Computer Vision tasks

Computer Vision, or **CV** for short, is a field of computer science focused on development of techniques that will help computers understand the content of digital images in a way similar to human understanding. There's a lot of different computer vision tasks, but today I want to focus only on four basic ones.

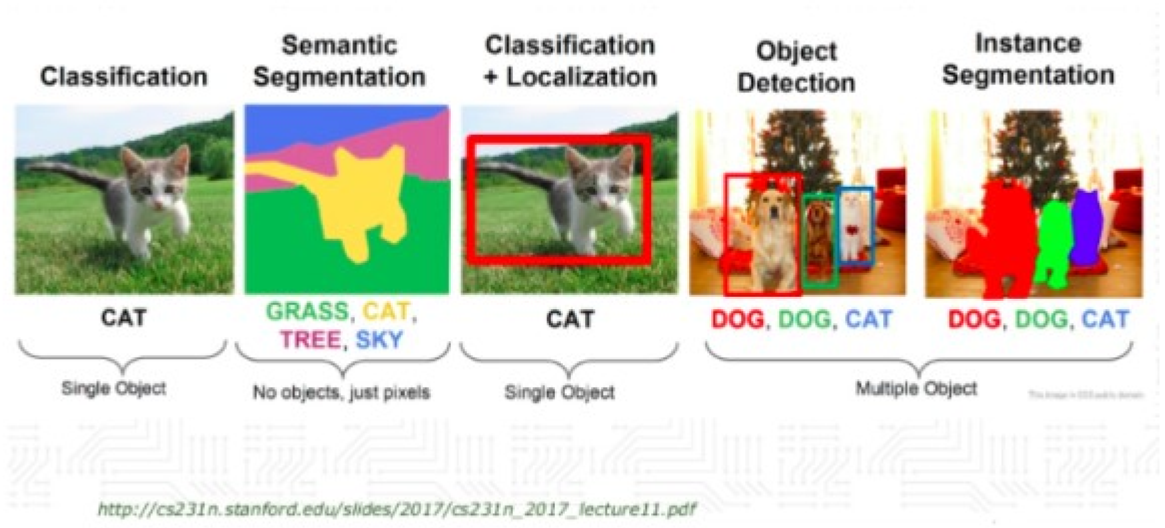


Figure 1: Different computer vision tasks. Source: Introduction to Artificial Intelligence and Computer Vision Revolution (https://www.slideshare.net/darian_f/introduction-to-the-artificial-intelligence-and-computer-vision-revolution).

Basic Computer Vision tasks:

1. **Image classification** – in this task we want to compute the probability (or probabilities) that the input image is in a particular **class**. It could be performed with **Convolutional Neural Networks** using `keras` package.
2. **Semantic segmentation** – very similar to image classification, but instead of classifying the whole image, we want to classify **each pixel** of this image. Note that we are not saying anything about location of the object.
3. **Object detection** – we want to classify and locate objects on the input image. Object localization is typically indicated by specifying a tightly cropped **bounding box**.
4. **Instance segmentation** – it's a combination of semantic segmentation and object detection. Like in semantic segmentation we want to classify each pixel to a different class, but we also want to distinguish between different objects of the same class.

Platypus

`platypus` is an R package for object detection and semantic segmentation. Currently using `platypus` you can perform:

- multi-class semantic segmentation using **U-Net** architecture
- multi-class object detection using **YOLOv3** architecture

You can install the latest version of `platypus` with `remotes` package:

```
remotes::install_github("maju116/platypus")
```

Note that in order to install `platypus` you need to install `keras` and `tensorflow` packages and `Tensorflow` version `>= 2.0.0` (`Tensorflow 1.x` will not be supported!)

Quick example: YOLOv3 bounding box prediction with pre-trained COCO weights

To create `YOLOv3` architecture use:

```
library(tidyverse)
library(platypus)
library(abind)

test_yolo <- yolo3(
  net_h = 416, # Input image height. Must be divisible by 32
  net_w = 416, # Input image width. Must be divisible by 32
  grayscale = FALSE, # Should images be loaded as grayscale or RGB
  n_class = 80, # Number of object classes (80 for COCO dataset)
  anchors = coco_anchors # Anchor boxes
)

test_yolo
#> Model
#> Model: "yolo3"
#> ____________________________________________________________
____________________
#> Layer (type)              Output Shape      Param #  Connected to
#> ============================================================
====================
#> input_img (InputLayer)    [(None, 416, 416, 0
#> ____________________________________________________________
____________________
#> darknet53 (Model)         multiple          40620640 input_img[0][0]
#> ____________________________________________________________
____________________
#> yolo3_conv1 (Model)       (None, 13, 13, 51 11024384 darknet53[1][2]
#> ____________________________________________________________
____________________
#> yolo3_conv2 (Model)       (None, 26, 26, 25 2957312
yolo3_conv1[1][0]
#>                                                      darknet53[1][1]
#> ____________________________________________________________
____________________
#> yolo3_conv3 (Model)       (None, 52, 52, 12 741376
yolo3_conv2[1][0]
#>                                                      darknet53[1][0]
#> ____________________________________________________________
____________________
#> grid1 (Model)             (None, 13, 13, 3, 4984063
yolo3_conv1[1][0]
#> ____________________________________________________________
____________________
#> grid2 (Model)             (None, 26, 26, 3, 1312511
yolo3_conv2[1][0]
```

```
#> ______________________________________________________________
____________________
#> grid3 (Model)              (None, 52, 52, 3, 361471
yolo3_conv3[1][0]
#> ==============================================================
====================
#> Total params: 62,001,757
#> Trainable params: 61,949,149
#> Non-trainable params: 52,608
#> ______________________________________________________________
____________________
```

You can now load YOLOv3 Darknet weights trained on COCO dataset. Download pre-trained weights from here and run:

```
test_yolo %>% load_darknet_weights("yolov3.weights")
```

Calculate predictions for new images:

```
test_img_paths <- list.files(system.file("extdata", "images", package =
"platypus"), full.names = TRUE, pattern = "coco")
test_imgs <- test_img_paths %>%
  map(~ {
    image_load(., target_size = c(416, 416), grayscale = FALSE) %>%
      image_to_array() %>%
      `/`(255)
  }) %>%
  abind(along = 4) %>%
  aperm(c(4, 1:3))
test_preds <- test_yolo %>% predict(test_imgs)

str(test_preds)
#> List of 3
#>  $ : num [1:2, 1:13, 1:13, 1:3, 1:85] 0.294 0.478 0.371 1.459 0.421
...
#>  $ : num [1:2, 1:26, 1:26, 1:3, 1:85] -0.214 1.093 -0.092 2.034
-0.286 ...
#>  $ : num [1:2, 1:52, 1:52, 1:3, 1:85] 0.242 -0.751 0.638 -2.419
-0.282 ...
```

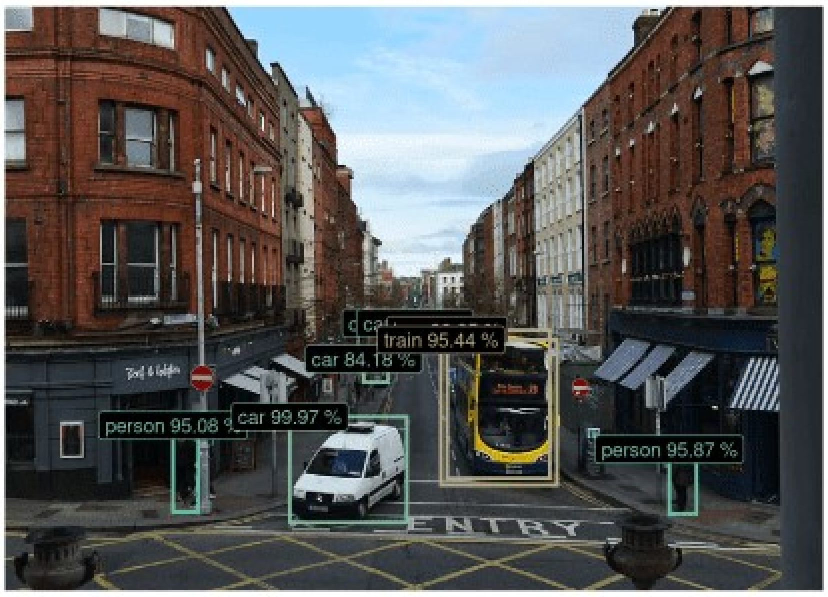
Transform raw predictions into bounding boxes:

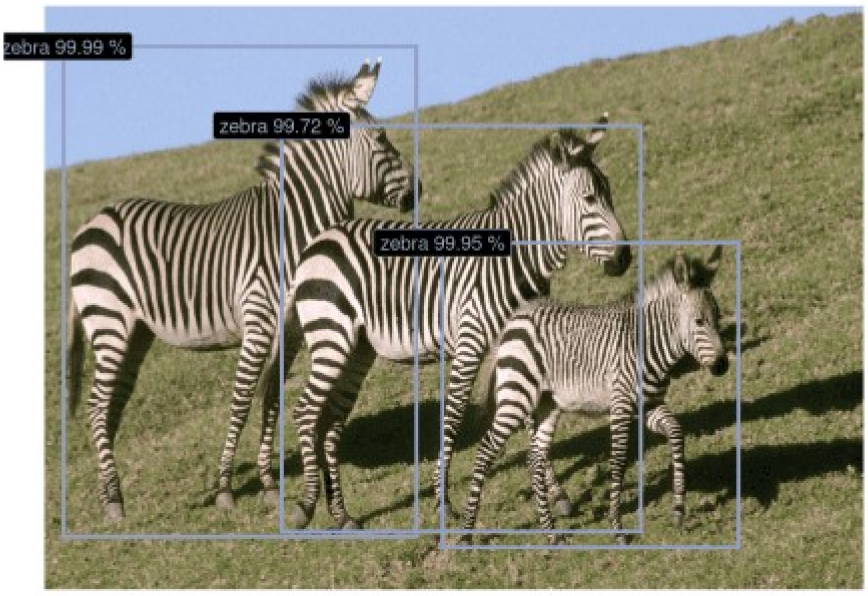
```
test_boxes <- get_boxes(
  preds = test_preds, # Raw predictions form YOLOv3 model
  anchors = coco_anchors, # Anchor boxes
  labels = coco_labels, # Class labels
  obj_threshold = 0.6, # Object threshold
  nms = TRUE, # Should non-max suppression be applied
  nms_threshold = 0.6, # Non-max suppression threshold
  correct_hw = FALSE # Should height and width of bounding boxes be
corrected to image height and width
)
```

```
test_boxes
#> [[1]]
#> # A tibble: 8 x 7
#>     xmin  ymin  xmax  ymax p_obj label_id label
#>
#> 1 0.207 0.718 0.236 0.865 0.951        1 person
#> 2 0.812 0.758 0.846 0.868 0.959        1 person
#> 3 0.349 0.702 0.492 0.884 1.00         3 car
#> 4 0.484 0.543 0.498 0.558 0.837        3 car
#> 5 0.502 0.543 0.515 0.556 0.821        3 car
#> 6 0.439 0.604 0.469 0.643 0.842        3 car
#> 7 0.541 0.554 0.667 0.809 0.999        6 bus
#> 8 0.534 0.570 0.675 0.819 0.954        7 train
#>
#> [[2]]
#> # A tibble: 3 x 7
#>     xmin   ymin  xmax  ymax p_obj label_id label
#>
#> 1 0.0236 0.0705 0.454 0.909 1.00        23 zebra
#> 2 0.290  0.206  0.729 0.901 0.997       23 zebra
#> 3 0.486  0.407  0.848 0.928 1.00        23 zebra
```

Plot / save images:

```
plot_boxes(
  images_paths = test_img_paths, # Images paths
  boxes = test_boxes, # Bounding boxes
  correct_hw = TRUE, # Should height and width of bounding boxes be
corrected to image height and width
  labels = coco_labels # Class labels
)
```




zebra 99.99 %
zebra 99.72 %
zebra 99.95 %