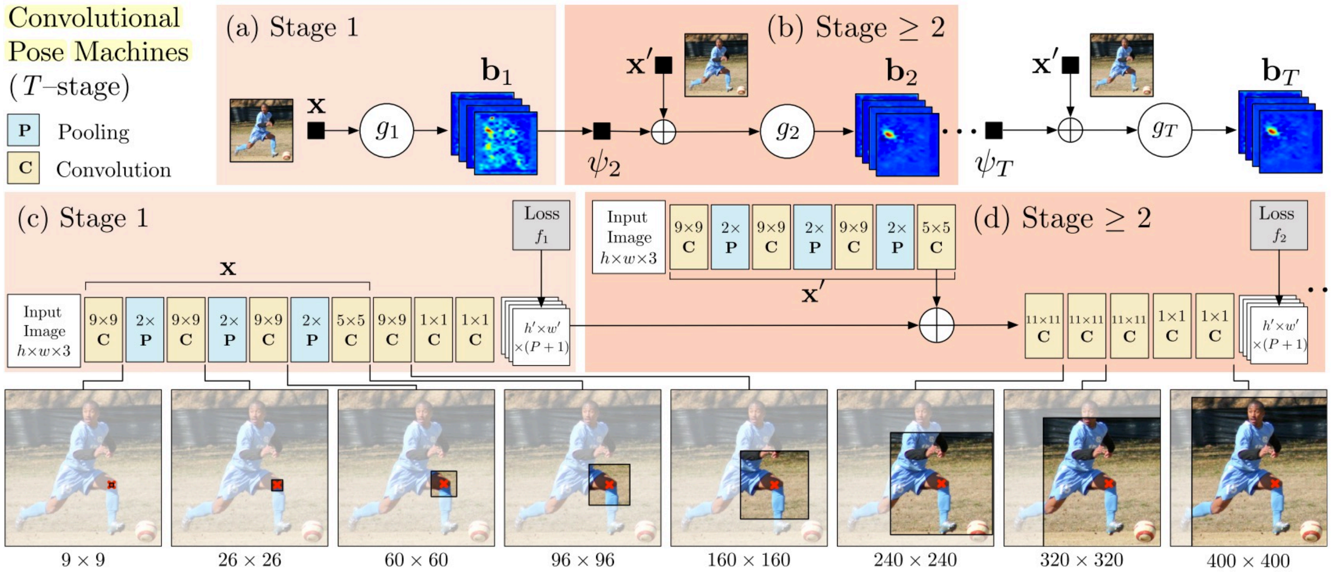


- Step 1: Use object detection to find the bbox of person.
- Step 2: Feed the person image into VGG to obtain the image features.
- Step 3: Feed the image features to a stage-1 CNN to obtain the keypoint heatmaps.
- Step 4: Feed the keypoint heatmaps and image feature to the next CNN to obtain better keypoint estimation.

Convolutional Pose Machines. *Shih-En Wei, Varun Ramakrishna etal. CVPR. 2016.*

Computer Vision Applications

- Pose Estimation: Convolutional Pose Machine, CPM

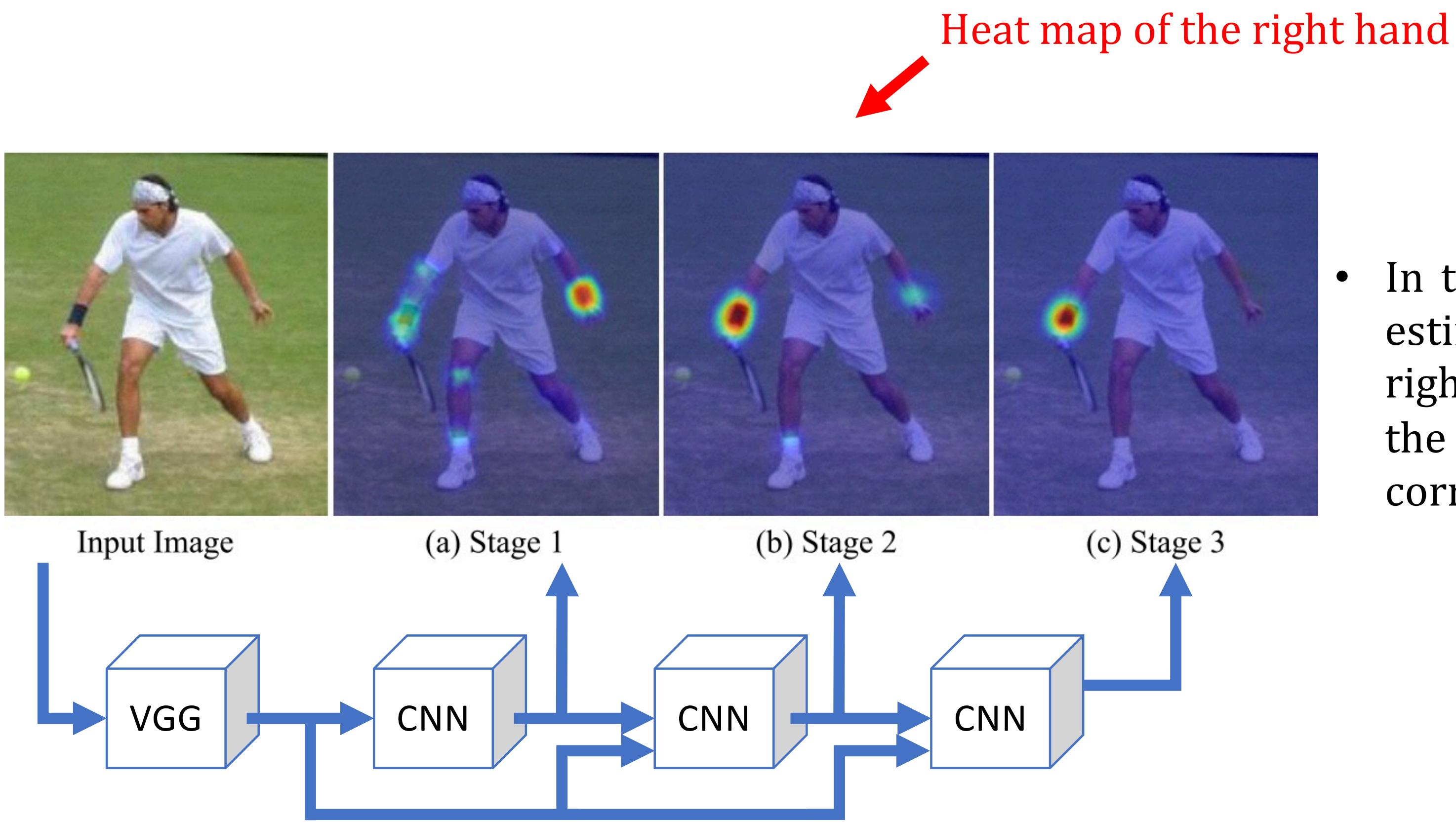


- Advantages of multiple stages:
  - Larger receptive field
  - Fine-tune the keypoint estimation

Convolutional Pose Machines. *Shih-En Wei, Varun Ramakrishna etal. CVPR. 2016.*

Computer Vision Applications

- Pose Estimation: Convolutional Pose Machine, CPM



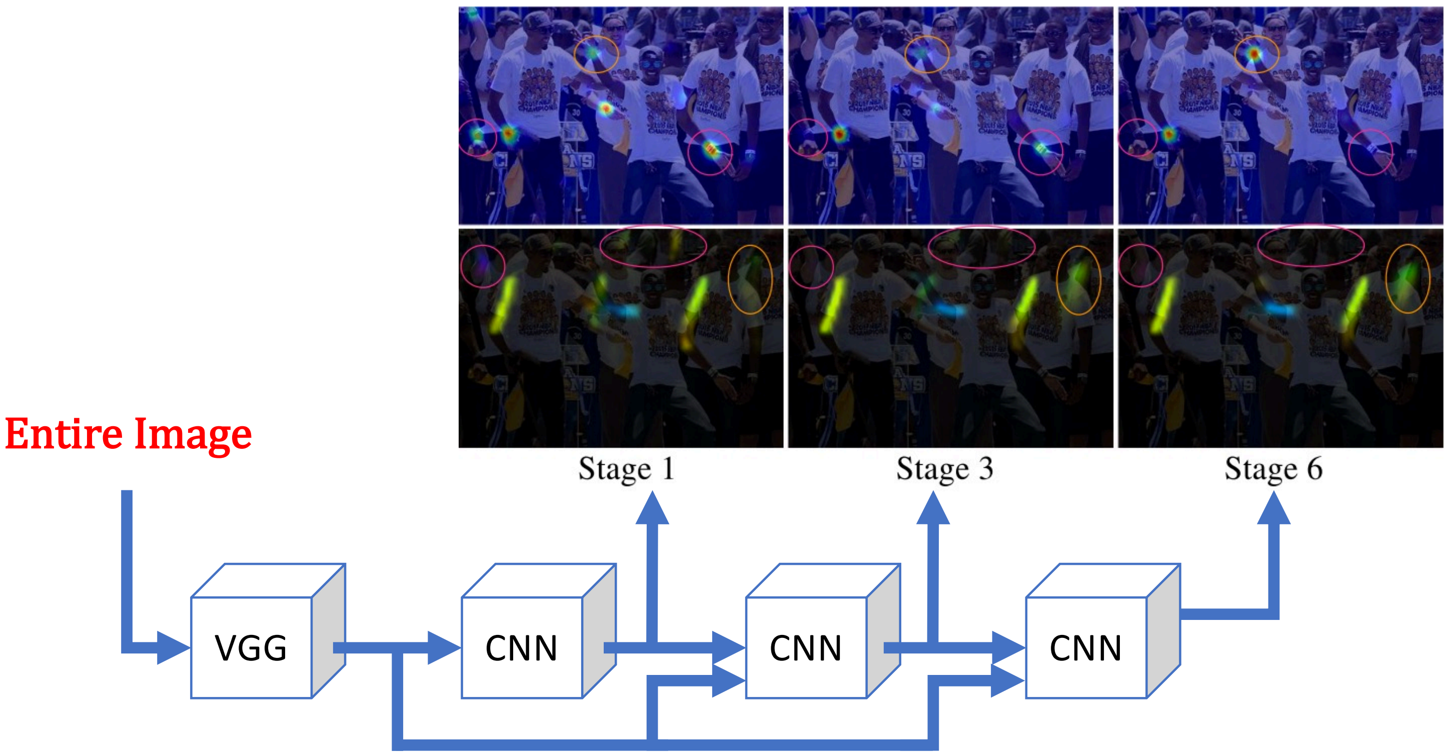
- In this example, the stage 1 fails to estimate the correct location of the right hand, but as using more stages, the model successfully estimates the correct right hand location.

Convolutional Pose Machines. *Shih-En Wei, Varun Ramakrishna etal. CVPR. 2016.*

Computer Vision Applications

- Pose Estimation: OpenPose

OpenPose = CPM + Bottom-up



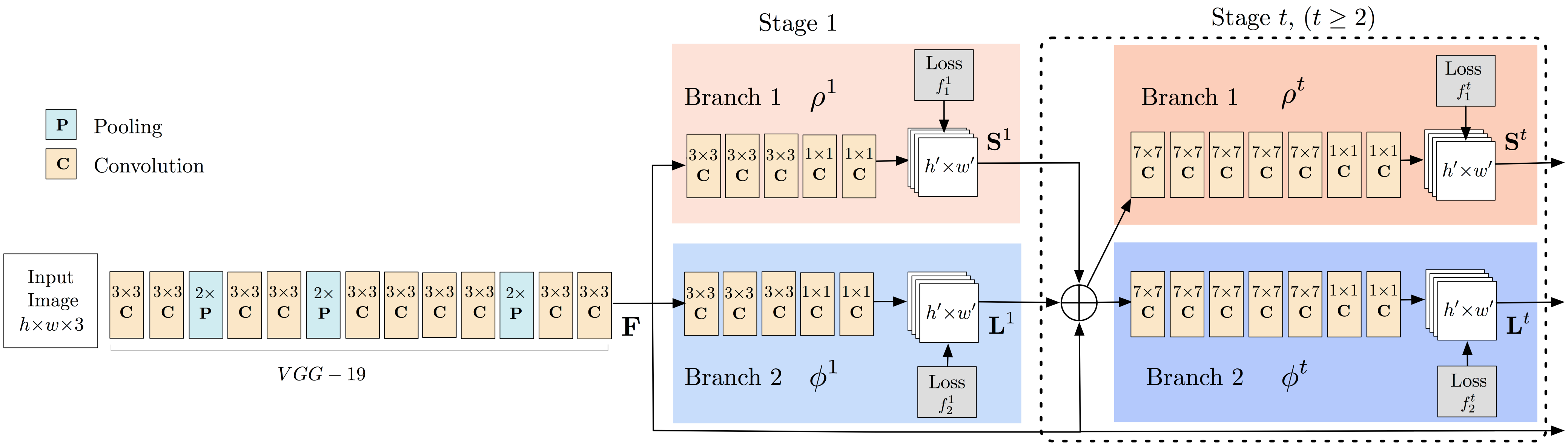
- Keypoint heatmaps
- “Connection” heatmaps

Realtime Multi-Person 2D Pose Estimation using Part Affinity Field. *Cao Zhe, Tomas Simon etal. CVPR. 2017.*

Computer Vision Applications

- Pose Estimation: OpenPose

OpenPose = CPM + Bottom-up



Realtime Multi-Person 2D Pose Estimation using Part Affinity Field. *Cao Zhe, Tomas Simon etal. CVPR. 2017.*

Computer Vision Applications

- Pose Estimation: Pose Proposal Networks, PPN

PPN = YOLO + OpenPose very fast

- Disadvantage of OpenPose: Parse the heatmaps pixel-wisely to find all keypoints and connections. The speed bottleneck is on CPU rather than GPU.

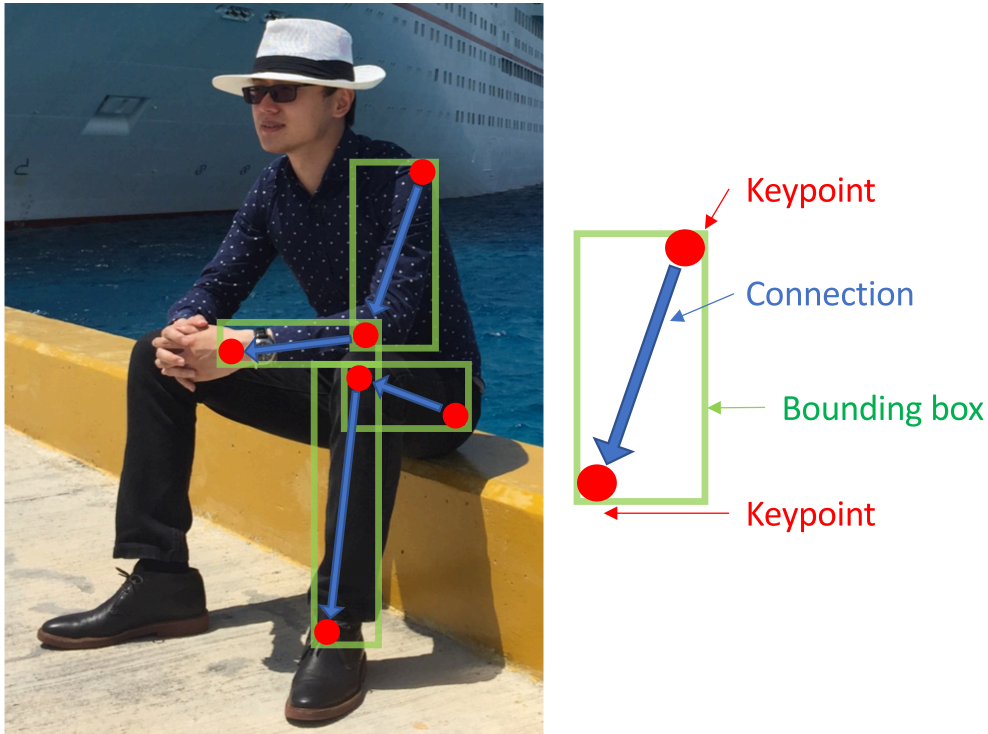
- PPN considers the pose estimation problem as an object detection problem, without requiring pixel-wisely parsing.

Pose Proposal Networks. *Taiki Sekii. ECCV. 2018.*

Computer Vision Applications

- Pose Estimation: PPN

PPN = YOLO + OpenPose   very fast

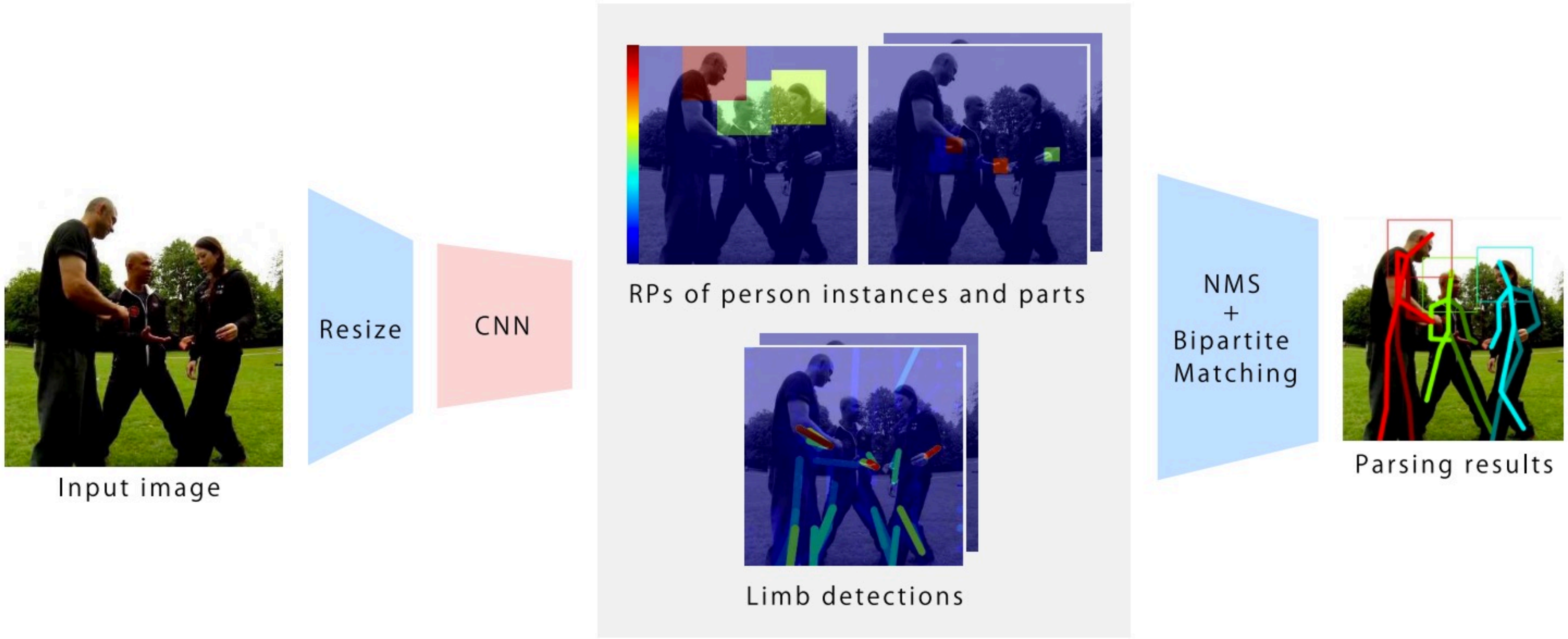


- One body connection has two keypoints.
- OpenPose estimates the red points and blue connections, while PPN estimates the green bounding boxes.
- PPN uses a greedy algorithm to connect all bounding boxes to form a person pose.

Pose Proposal Networks. *Taiki Sekii. ECCV. 2018.*

Computer Vision Applications

- Pose Estimation: PPN



Pose Proposal Networks. *Taiki Sekii. ECCV. 2018.*

Computer Vision Applications

- Pose Estimation: PPN Limitations
    - Poor performance for the crowd.
    - Poor performance for datasets that the person has a large size range.

Pose Proposal Networks. *Taiki Sekii. ECCV. 2018.*

Computer Vision Applications

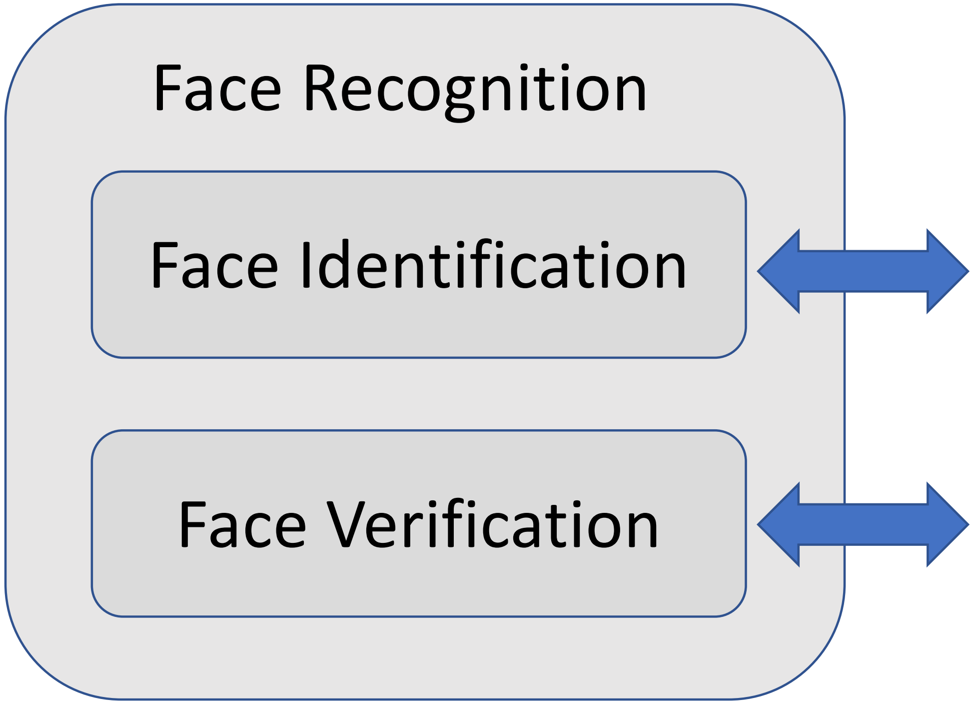
- Face Recognition: Problem Definition

Face Detection → **Face Alignment** → **Face Identification**

- Step 1: Detect the face location on the image.
- Step 2: Align the face to the center of the image.
- Step 3: Perform face recognition on the image.

Computer Vision Applications

- Face Recognition: Problem Definition

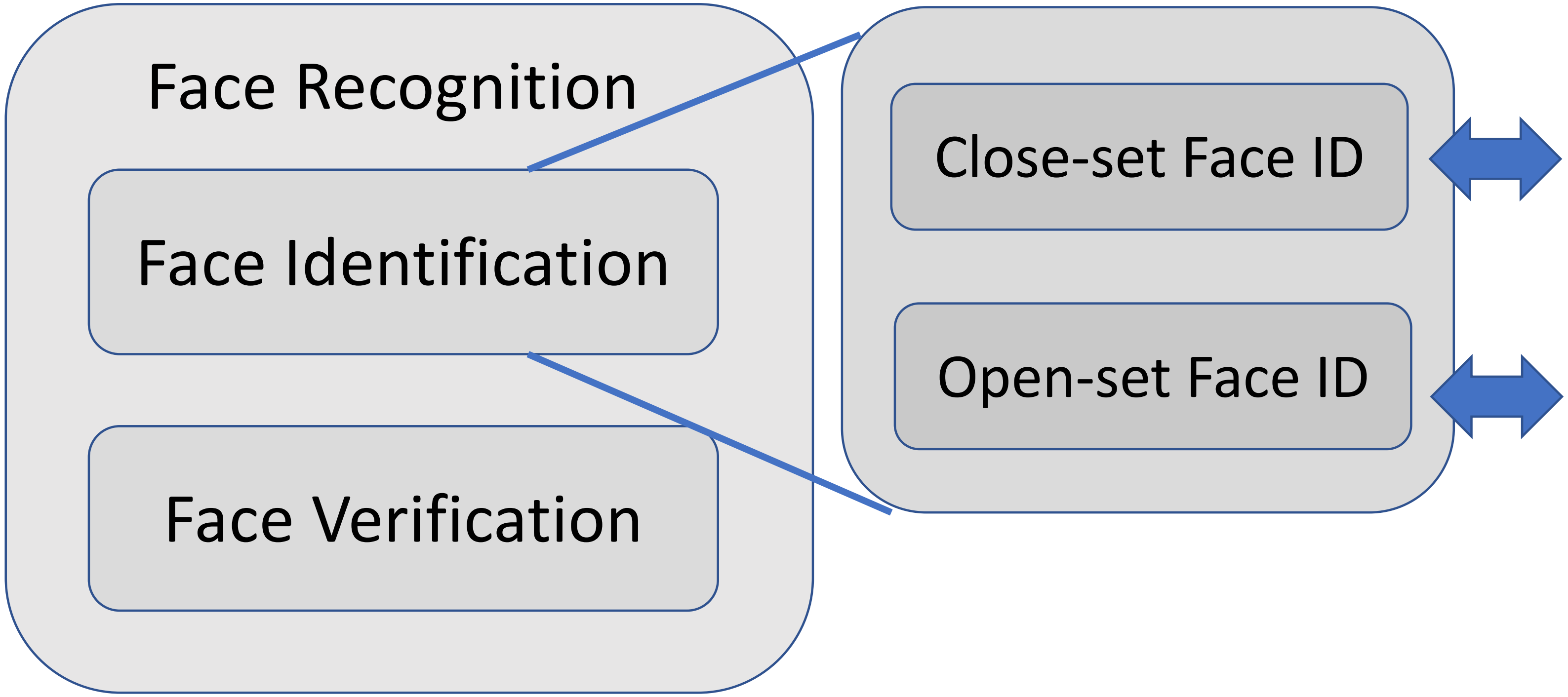


Two different tasks

- Given an image, classify the face ID.
- Given two images, classify whether they are the same person.

Computer Vision Applications

- Face Recognition



- The input face in the training set, i.e., a simple classification problem.
- The input face is not in the training set.

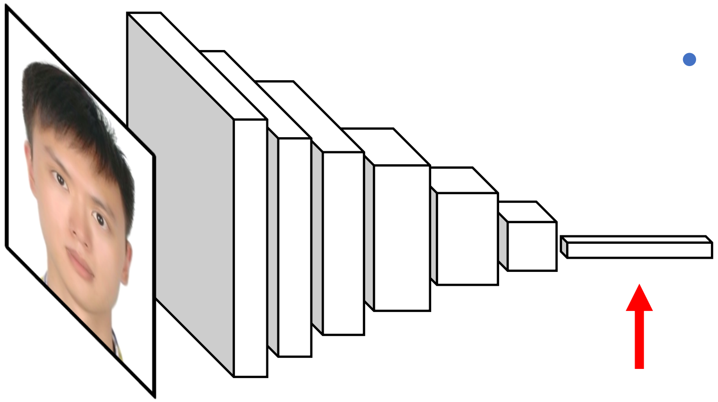
Computer Vision Applications

- Face Recognition

- The most commonly used method is Open-set Face ID:
  - The model is fixed, we cannot retrained the model.
  - When adding new person, a single image is used as the reference.

Computer Vision Applications

- Face Recognition



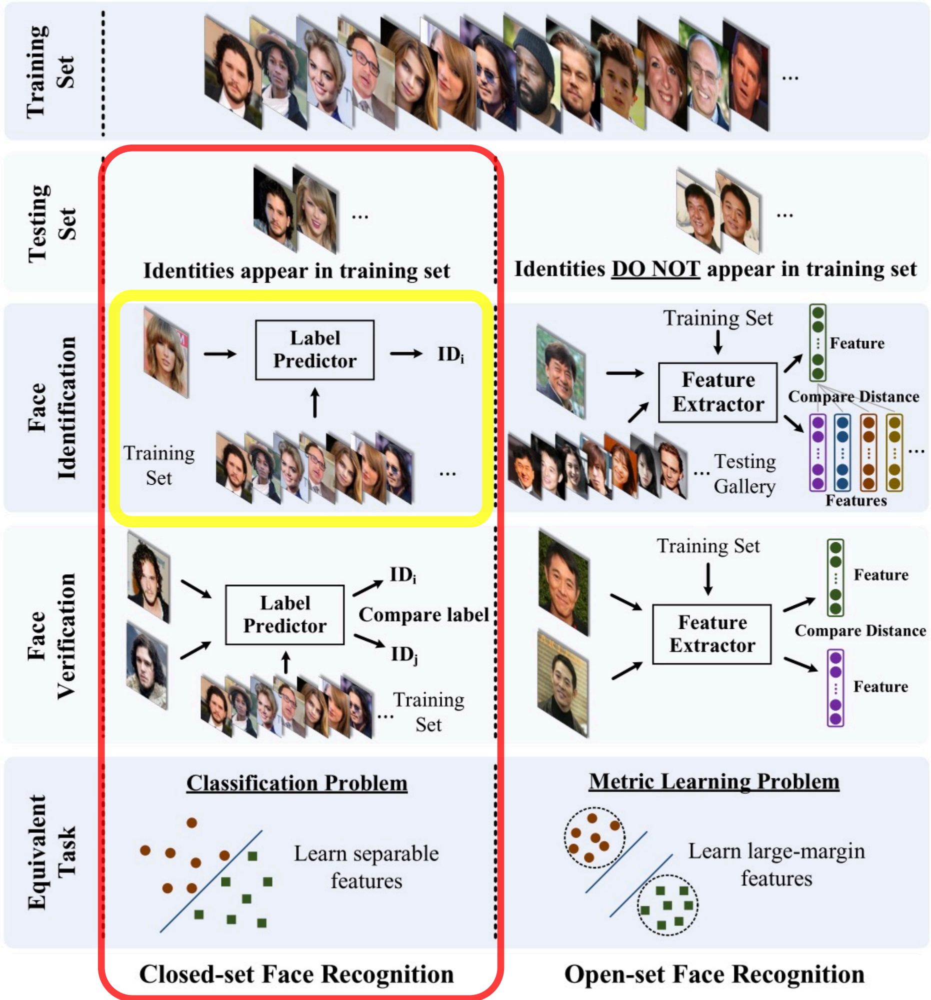
Feature Vector

- Open-set Face ID :
  - Pretrained an image encoder to extract discriminative features from the images.
  - Different people's face have very different feature vectors. While the feature vectors of the same person are similar even the images have different lighting conditions.
  - Find the face ID by comparing the feature vectors in the dataset.

Computer Vision Applications

- Face Recognition

- **Close-set Face Identification:** A simple classification problem, similar with MNIST. Given an image, output the class label.
- **Close-set Face Verification:** Also a simple classification problem. Given two images, output two class labels and compare whether the labels are equal.
- **Open-set Face Identification:** A feature extraction problem, it first extracts all feature vectors of the images in the dataset, then when input an image, find the ID that has the best match feature vector.
- **Open-set Face Verification:** Also a feature extraction problem, it extracts the feature vectors of two images and computes the similarity score. If the score higher than a threshold, these two images are the same person.



SphereFace: Deep Hypersphere Embedding for Face Recognition. *Weiyang Liu etal. CVPR. 2017.*

Computer Vision Applications

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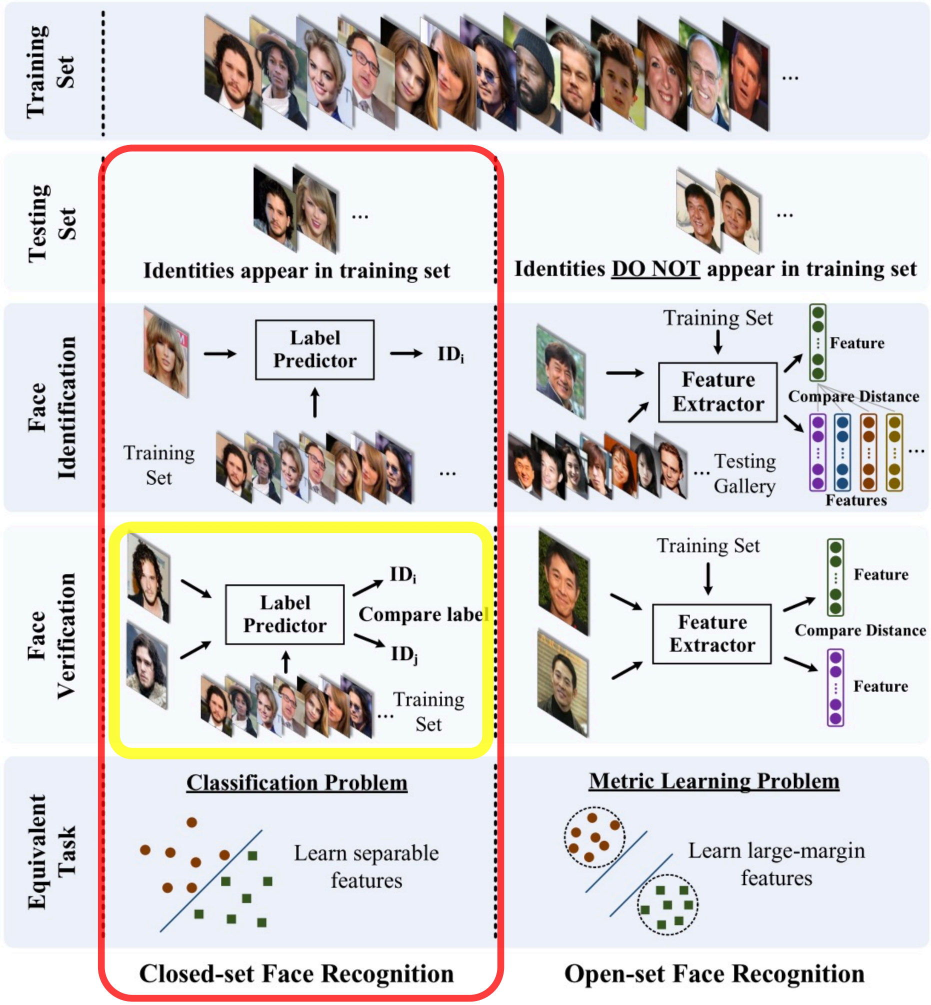

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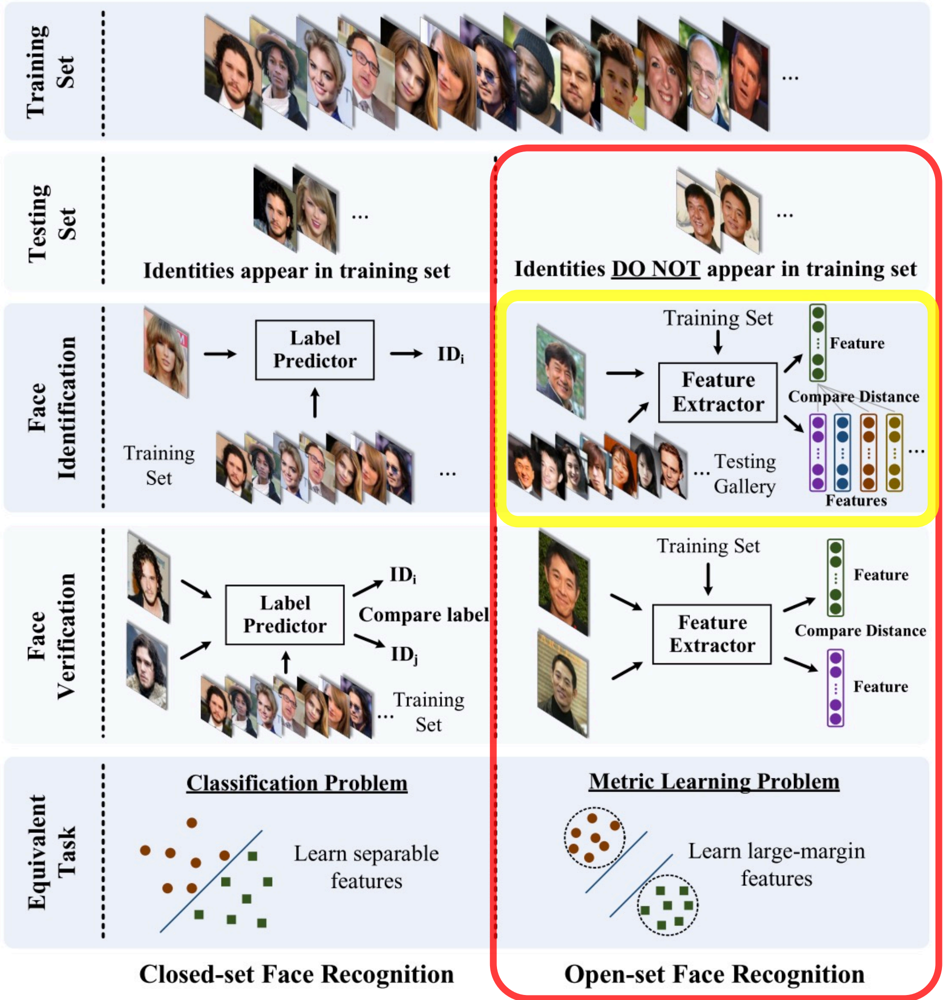

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Computer Vision Applications

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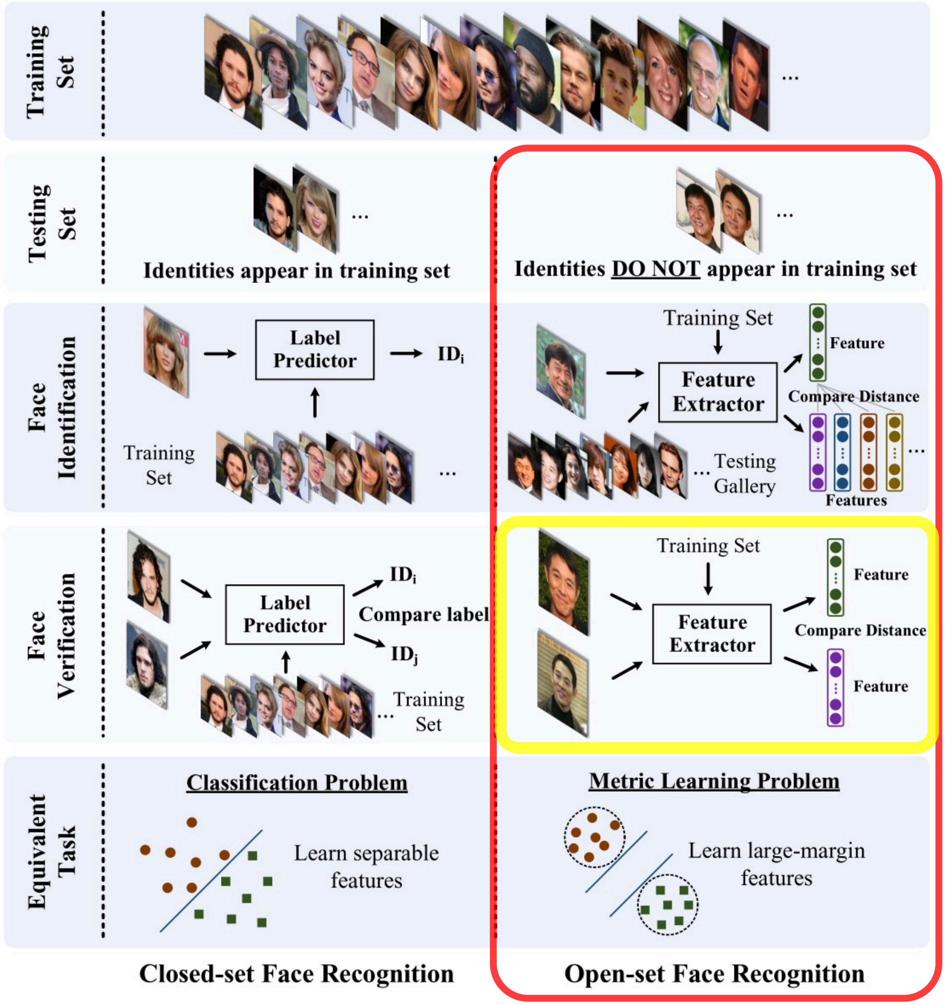

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Computer Vision Applications

- Face Recognition

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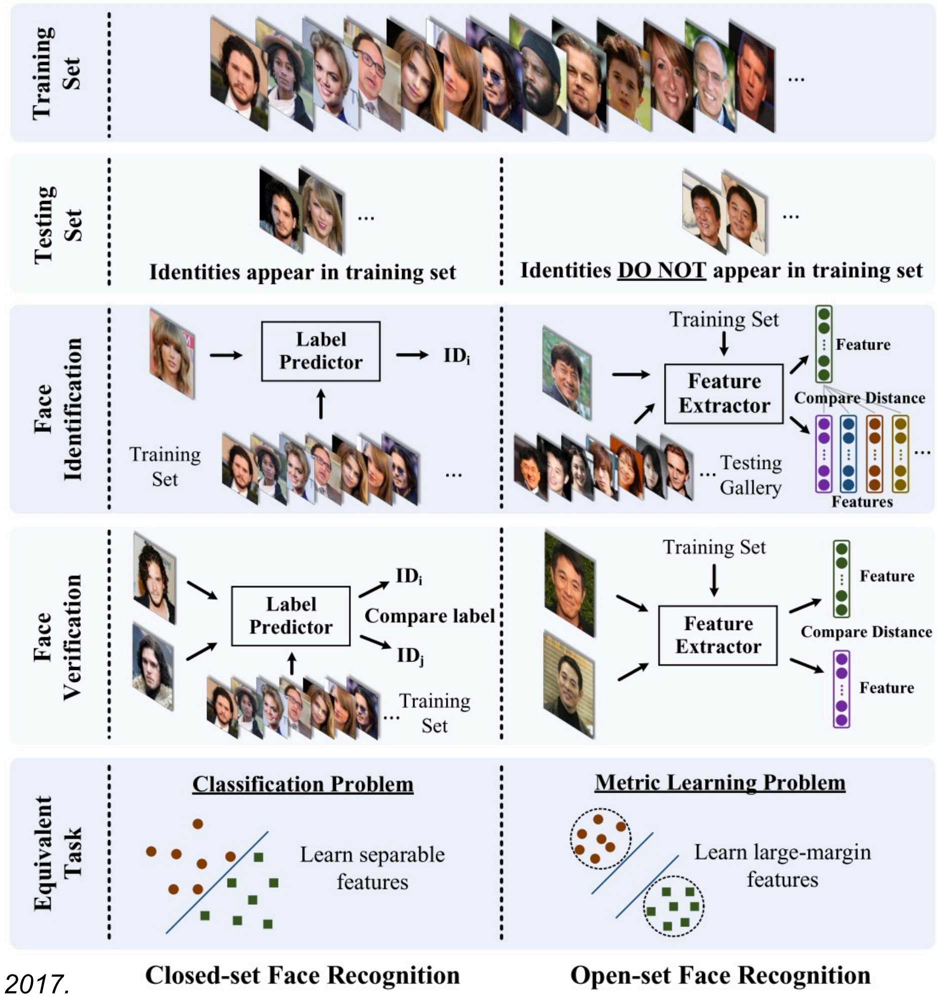


SphereFace: Deep Hypersphere Embedding for Face Recognition. *Weiyang Liu etal. CVPR. 2017.*

Computer Vision Applications

- Face Recognition

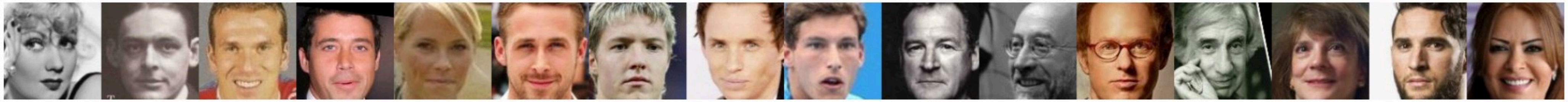
Design new network architecture
Design new loss function

Learn discriminative feature space by supervised learning.

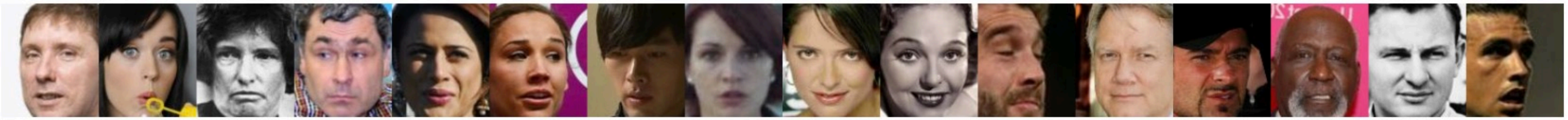
Computer Vision Applications

- Face Recognition: Dataset

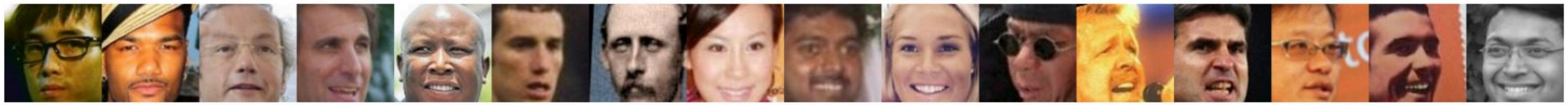
Image size of 112x112, 112x96, and 96x96 are commonly used in academic.
Larger image size usually has better accuracy but larger computation cost.



MS1M-refine-v2 112x112



MS1M-refine-v2 112x96



MS1M-refine-v2 96x96

Microsoft 1 Million Face Dataset

Computer Vision Applications

- Face Recognition

Always looking for better loss function … … …

… L-Softmax → SphereFace → ArcFace …

ICML 2016 CVPR 2017 CVPR 2018

ArcFace: Additive Angular Margin Loss for Deep Face Recognition. *Jiankang Deng etal. CVPR. 2018.*

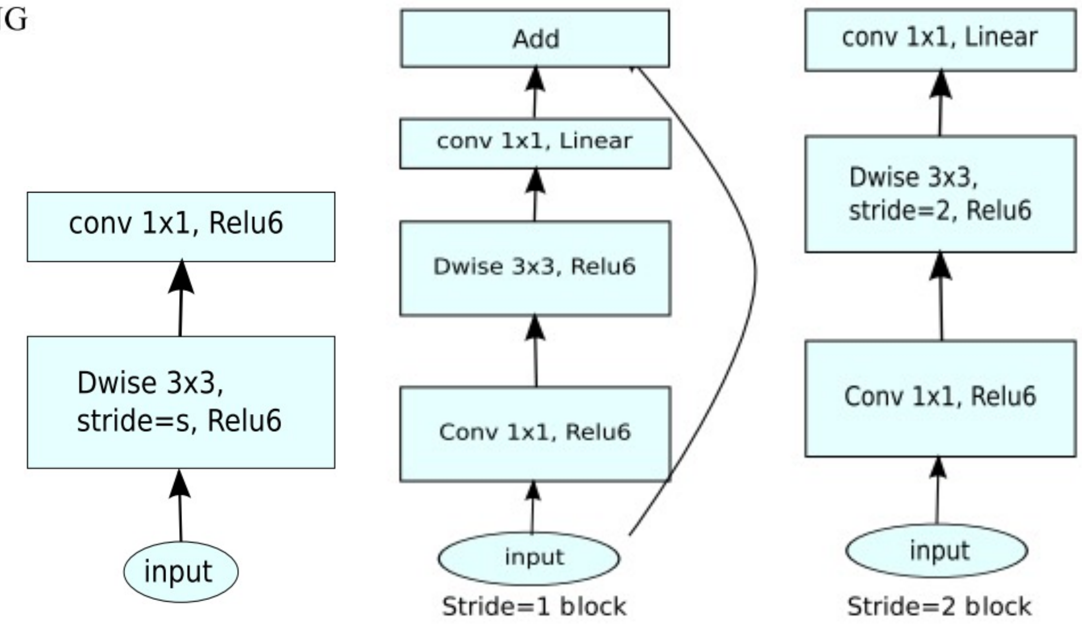
SphereFace: Deep Hypersphere Embedding for Face Recognition. *Weiyang Liu etal. CVPR. 2017.*

Computer Vision Applications

- Face Recognition: MobileFaceNet = ArcFace + MobileNetV2

MOBILEFACENET ARCHITECTURE FOR FEATURE EMBEDDING

Input	Operator	t	c	n	s
$112^2 \times 3$	conv3x3	-	64	1	2
$56^2 \times 64$	depthwise conv3x3	-	64	1	1
$56^2 \times 64$	bottleneck	2	64	5	2
$28^2 \times 64$	bottleneck	4	128	1	2
$14^2 \times 128$	bottleneck	2	128	6	1
$14^2 \times 128$	bottleneck	4	128	1	2
$7^2 \times 128$	bottleneck	2	128	2	1
$7^2 \times 128$	conv1x1	-	512	1	1
$7^2 \times 512$	linear GDConv7x7	-	512	1	1
$1^2 \times 512$	linear conv1x1	-	128	1	1



MobileNetV1 **MobileNetV2**

t: expansion factor c: num of channels n: num of repeat s: stride

Model size < 4MB，CPU runtime < 24ms

Computer Vision Applications

- More and more …

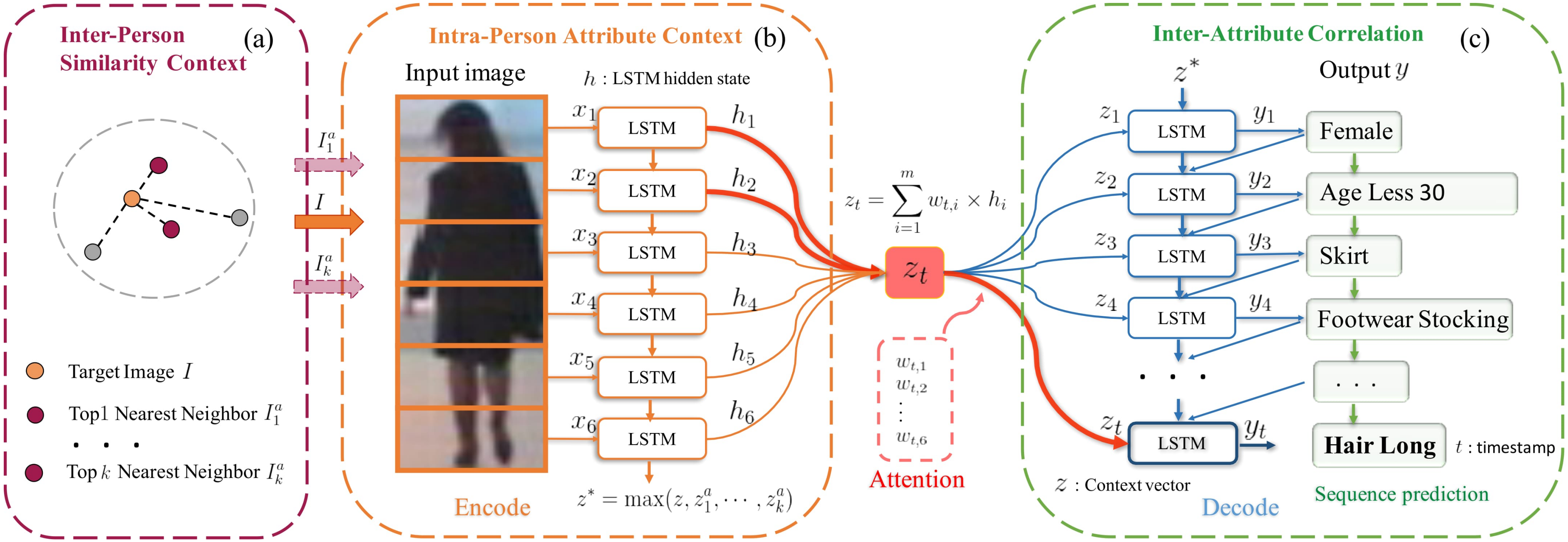
Person Re-identification（ReID）

- Track person in different cameras

Computer Vision Applications

- More and more …

Person Attribute Classification

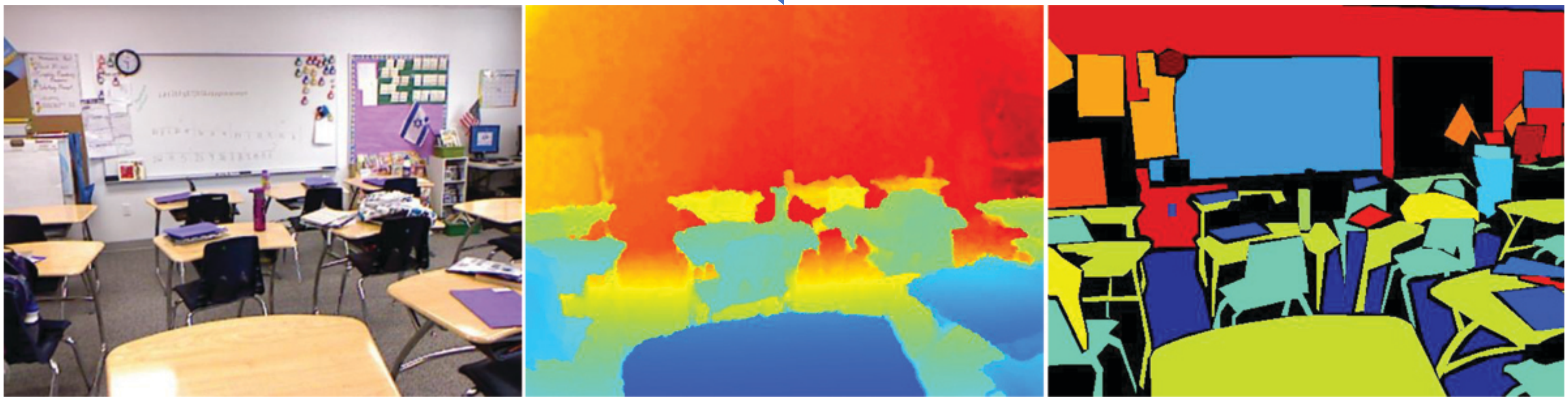


Attribute Recognition by Joint Recurrent Learning of Context and Correlation. *Jingya Wang etal. ICCV. 2017.*

Computer Vision Applications

- More and more …

Depth Estimation



NYU Depth Dataset V2

Computer Vision Applications

- More and more …

Style Transfer

Content Style Result

Arbitrary Style Transfer in Real-time with Adaptive Instance Normalization. *X. Huang, S. Belongie. ICCV 2017.*

Computer Vision Applications

- More and more …

Super-resolution

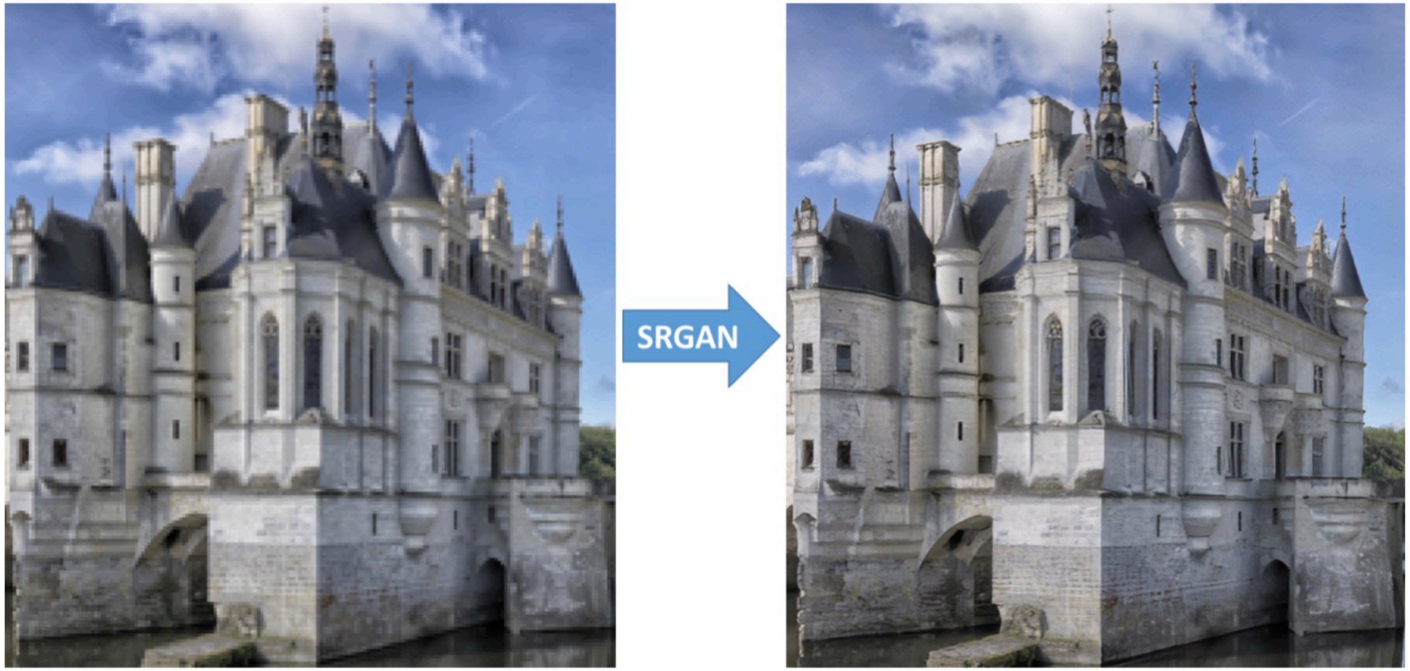


Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network. *C. Ledig, L. Theis et al. CVPR 2017.*

Computer Vision Applications

- More and more …

Image-to-image Translation

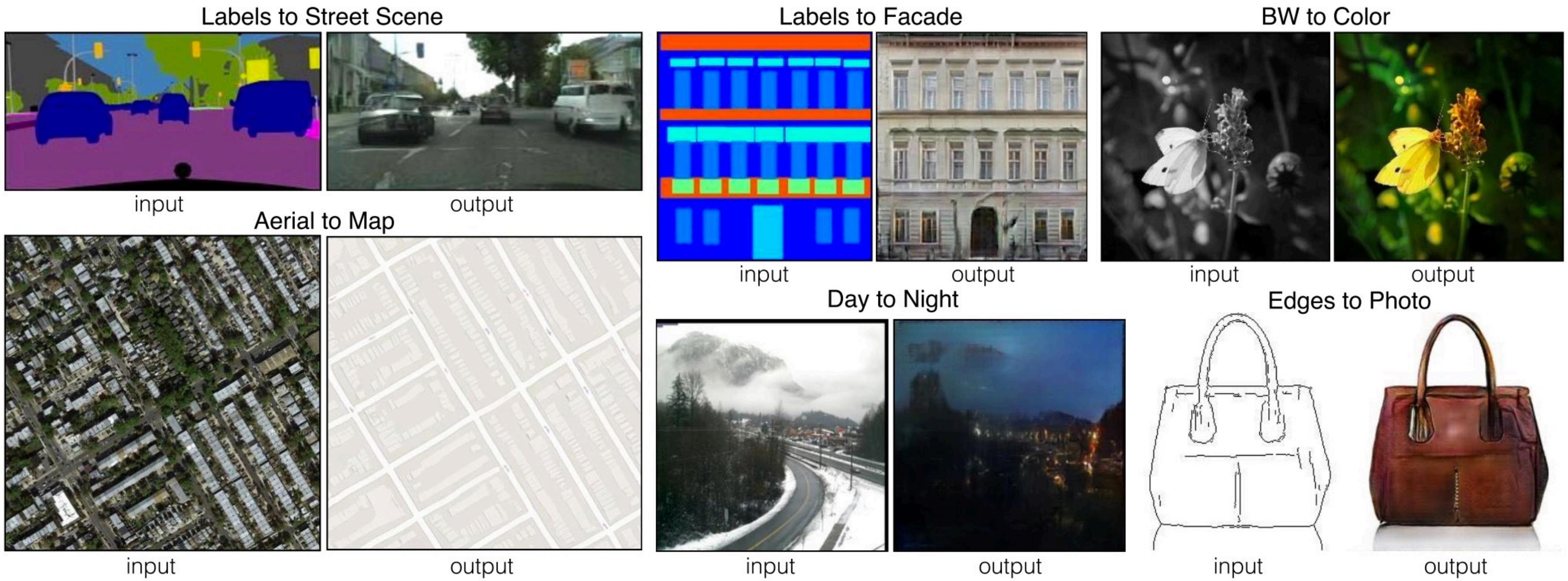
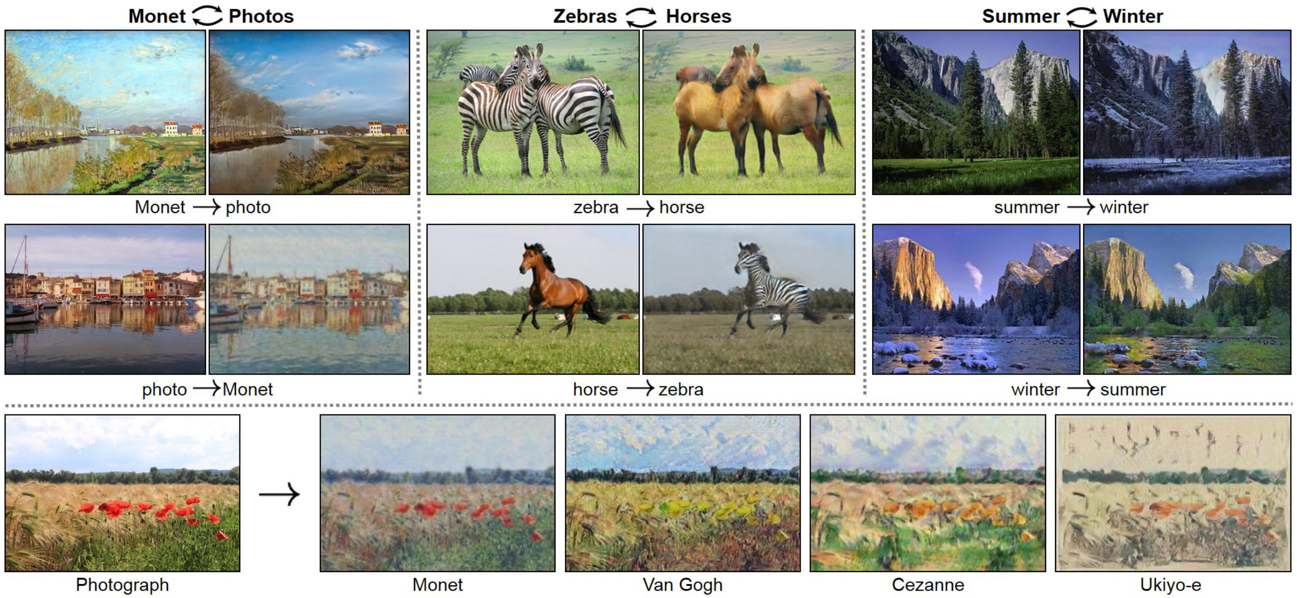


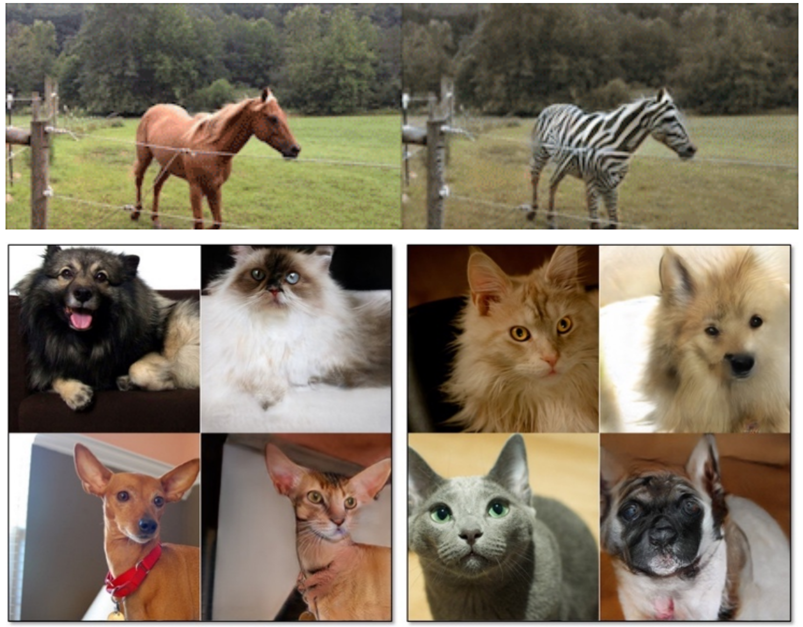
Image-to-Image Translation with Conditional Adversarial Networks. *P. Isola, J. Zhu et al. CVPR 2017.*

Computer Vision Applications

- More and more …

Unsupervised/Unpaired Image-to-image Translation



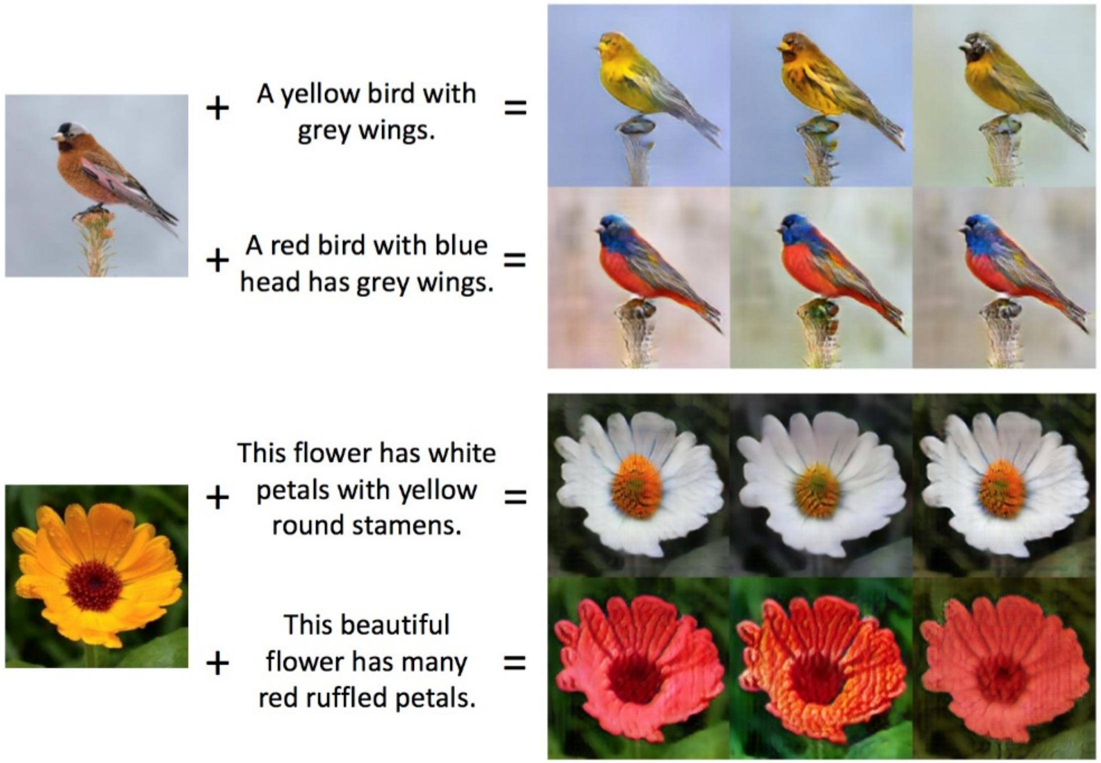


Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. *J. Zhu, T. Park et al. ICCV 2017.*

Computer Vision Applications

- More and more …

Semantic Image Synthesis



Semantic Image Synthesis via Adversarial Learning. H. Dong, S. Yu et al. ICCV 2017.

Computer Vision Applications

- More and more …

We will introduce the generative works in the GAN lesson.

Summary

Convolutional Neural Networks

PEKING UNIVERSITY

- Motivation
  - Curse of dimensionality, parameter sharing …
- Convolutional Algorithms
  - Convolution, channel, receptive field, dilated convolution …
- Pooling Algorithms
  - Max pooling, mean pooling, pyramid pooling …
- Hierarchical Representation Learning
  - Large receptive field, feature representation …
- Convolutional Architectures
  - VGG, ResNet, MobileNet, SqueezeNet …
- Transposed Convolutional Algorithms
  - Decoding, common transposed convolution …
- Computer Vision Applications
  - Detection, segmentation, recognition, pose estimation …

Convolutional Neural Networks

- Exercise 1:
  - Use TensorLayer to classify the CIFAR10 dataset

- Exercise 2: (Optional)
  - Choice an application and implement it

Questions?