Overview

Baselines and Model Zoo

<u>Detectron2 Beginner's Tutorial</u>

Training custom dataset

Review of Pretrained Models in Different Images in Dataset

Predicting on Videos

Overview

TODOs:

- 1. Reading documentation on Detectron2; general familiarization what are the implementation requirements? What are the benchmark datasets (coco, pascal)? How is accuracy measured, and how good it is usually at these different benchmarks?
- 2. Reading documentation on custom datasets with detectron2 and fine-tuning pipelines would we need to get segmentation masks or just bounding boxes?
- 3. Looking through SAYCam gold set frames what instructions would we want to give to turkers so that they annotated the frames correctly ? (see Clerkin et al 2017)
- 4. Try out a few SAYCam frames with Detectron2 in the Colab notebook. When does the model do OK? When does it do very different things from what you would do?

General Familiarization:

- 1. Implementation requirements
 - a. Detectron2 has its own input format and requires data to be registered.
 - b. They have a builtin function to transform data from coco or lvis format to detectron2 format
 - c. This tutorial uses Roboflow to preprocess labelled data in any format (including csv) and download in COCO JSON format
 - i. Then, the builtin function register_coco_instances registers the custom data with Detectron2 and can be used for training/validation/testing.
- 2. Benchmark datasets
 - a. COCO
 - b. PASCAL VOC
 - c. LVIS
 - d. Backbone models pretrained on ImageNet; default weights are ImageNet
- 3. Accuracy measure and performance on benchmarks

Custom datasets and fine-tuning pipelines:

- 1. Segmentation Masks and/or bounding boxes
 - a. If we're doing instance detection and segmentation, then we require both segmentation masks and bounding boxes
 - b. If we're doing panoptic segmentation, then we only require segmentation masks
 - i. TODO: see if panoptic segmentation inputs can have (and ignore) bounding boxes, or they require only segmentation masks

On instructions for turkers:

- 1. We might need to make a dictionary of baby items:
 - a. [play] gym vs playpen vs crib vs play mat
 - i. Maybe linking them to a list of words with pictures might be helpful
 - ii. We can also restrict it to folks who have lived with an infant in the past 5 vears
 - b. Is knowing what the high chair is important?

C.

- 2. Parents' clothing feels important, i.e. when the parent is wearing a jacket, this indicates that they are going outside; jacket seems like an important object, but none of these models classify clothing. Is clothing outside the scope of this project?
- 3. Instruct turkers to generalize as much as possible (don't specify type of table). See 1.b.v in Performance on SAYCam frames FMI

Performance on SAYCam frames:

- 1. Instance detection and segmentation
 - a. Model does ok with...
 - i. People (any part of body) -- often over classifies things as people
 - ii. With darker views and tinted hues
 - iii. Chairs: tries to classify a lot of furniture as chairs
 - b. Model does not do well with...
 - i. Baby toys/items
 - ii. Piano vs keyboard
 - iii. Outside objects (stick, grass, etc)
 - iv. Cats
 - v. Nontraditional furniture (stool, coffee table/side table)
 - Intuitively, these items could be classified with more traditional items/categories, (side tables, coffee tables, nightstands could all be labelled as tables)
 - vi. Windows and computers: all TVs
 - vii. Awkward angles (inside playpen, aerial view of drawer)
 - viii. Identifying things as pictures/art
 - ix. Sink vs tub
- 2. Panoptic segmentation
 - a. Model does ok with...
 - i. People (any part of body) -- classifies many things as people

- ii. With darker views and tinted hues
- iii. Wall/floor/ceilings
- iv. Most furniture (not superb, but better than instance segmentation)
- v. Outside objects: detects trees and grass
- vi. Windows, but still sometimes classifies them as TVs
- b. Model does not do well with...
 - i. Baby toys/items
 - ii. Cats
 - iii. Piano
 - iv. Awkward angles (inside playpen, aerial view of drawer)
 - v. Desktop computer screens (classifies as TVs)
 - vi. Awkward angles (inside playpen, aerial view of drawer)
 - vii. Natural objects outside of natural context (person holding stick or plant)
 - viii. Identifying things as pictures/art
 - ix. Sink vs tub

3. Overall

- a. All the models prioritize people, and I'm not sure if infants often identify people as people
- b. All ignore clothes worn
- c. Not very good at recognizing uncommon household items: art projects in one house are often mislabeled (easel is chair, concept of photo not recognized)
 - i. Do the infants learn this as art or do they learn the objects shown in the art more?
 - 1. This might be a point of interest in parent surveys

Baselines and Model Zoo

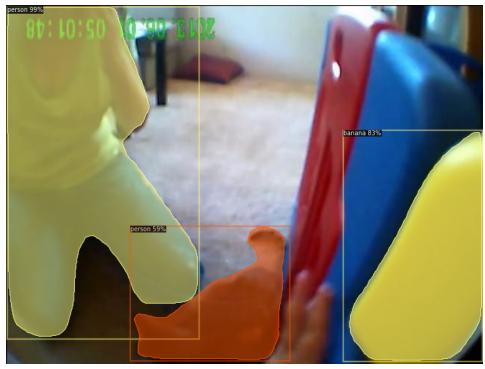
- 1. Three backbone combinations
 - a. ResNet+FPN
 - i. Best speed/accuracy tradeoff
 - b. ResNet conv4 backbone with conv5 head
 - i. Original Faster R-CNN
 - c. ResNet conv5 with dilations in conv5
 - i. Deformable ConvNet paper
 - d. All trained with ~37 COCO epochs
 - e. Pretrained Models on ImageNet-1k
 - i. Different from Detectron models (no Batchnorm in affine layer)
 - ii. ResNEt-50, ResNet-101, ResNeXt-101-32x8d

Detectron2 Beginner's Tutorial

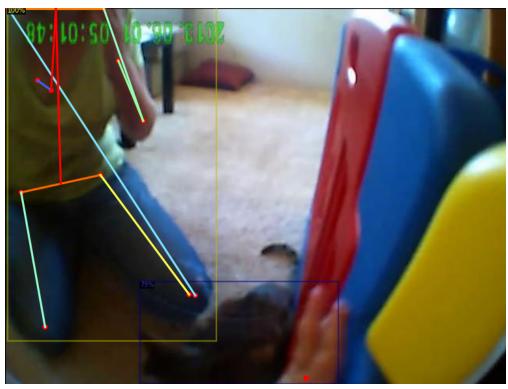
- 1. Some general notes
 - a. Cannot run locally on my mac: need CUDA compatible GPU (nvidia)
 - b.

a.

2. Using default predictor



- b. Definitely some misrepresentation and errors to improve upon through training
- 3. Inference with keypoint detection model



- b. No labels just recreating keypoints in key objects
- 4. Inference with panoptic segmentation

a.



a.

- b. Quite robust to begin with and includes objects/features like wall and rug (haven't seen this in other models)
- c. But, it confidently says the cat is a person, while the baseline model is more uncertain
- d. Shades in instead of using a bounding box, just like what we were thinking for MTurk

Training custom dataset

- 1. Can register dataset and/or register metadata
- 2. We can use labelled dataset and convert csvs to dictionaries for the model to use
- 3. Uses dataset dict, which includes
 - a. image filename
 - b. height and width of image
 - c. assigned image id
 - d. list of dictionary of annotations of image
 - i. Each dictionary contains
 - Bounding box instance (list of 4 numbers), format of bounding box, list of polygons for segmentation mask of instance, keypoints (each point has x, y and visibility value)
 - e. Filename of semantic segmentation ground truth: image with integer labels in place of pixel values
- 4. Register metadata for shared information across dataset, includes
 - a. For instance detection/segmentation
 - i. List of names for each instance category
 - ii. List of rbg tuples corresponding to colors for each category (optional, if not included it'll randomly input!)
 - iii. Dictionary mapping class ids to contiguous ids (numbers corresponding to classes)
 - b. For semantic and panoptic segmentation
 - i. List of names for each stuff category
 - ii. List of rbg tuples corresponding to colors for each category (optional, if not included it'll randomly input!)
 - iii. Panoptic root and json for panoptic evaluation
 - iv. Dictionary mapping semantic segmentation ids to contiguous ids (number corresponding to categories)

Review of Pretrained Models in Different Images in Dataset

- 1. The models do not recognize baby objects: playpen, crib, etc
 - a. We might need to build a dictionary of baby things
- 2. COCO knows people very well
 - a. All the models frequently classify things as people
- 3. Panoptic segmentation consistently does better than the instance segmentation models
- 4. The LVIS pretrained model is trained on a 1x schedule, so its performance is subpar in comparison to the COCO models, which are trained on a 3x schedule.
- 5. FPN vs C4 vs DC5

Predicting on Videos

- 1. Detectron2 ~can~ take videos and outputs frame by frame predictions
 - a. According to the demo docs, it has the ability to read in videos and output video visualizations. Still working on getting this functional.
 - b. There are a few different tutorials for inputting videos, detectron2 demo does it and found a stackoverflow page that does it as well