



Create COCO Annotations From Scratch

WANT TO CREATE A CUSTOM DATASET?

👉 Check out the [Courses page for a complete, end to end course](#) on creating a COCO dataset from scratch.

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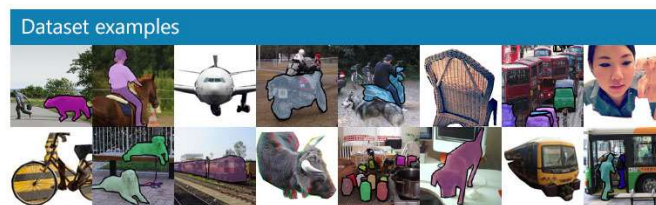
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WHAT IS THE COCO DATASET?

COCO annotations are inspired by the [Common Objects in Context \(COCO\) dataset](#). According to cocodataset.org/#home:

"COCO is a large-scale object detection, segmentation, and captioning dataset. COCO has several features: Object segmentation, Recognition in context, Superpixel stuff segmentation, 330K images (>200K labeled), 1.5 million object instances, 80 object categories, 91 stuff categories, 5 captions per image, 250,000 people with keypoints."

It is one of the best image datasets available, so it is widely used in cutting edge image recognition artificial intelligence research. It is used in open source projects such as [Facebook Research's Detectron](#), [Matterport's Mask R-CNN](#), [endernewton's Tensorflow Faster RCNN](#) for Object Detection, and others.



A few example images from <http://cocodataset.org/#home>

Because it is used by so many projects, you probably want to know how to make your own, so let's quit wasting time.



COCO Dataset Format - Complete Walkthrough



A detailed walkthrough of the COCO Dataset JSON Format, specifically for object detection (instance segmentations). The first step toward making your own COCO dataset is understanding how it works. This video should help.

If you're not a video person or want more detail, keep reading.

The COCO dataset is formatted in [JSON](#) and is a collection of “info”, “licenses”, “images”, “annotations”, “categories” (in most cases), and “segment info” (in one case).

```
{  
  "info": {...},  
  "licenses": [...],  
  "images": [...],  
  "annotations": [...],  
  "categories": [...], <-- Not in Capt.  
  "segment_info": [...] <-- Only in Pa  
}
```

INFO

The “info” section contains high level information about the dataset. If you are creating your own dataset, you can fill in whatever is appropriate.



```
description : COCO 2017 Dataset ,  
"url": "http://cocodataset.org",  
"version": "1.0",  
"year": 2017,  
"contributor": "COCO Consortium",  
"date_created": "2017/09/01"  
}
```

LICENSES

The “licenses” section contains a list of image licenses that apply to images in the dataset. If you are sharing or selling your dataset, you should make sure your licenses are correctly specified and that you are not infringing on copyright.

```
"licenses": [  
  {  
    "url": "http://creativecommons.org/licenses/by-nc/4.0/",  
    "id": 1,  
    "name": "Attribution-NonCommercial 4.0 International"  
  },  
  {  
    "url": "http://creativecommons.org/licenses/by-nc/4.0/",  
    "id": 2,  
    "name": "Attribution-NonCommercial 4.0 International"  
  },  
  ...  
]
```

IMAGES

The “images” section contains the complete list of images in your dataset. There are no labels, bounding boxes, or segmentations specified in this part, it's simply a list of images and information

learning application probably will only need the `file_name`.

Note that image ids need to be unique (among other images), but they do not necessarily need to match the file name (unless the deep learning code you are using makes an assumption that they'll be the same... developers are lazy, it wouldn't surprise me).

```
"images": [  
  {  
    "license": 4,  
    "file_name": "000000397133.jpg",  
    "coco_url": "http://images.cocodataset.org/2013/11/14/000000397133.jpg",  
    "height": 427,  
    "width": 640,  
    "date_captured": "2013-11-14 17:00:00",  
    "flickr_url": "http://farm7.staticflickr.com/6892/6892039713_397133.jpg",  
    "id": 397133  
  },  
  {  
    "license": 1,  
    "file_name": "000000037777.jpg",  
    "coco_url": "http://images.cocodataset.org/2013/11/14/000000037777.jpg",  
    "height": 230,  
    "width": 352,  
    "date_captured": "2013-11-14 20:00:00",  
    "flickr_url": "http://farm9.staticflickr.com/8928/8928037777_037777.jpg",  
    "id": 37777  
  },  
  ...  
]
```

FIVE COCO ANNOTATION TYPES



COCO has five annotation types: for [object detection](#), [keypoint detection](#), [stuff segmentation](#), [panoptic segmentation](#), and [image captioning](#). The annotations are stored using [JSON](#).

The documentation on the COCO annotation format isn't crystal clear, so I'll break them down as simply as I can. Each one is a little different.

OBJECT DETECTION (SEGMENTATION)



<http://cocodataset.org/#detection-2018>

This is the most popular one; it draws shapes around objects in an image. It has a list of categories and annotations.

CATEGORIES

The “categories” object contains a list of categories (e.g. dog, boat) and each of those belongs to a supercategory (e.g. animal, vehicle). The original COCO dataset contains 90 categories. You can use the existing COCO categories or create an entirely new list of your own. Each category id must be unique (among the rest of the categories).

```
"categories": [  
  {"supercategory": "person", "id": 1, "name": "person"},  
  {"supercategory": "vehicle", "id": 2, "name": "car"},  
  {"supercategory": "vehicle", "id": 3, "name": "truck"},  
  {"supercategory": "vehicle", "id": 4, "name": "bus"},  
  {"supercategory": "vehicle", "id": 5, "name": "train"},  
  {"supercategory": "vehicle", "id": 6, "name": "motorcycle"},  
  {"supercategory": "animal", "id": 7, "name": "dog"},  
  {"supercategory": "animal", "id": 8, "name": "cat"},  
  {"supercategory": "animal", "id": 9, "name": "bird"},  
  {"supercategory": "animal", "id": 10, "name": "horse"},  
  {"supercategory": "animal", "id": 11, "name": "sheep"},  
  {"supercategory": "animal", "id": 12, "name": "cow"},  
  {"supercategory": "animal", "id": 13, "name": "pig"},  
  {"supercategory": "animal", "id": 14, "name": "chicken"},  
  {"supercategory": "animal", "id": 15, "name": "goat"},  
  {"supercategory": "animal", "id": 16, "name": "tiger"},  
  {"supercategory": "animal", "id": 17, "name": "lion"},  
  {"supercategory": "animal", "id": 18, "name": "elephant"},  
  {"supercategory": "animal", "id": 19, "name": "bear"},  
  {"supercategory": "animal", "id": 20, "name": "wolf"},  
  {"supercategory": "animal", "id": 21, "name": "fox"},  
  {"supercategory": "animal", "id": 22, "name": "rabbit"},  
  {"supercategory": "animal", "id": 23, "name": "hamster"},  
  {"supercategory": "animal", "id": 24, "name": "mouse"},  
  {"supercategory": "animal", "id": 25, "name": "rat"},  
  {"supercategory": "animal", "id": 26, "name": "squirrel"},  
  {"supercategory": "animal", "id": 27, "name": "chipmunk"},  
  {"supercategory": "animal", "id": 28, "name": "marmoset"},  
  {"supercategory": "animal", "id": 29, "name": "monkey"},  
  {"supercategory": "animal", "id": 30, "name": "bat"},  
  {"supercategory": "animal", "id": 31, "name": "kangaroo"},  
  {"supercategory": "animal", "id": 32, "name": "platypus"},  
  {"supercategory": "animal", "id": 33, "name": "wallaby"},  
  {"supercategory": "animal", "id": 34, "name": "quokka"},  
  {"supercategory": "animal", "id": 35, "name": "bandicoot"},  
  {"supercategory": "animal", "id": 36, "name": "possum"},  
  {"supercategory": "animal", "id": 37, "name": "koala"},  
  {"supercategory": "animal", "id": 38, "name": "wombat"},  
  {"supercategory": "animal", "id": 39, "name": "echinoderm"},  
  {"supercategory": "animal", "id": 40, "name": "mollusk"},  
  {"supercategory": "animal", "id": 41, "name": "arthropod"},  
  {"supercategory": "animal", "id": 42, "name": "insect"},  
  {"supercategory": "animal", "id": 43, "name": "reptile"},  
  {"supercategory": "animal", "id": 44, "name": "amphibian"},  
  {"supercategory": "animal", "id": 45, "name": "fish"},  
  {"supercategory": "animal", "id": 46, "name": "bird"},  
  {"supercategory": "animal", "id": 47, "name": "mammal"},  
  {"supercategory": "animal", "id": 48, "name": "plant"},  
  {"supercategory": "animal", "id": 49, "name": "fungus"},  
  {"supercategory": "animal", "id": 50, "name": "bacteria"},  
  {"supercategory": "animal", "id": 51, "name": "virus"},  
  {"supercategory": "animal", "id": 52, "name": "protozoa"},  
  {"supercategory": "animal", "id": 53, "name": "invertebrate"},  
  {"supercategory": "animal", "id": 54, "name": "vertebrate"},  
  {"supercategory": "animal", "id": 55, "name": "mammal"},  
  {"supercategory": "animal", "id": 56, "name": "bird"},  
  {"supercategory": "animal", "id": 57, "name": "reptile"},  
  {"supercategory": "animal", "id": 58, "name": "amphibian"},  
  {"supercategory": "animal", "id": 59, "name": "fish"},  
  {"supercategory": "animal", "id": 60, "name": "invertebrate"},  
  {"supercategory": "animal", "id": 61, "name": "vertebrate"},  
  {"supercategory": "animal", "id": 62, "name": "mammal"},  
  {"supercategory": "animal", "id": 63, "name": "bird"},  
  {"supercategory": "animal", "id": 64, "name": "reptile"},  
  {"supercategory": "animal", "id": 65, "name": "amphibian"},  
  {"supercategory": "animal", "id": 66, "name": "fish"},  
  {"supercategory": "animal", "id": 67, "name": "invertebrate"},  
  {"supercategory": "animal", "id": 68, "name": "vertebrate"},  
  {"supercategory": "animal", "id": 69, "name": "mammal"},  
  {"supercategory": "animal", "id": 70, "name": "bird"},  
  {"supercategory": "animal", "id": 71, "name": "reptile"},  
  {"supercategory": "animal", "id": 72, "name": "amphibian"},  
  {"supercategory": "animal", "id": 73, "name": "fish"},  
  {"supercategory": "animal", "id": 74, "name": "invertebrate"},  
  {"supercategory": "animal", "id": 75, "name": "vertebrate"},  
  {"supercategory": "animal", "id": 76, "name": "mammal"},  
  {"supercategory": "animal", "id": 77, "name": "bird"},  
  {"supercategory": "animal", "id": 78, "name": "reptile"},  
  {"supercategory": "animal", "id": 79, "name": "amphibian"},  
  {"supercategory": "animal", "id": 80, "name": "fish"},  
  {"supercategory": "animal", "id": 81, "name": "invertebrate"},  
  {"supercategory": "animal", "id": 82, "name": "vertebrate"},  
  {"supercategory": "animal", "id": 83, "name": "mammal"},  
  {"supercategory": "animal", "id": 84, "name": "bird"},  
  {"supercategory": "animal", "id": 85, "name": "reptile"},  
  {"supercategory": "animal", "id": 86, "name": "amphibian"},  
  {"supercategory": "animal", "id": 87, "name": "fish"},  
  {"supercategory": "animal", "id": 88, "name": "invertebrate"},  
  {"supercategory": "animal", "id": 89, "name": "vertebrate"},  
  {"supercategory": "animal", "id": 90, "name": "mammal"}  
]
```



```
{ "supercategory": "indoor", "id": 89,  
  { "supercategory": "indoor", "id": 90,  
    ]
```

ANNOTATIONS

The “annotations” section is the trickiest to understand. It contains a list of every individual object annotation from every image in the dataset. For example, if there are 64 bicycles spread out across 100 images, there will be 64 bicycle annotations (along with a ton of annotations for other object categories). Often there will be multiple instances of an object in an image. Usually this results in a new annotation item for each one.

I say “usually” because regions of interest indicated by these annotations are specified by “segmentations”, which are usually a list of polygon vertices around the object, but can also be a run-length-encoded (RLE) bit mask. Typically, RLE is used for groups of objects (like a large stack of books). I’ll explain how this works later in the article.

Area is measured in pixels (e.g. a 10px by 20px box would have an area of 200).

Is Crowd specifies whether the segmentation is for a single object or for a group/cluster of objects.

The image id corresponds to a specific image in the dataset.

The COCO bounding box format is [top left x position, top left y position, width, height].

The category id corresponds to a single category specified in the categories section



The following JSON shows 2 different annotations.

1. The first annotation:

- Has a segmentation list of vertices (x, y pixel positions)
- Has an area of 702 pixels (pretty small) and a bounding box of [473.07,395.93,38.65,28.67]
- Is not a crowd (meaning it's a single object)
- Is category id of 18 (which is a dog)
- Corresponds with an image with id 289343 (which is a person on a strange bicycle and a tiny dog)

2. The second annotation:

- Has a Run-Length-Encoding style segmentation
- Has an area of 220834 pixels (much larger) and a bounding box of [0,34,639,388]
- Is a crowd (meaning it's a group of objects)
- Is a category id of 1 (which is a person)
- Corresponds with an image with id 250282 (which is a vintage class photo of about 50 school children)

```
"annotations": [  
  {
```




```

    "iscrowd": 0,
    "image_id": 289343,
    "bbox": [473.07, 395.93, 38.65, 28.65],
    "category_id": 18,
    "id": 1768
  },
  ...
  {
    "segmentation": {
      "counts": [179, 27, 392, 41, ..., 51],
      "size": [426, 640]
    },
    "area": 220834,
    "iscrowd": 1,
    "image_id": 250282,
    "bbox": [0, 34, 639, 388],
    "category_id": 1,
    "id": 900100250282
  }
]

```

KEYPOINT DETECTION FORMAT



<http://cocodataset.org/#keypoints-2018>

Keypoints add additional information about a segmented object. They specify a list of points of interest, connections between those points, where



CATEGORIES

As of the 2017 version of the dataset, there is only one category ("person") in the COCO dataset with keypoints, but this could theoretically be expanded to any category that might have different points of interest. For example a shark (tail, fins, eyes, gills, etc) or a robotic arm (grabber, joints, base).

In the case of a person, "keypoints" indicate different body parts. The "skeleton" indicates connections between points. For example, [16, 14] means "left_ankle" connects to "left_knee".

```
"categories": [
  {
    "supercategory": "person",
    "id": 1,
    "name": "person",
    "keypoints": [
      "nose", "left_eye", "right_eye",
      "left_shoulder", "right_shoulder",
      "left_wrist", "right_wrist", "left_ankle",
      "left_knee", "right_knee", "left_heel", "right_heel"
    ],
    "skeleton": [
      [16, 14], [14, 12], [17, 15], [15, 13],
      [6, 8], [7, 9], [8, 10], [9, 11], [2, 3], [3, 4], [4, 5], [1, 2], [1, 3], [5, 6], [6, 7], [10, 11], [11, 12], [12, 13], [13, 14], [14, 15], [15, 16], [16, 17], [17, 18], [18, 19], [19, 20], [20, 21], [21, 22], [22, 23], [23, 24], [24, 25], [25, 26], [26, 27], [27, 28], [28, 29], [29, 30], [30, 31], [31, 32], [32, 33], [33, 34], [34, 35], [35, 36], [36, 37], [37, 38], [38, 39], [39, 40], [40, 41], [41, 42], [42, 43], [43, 44], [44, 45], [45, 46], [46, 47], [47, 48], [48, 49], [49, 50], [50, 51], [51, 52], [52, 53], [53, 54], [54, 55], [55, 56], [56, 57], [57, 58], [58, 59], [59, 60], [60, 61], [61, 62], [62, 63], [63, 64], [64, 65], [65, 66], [66, 67], [67, 68], [68, 69], [69, 70], [70, 71], [71, 72], [72, 73], [73, 74], [74, 75], [75, 76], [76, 77], [77, 78], [78, 79], [79, 80], [80, 81], [81, 82], [82, 83], [83, 84], [84, 85], [85, 86], [86, 87], [87, 88], [88, 89], [89, 90], [90, 91], [91, 92], [92, 93], [93, 94], [94, 95], [95, 96], [96, 97], [97, 98], [98, 99], [99, 100]
    ]
  }
]
```

ANNOTATIONS

Annotations for keypoints are just like in Object Detection (Segmentation) above, except a number



x and y indicate pixel positions in the image.

v indicates visibility— v=0: not labeled (in which case x=y=0), v=1: labeled but not visible, and v=2: labeled and visible

229, 256, 2 means there's a keypoint at pixel x=229, y=256 and 2 indicates that it is a visible keypoint

```
"annotations": [
  {
    "segmentation": [[204.01,306.23,
    "num_keypoints": 15,
    "area": 5463.6864,
    "iscrowd": 0,
    "keypoints": [229,256,2,...,223,
    "image_id": 289343,
    "bbox": [204.01,235.08,60.84,177
    "category_id": 1,
    "id": 201376
  }
]
```

STUFF SEGMENTATION FORMAT



<http://cocodataset.org/#stuff-2018>

Stuff segmentation is identical to object detection (except is_crowd is unnecessary). You can learn more about it here: <http://cocodataset.org/#stuff-eval>

PANOPTIC SEGMENTATION



<http://cocodataset.org/#panoptic-2018>

I'm still working on this part (as of Jan 19, 2019).

Check back soon!

IMAGE CAPTIONING

Image caption annotations are pretty simple. There are no categories in this JSON file, just annotations with caption descriptions. Both of the pictures I checked actually had 4 separate captions for each image, presumably from different people.

```
"annotations": [
  {
    "image_id": 289343,
    "id": 433580,
    "caption": "A person riding a ve
  },
  ...
  {
    "image_id": 250282,
    "id": 511309,
    "caption": "A group of school ch
  },
]
```

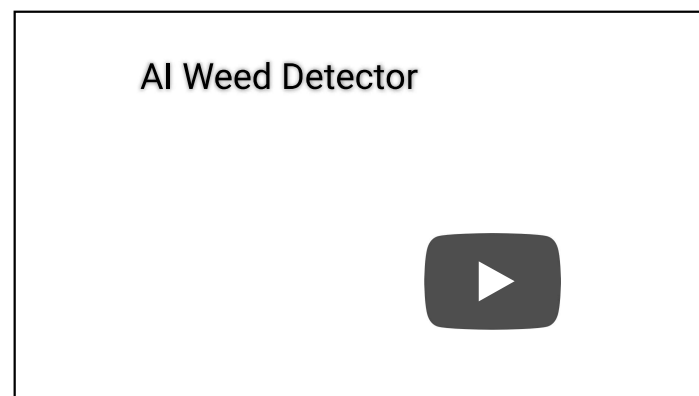
CREATING A CUSTOM COCO DATASET



WITH SYNTHETIC GENERATION

If you want to save 100 to 1000 hours per project, I recommend you create your COCO dataset synthetically. I even created a course to teach you how. Essentially, you write code that composes foreground images of objects over top of random image backgrounds. It may not work for every application, but you might be surprised at what can be achieved.

Here's an example of a synthetic COCO dataset I created to detect lawn weeds:



And here's another example, where I made a custom COCO dataset of cigarette butts and was able to detect them in images:



[Using Mask R-CNN with a Custom COCO-like Dataset](#)

Check out this tutorial to learn how to use Mask R-CNN on COCO-like datasets.

**Complete Guide to
Creating COCO Datasets**



Python.

MANUALLY, USING VERTICES

You can also, of course, create annotations with vertices. This is how 99%+ of the original COCO dataset was created.

The original researchers used Amazon Mechanical Turk to hire people for SUPER cheap to use a web app and tediously draw shapes around objects. The code they used can be found here

<https://github.com/tylin/coco-ui>, but I found it to be fairly unusable since it's all hooked up to AWS and Mechanical Turk. You might be able to tweak it for your own purposes if you really want to.

There's another, more recent, open-source project: COCO Annotator that is worth looking into instead. I've used it briefly and it seems very good.

<https://github.com/jsbroks/coco-annotator>

WHY YOU SHOULDN'T TRY TO CREATE YOUR OWN THIS WAY

I haven't taken the time to find a great solution here because I'm more interested in creating [synthetic datasets](#). Why? Because if it takes me 2 minutes on average to manually annotate an image and I have to annotate at least 2000 labeled images for a *small* dataset (COCO has 200K labeled images), it would take me 4000 minutes, which is over 66 straight hours. I'll pass.

USING BIT MASKS



generate polygons if you start with a masked image. This is particularly interesting if you have a synthetic dataset (e.g. created by a game engine) that outputs masks.

I'm going to use the following two images for an example. The COCO dataset only contains 90 categories, and surprisingly "lamp" is not one of them. I'm going to create this COCO-like dataset with 4 categories: houseplant, book, bottle, and lamp. (The first 3 are in COCO)



The first step is to create bit masks for each item of interest in the scene. That's 5 objects between the 2 images here. In the method I'm teaching here, it doesn't matter what color you use, as long as there is a distinct color for each object. You also don't need to be consistent with what colors you use, but you will need to make a note of what colors you used for each category. I used [GIMP](#) to make these images.

Important note #1: Even if there were 2 books in one scene, they would need different colors, because overlapping books would be impossible to distinguish by the code we are going to write.

Important note #2: Make sure each pixel is a solid color. Some image applications will perform

edges below.

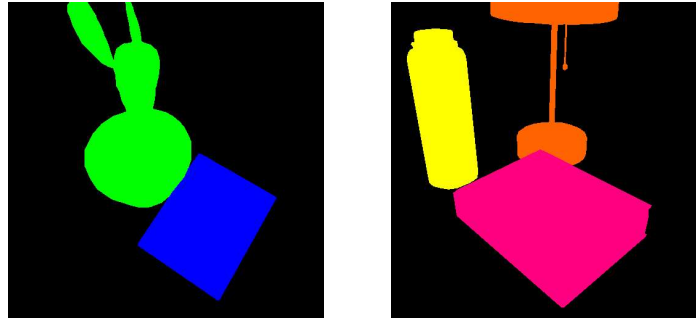


Image 1 colors: (0, 255, 0): houseplant; (0, 0, 255):
book

Image 2 colors: (255, 255, 0): bottle; (255, 0, 128):
book; (255, 100, 0): lamp

I've also assigned the following categories (you can
choose any integers you want): 1 = houseplant, 2 =
book, 3 = bottle, 4 = lamp

HIGH LEVEL OVERVIEW OF CREATING ANNOTATIONS

This is the only difficult part, really. Here are the
steps required for this method:

1. Write code to automatically split up the image
into individual masks
2. Write code to create polygons out of each
individual mask
3. Convert the information to JSON

Create sub-masks

Here's a python function that will take in a mask
Image object and return a dictionary of sub-masks,
keyed by RGB color. Note that it adds a padding
pixel which we'll account for later.



```
def create_sub_masks(mask_image):
    width, height = mask_image.size

    # Initialize a dictionary of sub-masks
    sub_masks = {}

    for x in range(width):
        for y in range(height):
            # Get the RGB values of the pixel
            pixel = mask_image.getpixel((x, y))

            # If the pixel is not black.
            if pixel != (0, 0, 0):
                # Check to see if we've seen this pixel before
                pixel_str = str(pixel)
                sub_mask = sub_masks.get(pixel_str)

                if sub_mask is None:
                    # Create a sub-mask (containing the pixel)
                    # Note: we add 1 pixel to the width and height
                    # because the contours are 1 pixel thick
                    # where pixels bleed into each other
                    sub_masks[pixel_str] = create_mask(mask_image, x, y, 1, 1)

                # Set the pixel value to 1
                sub_masks[pixel_str].putpixel((x, y), 1)

    return sub_masks
```

Create sub-mask annotation

Here's a python function that will take a sub-mask, create polygons out of the shapes inside, and then return an annotation dictionary. This is where we remove the padding mentioned above.



```

from skimage import measure

from shapely.geometry import Polygon, MultiPolygon

def create_sub_mask_annotation(sub_mask,
    # Find contours (boundary lines) around the mask
    # Note: there could be multiple contours if the mask
    # is partially occluded. (E.g. an element in the mask
    contours = measure.find_contours(sub_mask)

    segmentations = []
    polygons = []
    for contour in contours:
        # Flip from (row, col) representation to (x, y)
        # and subtract the padding pixel
        for i in range(len(contour)):
            row, col = contour[i]
            contour[i] = (col - 1, row - 1)

        # Make a polygon and simplify it
        poly = Polygon(contour)
        poly = poly.simplify(1.0, preserve_topology=False)
        polygons.append(poly)
        segmentation = np.zeros(poly.bounds[2] - poly.bounds[0], dtype=bool)
        segmentation.append(segmentation)

    # Combine the polygons to calculate bounding box
    multi_poly = MultiPolygon(polygons)
    x, y, max_x, max_y = multi_poly.bounds
    width = max_x - x
    height = max_y - y
    bbox = (x, y, width, height)
    area = multi_poly.area

    annotation = {
        'segmentation': segmentations,
        'bbox': bbox,
        'area': area
    }

```



```

        'id': annotation_id,
        'bbox': bbox,
        'area': area
    }

    return annotation

```

Putting it all together

Finally, we'll use these two functions on our images

```

import json

plant_book_mask_image = Image.open('/path/to/plant_book_mask.png')
bottle_book_mask_image = Image.open('/path/to/bottle_book_mask.png')

mask_images = [plant_book_mask_image, bottle_book_mask_image]

# Define which colors match which categories
houseplant_id, book_id, bottle_id, lamp_id = 1, 2, 3, 4
category_ids = {
    1: {
        '(0, 255, 0)': houseplant_id,
        '(0, 0, 255)': book_id,
    },
    2: {
        '(255, 255, 0)': bottle_id,
        '(255, 0, 128)': book_id,
        '(255, 100, 0)': lamp_id,
    }
}

is_crowd = 0

# These ids will be automatically increased

```



```
# Create the annotations
annotations = []
for mask_image in mask_images:
    sub_masks = create_sub_masks(mask_image)
    for color, sub_mask in sub_masks.items():
        category_id = category_ids[image_id]
        annotation = create_sub_mask_annotation(sub_mask, color)
        annotations.append(annotation)
        annotation_id += 1
    image_id += 1

print(json.dumps(annotations))
```

Output JSON

And here's our output! (I omitted a lot of the vertices for readability)

```
[{
  "segmentation": [[228.0, 332.5, 248.0, 333.0, 201.0, 95.5, 228.0],
  "iscrowd": 0,
  "image_id": 1,
  "category_id": 1,
  "id": 1,
  "bbox": [95.5, -0.5, 201.0, 333.0],
  "area": 33317.25
},
{
  "segmentation": [[340.0, 483.5, 343.0, 483.5, 343.0, 483.5, 340.0],
  "iscrowd": 0,
  "image_id": 1,
  "category_id": 2,
  "id": 2,
  "bbox": [340.0, 483.5, 343.0, 483.5]
```



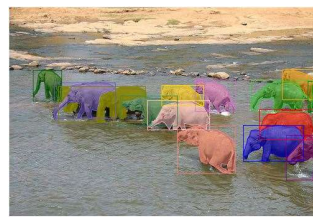
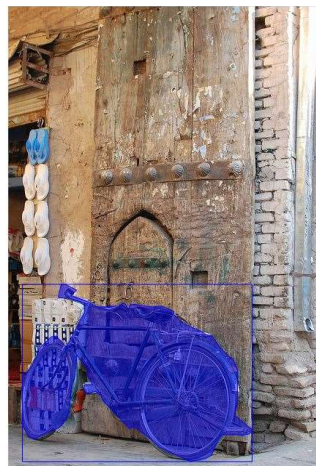
```
{
  "segmentation": [[95.0, 303.5, 108.0,
  "iscrowd": 0,
  "image_id": 2,
  "category_id": 3,
  "id": 3,
  "bbox": [25.5, 42.5, 116.0, 261.0],
  "area": 22243.5
},
{
  "segmentation": [[282.0, 494.5, 415.0,
  "iscrowd": 0,
  "image_id": 2,
  "category_id": 2,
  "id": 4,
  "bbox": [100.5, 238.5, 324.0, 256.0],
  "area": 47241.0
},
{
  "segmentation": [[298.0, 263.5, 311.0,
  "iscrowd": 0,
  "image_id": 2,
  "category_id": 4,
  "id": 5,
  "bbox": [161.5, -0.5, 210.0, 264.0],
  "area": 14593.25
}]
}]
```

PREVIEWING COCO ANNOTATIONS FOR AN IMAGE

time I went digging, so I decided to write my own. After a couple dead-end attempts to make a GUI application in Python for this, I ended up making something in Jupyter Notebook that lets you import a dataset as json and view segmentations in images.

To keep things simple, I created a subset of the COCO instances val2017 dataset that contains only 2 images.

Here's what these images will look like if you run your own Jupyter Notebook (Gist can't show the polygon segmentations for some reason).





COCO Image Viewer

This notebook will allow you to view details about dataset and preview segmentations on annotated images. For more about it at: <http://cocodataset.org/> (<http://cocodataset.org/>)

Note: Gist probably won't show the segmentations, but if you run this code in your own Jupyter Notebook, you'll see them.

The rest of the tutorial can be found at: <http://www.immersivelimit.com/tutorials/create-coco-annotations-from-scratch> (<http://www.immersivelimit.com/tutorials/create-coco-annotations-from-scratch>)

In [1]:

```
import IPython
import os
import json
import random
import numpy as np
import requests
from io import BytesIO
import base64
from math import trunc
```

COCO_Image_Viewer.ipynb hosted with ❤ by [view raw](#) GitHub

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- ☐ Needs improvement.

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