User Manual for the DataSynth Pipeline

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Introduction

This GitHub repository includes the unity project and Python code. The manual describes the functionalities and basics of using the synthetic data pipeline.

One of the most time-consuming parts of training an object detection model for a specific application is acquiring the training data. Thousands of varied images with bounding box annotations around the objects are necessary for a good model, traditionally obtained by manually taking pictures and then manually defining boxes for every single occurrence of the object in each image. This labeling process is additionally prone to errors when done by hand.

The first alternative to this is using an already available dataset of labeled images like Microsoft's COCO dataset of over 200 thousand labeled images. This won't work as soon as the model needs to be more specific. The next alternative that has seen an upswing in popularity in the last years is synthetic data. The images can be generated in a virtual environment built from 3D models. Through this approach total control of the dataset is gained depending on how we set up the environment and take virtual pictures. Another benefit is that every generated image can be automatically pixel-perfectly annotated from the 3D data.

The provided Python notebooks can then be used for converting the data to the right format, to be used for training a YOLOv8 object detection model.

1 Unity

The first thing to do after opening the Unity project is to check if it looks like in figure 1. If you can't see the GameObjects on the left (the lights, Main Camera, Volume, Scenario) it means that the DataSynth scene is not open. You can find it under the *Scenes* folder in the bottom left and then open it by double-clicking on it.

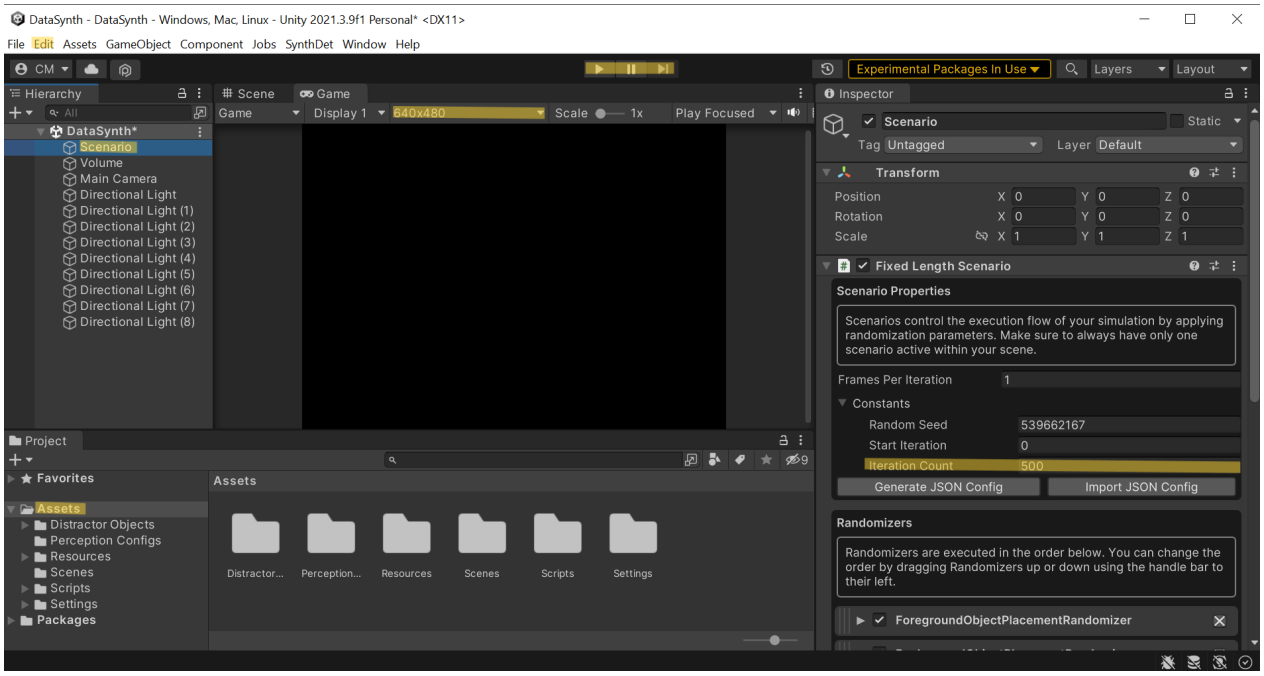

Figure 1: The unity layout where important tabs and fields have been highlighted in yellow.

The unity project is called *DataSynth* and is built using the Unity Perception package. The process works by having a *Scenario* that calls on *Randomizers* which in turn randomizes most of the things in the scene. These can be found in the **inspector** (the right-most window) after selecting the Scenario under the DataSynth scene on the left. Some of these Randomizers are built-in (documentation can be found under Unity Perception) and the rest are custom-made using scripting. *Randomizertags* can be added to different GameObjects and tells the Randomizers what objects to affect. Apart from the scenario, there is also a *Volume* (which controls for example the different camera effects, blur, etc.), *Main Camera* (which takes the images), and several *Directional Lights*.

1.1 Project Structure

All the Project files are found in the *Asset folder* which is located under the Project tab in the bottom left corner of the screen. All the important folders will be described below.

1.1.1 Resources

The most important folder is the Resources folder. In this folder is a *ScriptableObject* file called *settings* which contains the parameters that can be controlled during the data creation. By clicking on it the settings should come up in the inspector tab on the right side of the screen. In this folder there is also the *3Dmodels* folder. All prefabs in this folder will be used in the creation of the synthetic data.

1.1.2 Distractor Objects

Here all the textures and models used for the distractor objects can be found, including background and occluder objects.

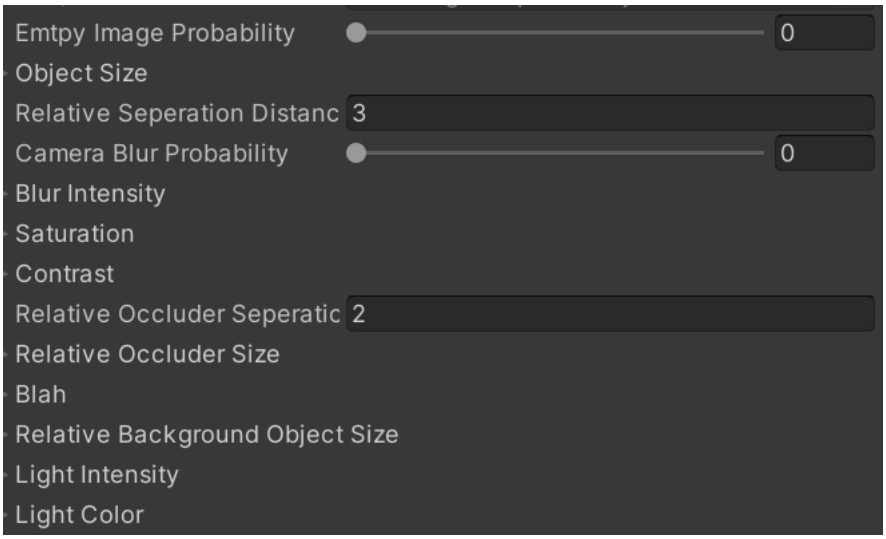

Figure 2: The settings file viewed in the Unity inspector

1.1.3 Scripts

All scripts can be found in this folder, for example, the custom Randomizers, Randomizertags, and other utilities.

1.2 Settings

In the setting files there are several parameters that can be changed which will influence the data generation. An explanation of each parameter is given below together with a standard value (these are just the values which have used for our latest models, they are not necessarily optimal). "Object of interest" refers to the prefabs that Unity will automatically annotate, i.e. the prefabs in the *3Dmodels* folder.

- **Empty Image Probability** - [0, 1] The probability that a generated image will include no objects of interest. Increasing the amount of empty images could improve the model by decreasing false positives. Standard: 0
- **Object Size** - The range of values that the size of the objects of interest can take. The size is given as a factor of the normalized size (normalized compared to the Unity coordinate system). Standard: [0.2, 1.1]
- **Relative Seperation** - The minimum seperation distance between the objects of interest relative to their size. Used to make sure the objects of interest don't intersect too much and cause weird visual effects. Standard: 3
- **Camera Blur Probability** - [0, 1] The probability that a camera blur effect will be applied to the image. The blur is created by changing the cameras depth of field so that the objects are not in focus. Standard: 0.1
- **Blur Intensity** - [0, 1] The range of values that the blur intensity can take. Standard: [0, 0.5]
- **Saturation** - [-100, 100] The range of values that the saturation can take. Standard: [-10, 10]
- **Contrast** - [-100, 100] The range of values that the contrast can take. Standard: [-10, 10]
- **Relative Occluder Seperation** - The minimum separation distance between the occlusion objects relative to the objects of interest size. Standard: 2

- **Relative Occluder Size** - The range of values that the size of the occlusion objects can take relative to the size of the objects of interest. Standard: [0.3, 0.5]
- **Relative Background Object Size** - How big the background objects are in relation to the objects of interest. A research paper from Google Cloud AI [**?**] found that the range [0.9, 1.5] gave the best results Standard: [0.9, 1.5]
- **Light Intensity** - The range of intensities that the lights randomly sample from each iteration. Standard: [8000, 50000]
- **Light Color** - The ranges of the hue offset applied that the lights randomly sample from each iteration. [0.4, 1] and alpha=1

1.2.1 Other Important Settings

- The number of lights in the scene can be changed by simply deleting or copying and pasting them in the left-most window.
- It is possible to restrict the possible rotation that an object of interest can take. By adding a component called *My Rotation Randomizer Tag* to the prefab there is a drop-down meny where an intervall of allowed rotations can be set (see where components can be added in Figure 3).
- By adding a component called *Material Property Randomizer Tag* to a prefab it is possible to randomize different material properties such as smoothness or metalness.
- To change the destination of where Unity places the created images and annotations go into *Edit* $\rightarrow$ *ProjectSettings*. In the project settings you should find *Perception* on the left. In there you can change the **Base Path** to be your desired destination folder.
- By clicking on the scenario, you can control the number of images created by changing the Iteration Count under *Fixed Length Scenario* in the inspector.
- The resolution of the created images can be changed under the Game tab in the middle of the screen. This project can currently only support non-wide aspect ratios for the objects to fill the whole image, such as 4:3.

1.3 How to create a prefab

After importing a 3D model in FBX format you can drag it into the scene (left window) and then drag it back into the Asset tree. Unity will then give you a pop-up window where you will choose to create an **original** prefab. Make sure to delete the object from the scene! Now select the FBX model (not the prefab) and click the *Extract Materials* button under the *Materials* tab in the inspector (Tip: put the material in the **Materials** folder under **Resources**). Now you can assign whatever imported textures you want to the material. Lastly, you have to reassign the material to the prefab. Select the prefab and under $MeshRenderer \rightarrow Materials$ you can select the material. You can now see how the object will render at the bottom of the inspector while the prefab is selected. If you want the object to be included in the synthetic data creation, put the prefab somewhere in the **3Dmodels** folder. Otherwise, put it into the **Prefabs** folder. You can also put the textures in the **Textures** folder and the FBX file into the **Models** folder if you want to.

Note! If Unity gives you warnings about ”animation clip” you can just ignore it.

1.4 Quickstart

To start creating images, press the start symbol in the top middle of the screen. There you can also pause the process using the pause button. The third button can be pressed to step forward one image at a time while the process is paused.

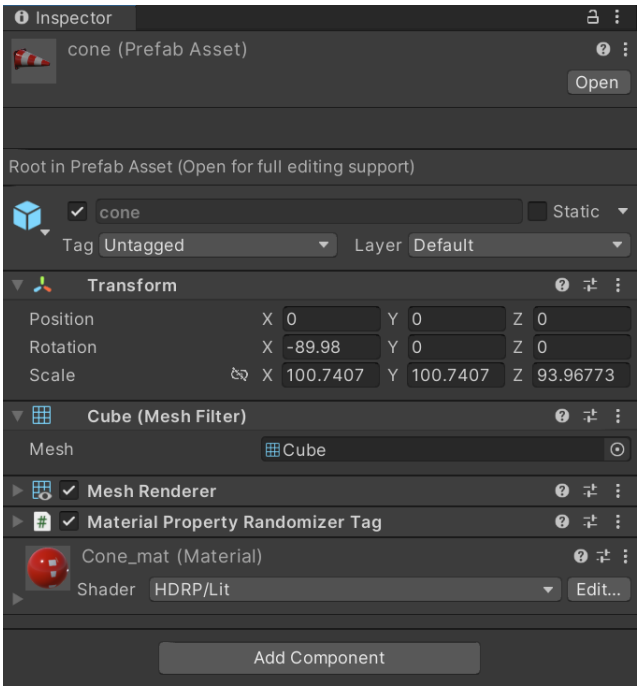

Figure 3: The image shows the inspector tab when selecting a prefab. The button for adding components can be seen in the bottom of the image

2 Data Conversion and Training (YOLOv8.ipynb)

This Python notebook converts the annotated data from Unity to a format that can be used for the training of a YOLOv8 model. It prepares the yaml file with instructions including the location of the converted data images and annotation .txt files, and the classes with respective IDs for labeling. Background photos of the real world can also be included in the prepared dataset.

Before running the notebook you need to define the four following variables:

- **solo_folder** - String containing the path to the source folder where the data is located. It should end with 'solo' unless you have moved the data after its creation.
- **dst** - String containing the path to where the destination folder should be placed. This is where the converted data will be placed. The script will try to create the folder if it doesn't already exist.
- **background_photos** - String containing the path to the folder where the real background photos are located. This is not necessary if backgrounds images are not going to be used during training.
- **dataset_name** - The chosen name of the current dataset and model.

Several arguments can be changed, some of which are described below.

2.1 convert_format_perception_to_yolo

- **train_cutoff** - The number of images used for training. (Recommended to be a rounded fraction of *dataset_size*, a quantity that's detected automatically.)
- **val_cutoff** - The validation data cutoff. (With *dataset_size* as input, all images but the training images will be used for validation. A lower value will put aside the remaining images for testing.)
- **copy_images** - Boolean for choosing whether to copy or move images to the destination folder. (Moving the images results in a much faster runtime but removes them from the solo folder.)
- **minVisibility** - The minimum fraction of visible pixels for each object to be annotated.

2.2 include_bg_photos

Real background photos in the training can help the model to be less prone to false positives. These photos should not include the objects trained on, therefore they don't need labels.

- **desired_fraction** - The desired fraction of real background images found in the final dataset. Around 0 - 10 % background images have been shown to work well to reduce false positives in previous papers, but test without first to see if the model has a problem with false positives or not. (If the folder with background images includes fewer images than needed, all available images are used.)

2.3 model.train

After the dataset preparation, the model training can be started, and the resulting weights can be used to export the model in another format (for example onnx) if needed.

The training can be thoroughly customized, though mostly keeping the default arguments results in a good model. The following arguments could need to be changed depending on the use case. To find all the arguments that can be used, see the documentation on Ultralytics website.

- **epochs** - Depends on the number of classes, the dataset size, and more. (As a reference, with just a few thousand images and one class, it can be enough with 20 to 40 epochs.)
- **imgsz** - Defines the image resolution by the largest side's pixel count.
- **freeze** - Defines the number of layers from the start of the network whose weights are frozen, meaning they keep the values from the pre-trained model. Freezing the feature detector block, which consists of the first 10 layers, by choosing freeze=10 proved beneficial.
- **batch** - Defines the batch size used during training. A small batch size (< 5 % of the dataset) has yielded the best results. E.g. our best current model was trained on 2000 images with batch size 8.

3 Inference (YOLO_inference.ipynb)

The separate notebook for inference includes code cells that can run inference on given images, videos, or video streams.

Validation of the model can be done if an annotated test dataset is provided. The code then prints out statistics such as recall, precision, mAP50, and mAP50-95. Ultralytics also automatically saves images of the predictions, as well as graphs of the results where the Python script is located under a folder called *detect*.

4 Hailo

For the model to be used with the Hailo AI accelerator chip a model conversion and optimization is needed. Using Hailo model zoo, the following command can be run after installation for a basic conversion from the model in onnx format to a binary hef file that can run on the accelerator chip:

```
hailomz compile --ckpt yolov8s_model.onnx --calib-path calibration_images
   --yaml hailo_model_zoo/cfg/networks/yolov8s.yaml --classes 1
```

The calibration images can for example be the training images.