train_fashion

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1 Mask R-CNN - Train on Fashion Dataset

This notebook shows how to train Mask R-CNN on Modanet dataset. It is better to have a GPU, though, because the network backbone is a Resnet101, which would be too slow to train on a CPU. On a GPU, you can start to get okay-ish results in a few minutes, and good results in less than an hour.

In [1]:
```
import os
import sys
import random
import math
import re
import time
import numpy as np
import cv2
import matplotlib
import matplotlib.pyplot as plt

# Root directory of the project
ROOT_DIR = os.path.abspath("../../")

# Import Mask RCNN
sys.path.append(ROOT_DIR)  # To find local version of the library
from mrcnn.config import Config
from mrcnn import utils
import mrcnn.model as modellib
from mrcnn import visualize
from mrcnn.model import log

from pycocotools.coco import COCO

%matplotlib inline

# Directory to save logs and trained model
MODEL_DIR = os.path.join(ROOT_DIR, "logs")

# Local path to trained weights file
```

```
COCO_MODEL_PATH = os.path.join(ROOT_DIR, "mask_rcnn_coco.h5")
# Download COCO trained weights from Releases if needed
if not os.path.exists(COCO_MODEL_PATH):
    utils.download_trained_weights(COCO_MODEL_PATH)
```

```
Using TensorFlow backend.
```

1.1 Configurations

In [2]:
```
class FashionConfig(Config):
    """Configuration for training on the toy shapes dataset.
    Derives from the base Config class and overrides values specific
    to the toy shapes dataset.
    """
    # Give the configuration a recognizable name
    NAME = "fashion"

    # Train on 1 GPU and 8 images per GPU. We can put multiple images on each
    # GPU because the images are small. Batch size is 8 (GPUs * images/GPU).
    GPU_COUNT = 1
    IMAGES_PER_GPU = 1

    # Number of classes (including background)
    NUM_CLASSES = 1 + 13  # background + 3 shapes

    # Use small images for faster training. Set the limits of the small side
    # the large side, and that determines the image shape.
    IMAGE_MIN_DIM = 128
    IMAGE_MAX_DIM = 128

    # Use smaller anchors because our image and objects are small
    RPN_ANCHOR_SCALES = (8, 16, 32, 64, 128)  # anchor side in pixels

    # Reduce training ROIs per image because the images are small and have
    # few objects. Aim to allow ROI sampling to pick 33% positive ROIs.
    TRAIN_ROIS_PER_IMAGE = 32

    # Use a small epoch since the data is simple
    STEPS_PER_EPOCH = 100

    # use small validation steps since the epoch is small
    VALIDATION_STEPS = 5

config = FashionConfig()
config.display()
```

```
Configurations:
```

```
BACKBONE                       resnet101
BACKBONE_STRIDES               [4, 8, 16, 32, 64]
BATCH_SIZE                     1
BBOX_STD_DEV                   [0.1 0.1 0.2 0.2]
COMPUTE_BACKBONE_SHAPE         None
DETECTION_MAX_INSTANCES        100
DETECTION_MIN_CONFIDENCE       0.7
DETECTION_NMS_THRESHOLD        0.3
FPN_CLASSIF_FC_LAYERS_SIZE     1024
GPU_COUNT                      1
GRADIENT_CLIP_NORM             5.0
IMAGES_PER_GPU                 1
IMAGE_CHANNEL_COUNT            3
IMAGE_MAX_DIM                  128
IMAGE_META_SIZE                26
IMAGE_MIN_DIM                  128
IMAGE_MIN_SCALE                0
IMAGE_RESIZE_MODE              square
IMAGE_SHAPE                    [128 128   3]
LEARNING_MOMENTUM              0.9
LEARNING_RATE                  0.001
LOSS_WEIGHTS                   {'rpn_class_loss': 1.0, 'rpn_bbox_loss': 1.0, 'mrcnn_class_loss':
MASK_POOL_SIZE                 14
MASK_SHAPE                     [28, 28]
MAX_GT_INSTANCES               100
MEAN_PIXEL                     [123.7 116.8 103.9]
MINI_MASK_SHAPE                (56, 56)
NAME                           fashion
NUM_CLASSES                    14
POOL_SIZE                      7
POST_NMS_ROIS_INFERENCE        1000
POST_NMS_ROIS_TRAINING         2000
PRE_NMS_LIMIT                  6000
ROI_POSITIVE_RATIO             0.33
RPN_ANCHOR_RATIOS              [0.5, 1, 2]
RPN_ANCHOR_SCALES              (8, 16, 32, 64, 128)
RPN_ANCHOR_STRIDE              1
RPN_BBOX_STD_DEV               [0.1 0.1 0.2 0.2]
RPN_NMS_THRESHOLD              0.7
RPN_TRAIN_ANCHORS_PER_IMAGE    256
STEPS_PER_EPOCH                100
TOP_DOWN_PYRAMID_SIZE          256
TRAIN_BN                       False
TRAIN_ROIS_PER_IMAGE           32
USE_MINI_MASK                  True
USE_RPN_ROIS                   True
VALIDATION_STEPS               5
WEIGHT_DECAY                   0.0001
```

1.2 Notebook Preferences

```
In [3]: def get_ax(rows=1, cols=1, size=8):
            """Return a Matplotlib Axes array to be used in
            all visualizations in the notebook. Provide a
            central point to control graph sizes.

            Change the default size attribute to control the size
            of rendered images
            """
            _, ax = plt.subplots(rows, cols, figsize=(size*cols, size*rows))
            return ax
```

1.3 Dataset

Extend the Dataset class and add a method to load the shapes dataset, `load_shapes()`, and override the following methods:

- load_image()
- load_mask()
- image_reference()

```
In [4]: import io
        import lmdb
        import sqlite3
        import pandas as pd
        import json
        from PIL import Image
        from IPython.display import display
```

```
In [7]: class PhotoData(object):
            def __init__(self, path):
                self.env = lmdb.open(
                    path, map_size=2**36, readonly=True, lock=False
                )

            def __iter__(self):
                with self.env.begin() as t:
                    with t.cursor() as c:
                        for key, value in c:
                            yield key, value

            def __getitem__(self, index):
                key = str(index).encode('ascii')
                with self.env.begin() as t:
```

```
            data = t.get(key)
        if not data:
            return None
        with io.BytesIO(data) as f:
            image = Image.open(f)
            image.load()
            return image

    def __len__(self):
        return self.env.stat()['entries']

photo_data = PhotoData(r'..\..\..\photos.lmdb')
print(len(photo_data))
```

```
1097474
```

```
In [8]: from pycocotools import mask as maskUtils

        class FashionDataset(utils.Dataset):

            def load_fashion(self, count=5, start=0):
                json_file = r'..\..\..\modanet2018_instances_train.json'
                d = json.load(open(json_file))
                coco=COCO(json_file)
                class_ids = sorted(coco.getCatIds())
                for id in class_ids:
                    self.add_class("fashion", id, "")

                image_ids = []
                for c in range(count):
                    if c < 5:
                        print(d['images'][c+start]['id'])
                    image_ids.append(d['images'][c+start]['id'])

                # Add images
                for i in image_ids:
                    annIds = coco.getAnnIds(imgIds=i, catIds=class_ids, iscrowd=None)
                    anns = coco.loadAnns(annIds)
                    width = coco.imgs[i]["width"]
                    height = coco.imgs[i]["height"]
                    self.add_image("fashion", image_id=i, path=None,
                                   width=width, height=height, annotations=anns)


            def load_image(self, image_id):
                imgId = self.image_info[image_id]['id']
                image = photo_data[imgId]
```

```
        out = np.array(image.getdata()).astype(np.int32).reshape((image.size[1], image.s
        return out


    def image_reference(self, image_id):
        """Return the shapes data of the image."""
        pass


    def load_mask(self, image_id):
        """Load instance masks for the given image.

        Different datasets use different ways to store masks. This
        function converts the different mask format to one format
        in the form of a bitmap [height, width, instances].

        Returns:
        masks: A bool array of shape [height, width, instance count] with
            one mask per instance.
        class_ids: a 1D array of class IDs of the instance masks.
        """
        # If not a COCO image, delegate to parent class.
        image_info = self.image_info[image_id]

        instance_masks = []
        class_ids = []
        annotations = self.image_info[image_id]["annotations"]
        # Build mask of shape [height, width, instance_count] and list
        # of class IDs that correspond to each channel of the mask.
        for annotation in annotations:
            class_id = annotation['category_id']
            if class_id:
                m = self.annToMask(annotation, image_info["height"],
                                   image_info["width"])
                # Some objects are so small that they're less than 1 pixel area
                # and end up rounded out. Skip those objects.
                if m.max() < 1:
                    continue
                # Is it a crowd? If so, use a negative class ID.
                if annotation['iscrowd']:
                    # Use negative class ID for crowds
                    class_id *= -1
                    # For crowd masks, annToMask() sometimes returns a mask
                    # smaller than the given dimensions. If so, resize it.
                    if m.shape[0] != image_info["height"] or m.shape[1] != image_info["w
                        m = np.ones([image_info["height"], image_info["width"]], dtype=b
                instance_masks.append(m)
                class_ids.append(class_id)
```

```
        # Pack instance masks into an array
        if class_ids:
            mask = np.stack(instance_masks, axis=2).astype(np.bool)
            class_ids = np.array(class_ids, dtype=np.int32)
            return mask, class_ids
        else:
            # Call super class to return an empty mask
            return super(CocoDataset, self).load_mask(image_id)


    def annToRLE(self, ann, height, width):
        """
        Convert annotation which can be polygons, uncompressed RLE to RLE.
        :return: binary mask (numpy 2D array)
        """
        segm = ann['segmentation']
        if isinstance(segm, list):
            # polygon -- a single object might consist of multiple parts
            # we merge all parts into one mask rle code
            rles = maskUtils.frPyObjects(segm, height, width)
            rle = maskUtils.merge(rles)
        elif isinstance(segm['counts'], list):
            # uncompressed RLE
            rle = maskUtils.frPyObjects(segm, height, width)
        else:
            # rle
            rle = ann['segmentation']
        return rle

    def annToMask(self, ann, height, width):
        """
        Convert annotation which can be polygons, uncompressed RLE, or RLE to binary mas
        :return: binary mask (numpy 2D array)
        """
        rle = self.annToRLE(ann, height, width)
        m = maskUtils.decode(rle)
        return m
```

In [25]:
```
# Training dataset
train_count = 1
val_count = 1
dataset_train = FashionDataset()
dataset_train.load_fashion(train_count)
dataset_train.prepare()

# Validation dataset - overfit 1 image
dataset_val = FashionDataset()
```

```
dataset_val.load_fashion(val_count)
dataset_val.prepare()
```

```
loading annotations into memory...
Done (t=3.52s)
creating index...
index created!
736791
loading annotations into memory...
Done (t=3.61s)
creating index...
index created!
736791
```

In [26]:
```
# Load and display random samples
image_ids = np.random.choice(dataset_train.image_ids, 1)
for image_id in image_ids:
    image = dataset_train.load_image(image_id)
    mask, class_ids = dataset_train.load_mask(image_id)
    visualize.display_top_masks(image, mask, class_ids, dataset_train.class_names)
```

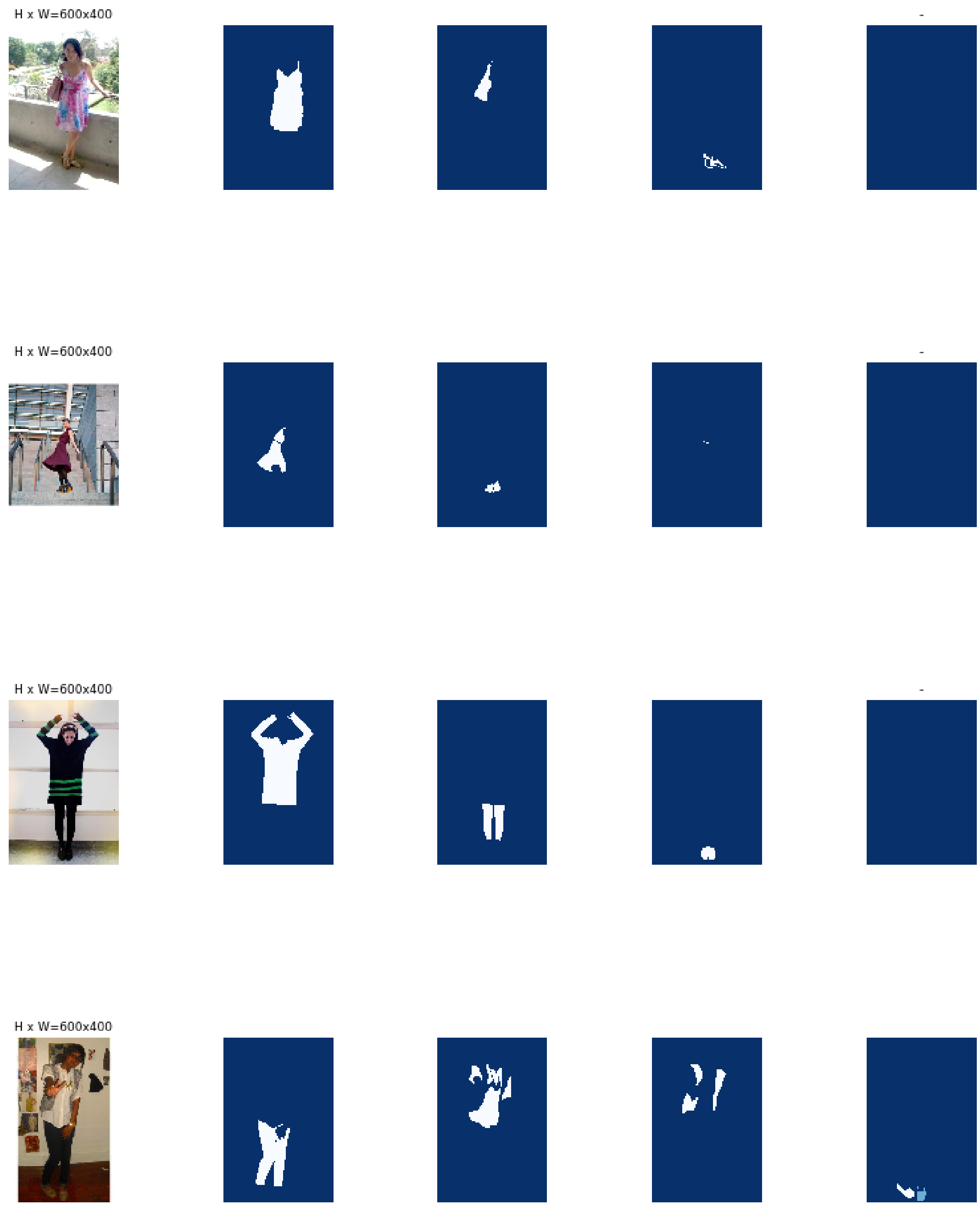
1.4 More data samples

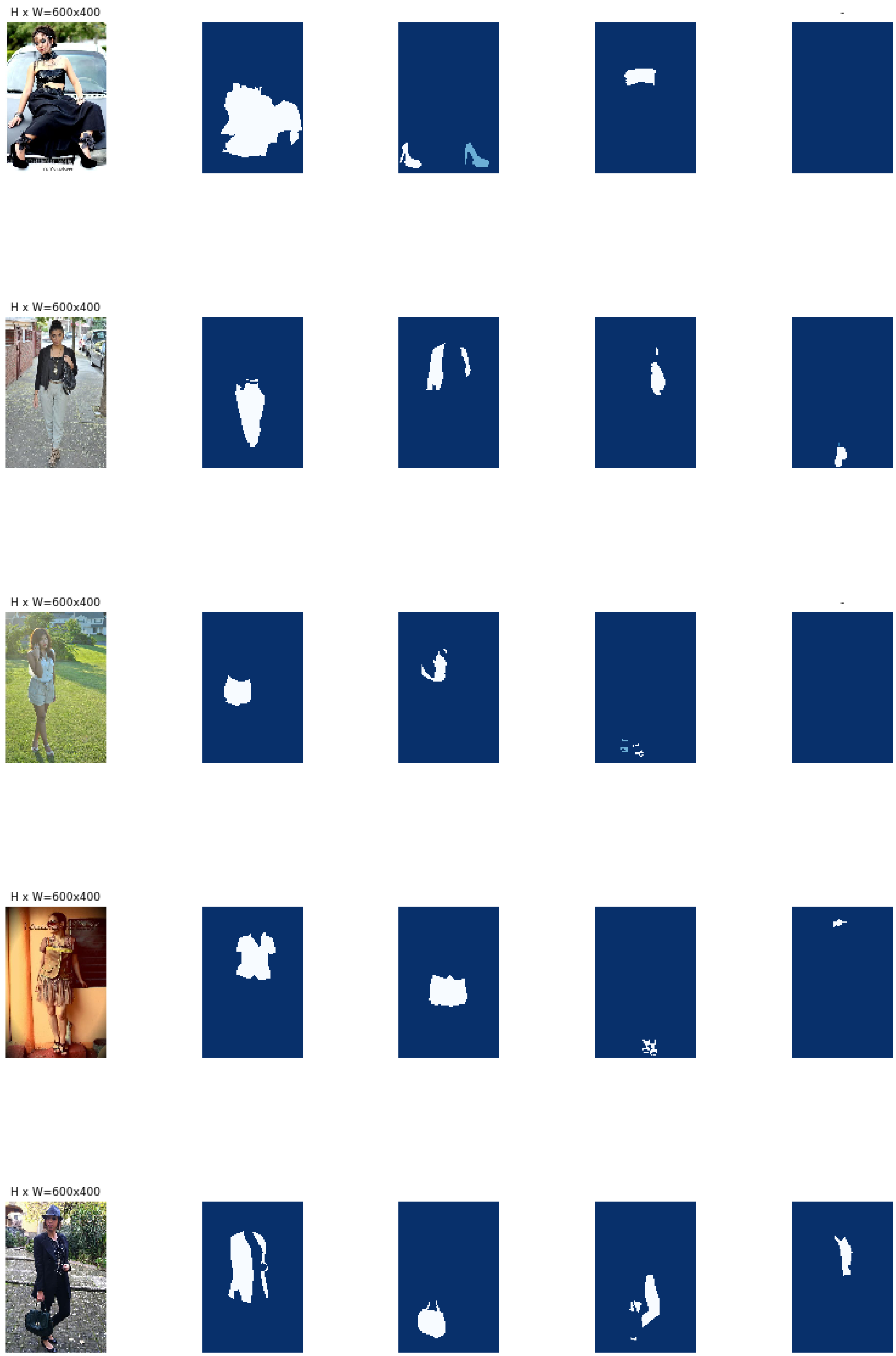
In [27]:
```
%%javascript
IPython.OutputArea.prototype._should_scroll = function(lines) {
    return false;
}
```

```
<IPython.core.display.Javascript object>
```

In [28]:
```
sample_data = FashionDataset()
sample_data.load_fashion(10, start=10)
sample_data.prepare()
for image_id in sample_data.image_ids:
    image = sample_data.load_image(image_id)
    mask, class_ids = sample_data.load_mask(image_id)
    visualize.display_top_masks(image, mask, class_ids, sample_data.class_names)
```

```
loading annotations into memory...
Done (t=3.69s)
creating index...
index created!
764947
765216
765262
765317
765326
```




H x W=600x400
H x W=600x400
H x W=600x400
H x W=600x400
H x W=600x400

1.5 Create Model

```
In [29]: # Create model in training mode
         model = modellib.MaskRCNN(mode="training", config=config,
                                   model_dir=MODEL_DIR)
```

```
In [30]: # Which weights to start with?
         init_with = "coco"  # imagenet, coco, or last

         if init_with == "imagenet":
             model.load_weights(model.get_imagenet_weights(), by_name=True)
         elif init_with == "coco":
             # Load weights trained on MS COCO, but skip layers that
             # are different due to the different number of classes
             # See README for instructions to download the COCO weights
             model.load_weights(COCO_MODEL_PATH, by_name=True,
                                exclude=["mrcnn_class_logits", "mrcnn_bbox_fc",
                                         "mrcnn_bbox", "mrcnn_mask"])
         elif init_with == "last":
             # Load the last model you trained and continue training
             model.load_weights(model.find_last(), by_name=True)
```

1.6 Training

Train in two stages: 1. Only the heads. Here we're freezing all the backbone layers and training only the randomly initialized layers (i.e. the ones that we didn't use pre-trained weights from MS COCO). To train only the head layers, pass `layers='heads'` to the `train()` function.

2. Fine-tune all layers. For this simple example it's not necessary, but we're including it to show the process. Simply pass `layers="all` to train all layers.

```
In [31]: # Train the head branches
         # Passing layers="heads" freezes all layers except the head
         # layers. You can also pass a regular expression to select
         # which layers to train by name pattern.
```

```
model.train(dataset_train, dataset_val,
            learning_rate=config.LEARNING_RATE,
            epochs=1,
            layers='heads')
```

```
Starting at epoch 0. LR=0.001

Checkpoint Path: C:\Training\DeepLearningGit\virtualFitting\mask_rcnn\logs\fashion20190514T0059\
Selecting layers to train
fpn_c5p5               (Conv2D)
fpn_c4p4               (Conv2D)
fpn_c3p3               (Conv2D)
fpn_c2p2               (Conv2D)
fpn_p5                 (Conv2D)
fpn_p2                 (Conv2D)
fpn_p3                 (Conv2D)
fpn_p4                 (Conv2D)
In model:  rpn_model
    rpn_conv_shared        (Conv2D)
    rpn_class_raw          (Conv2D)
    rpn_bbox_pred          (Conv2D)
mrcnn_mask_conv1       (TimeDistributed)
mrcnn_mask_bn1         (TimeDistributed)
mrcnn_mask_conv2       (TimeDistributed)
mrcnn_mask_bn2         (TimeDistributed)
mrcnn_class_conv1      (TimeDistributed)
mrcnn_class_bn1        (TimeDistributed)
mrcnn_mask_conv3       (TimeDistributed)
mrcnn_mask_bn3         (TimeDistributed)
mrcnn_class_conv2      (TimeDistributed)
mrcnn_class_bn2        (TimeDistributed)
mrcnn_mask_conv4       (TimeDistributed)
mrcnn_mask_bn4         (TimeDistributed)
mrcnn_bbox_fc          (TimeDistributed)
mrcnn_mask_deconv      (TimeDistributed)
mrcnn_class_logits     (TimeDistributed)
mrcnn_mask             (TimeDistributed)
```

```
C:\anaconda3\envs\mask_rcnn\lib\site-packages\tensorflow\python\ops\gradients_impl.py:110: UserW
  "Converting sparse IndexedSlices to a dense Tensor of unknown shape. "
```

```
Epoch 1/1
100/100 [==============================] - 232s 2s/step - loss: 1.3216 - rpn_class_loss: 0.0565
```

In [32]:
```
# Fine tune all layers
# Passing layers="all" trains all layers. You can also
```

```python
# pass a regular expression to select which layers to
# train by name pattern.
model.train(dataset_train, dataset_val,
            learning_rate=config.LEARNING_RATE / 10,
            epochs=1,
            layers="all")
```

```
Starting at epoch 1. LR=0.0001

Checkpoint Path: C:\Training\DeepLearningGit\virtualFitting\mask_rcnn\logs\fashion20190514T0059\
Selecting layers to train
conv1                  (Conv2D)
bn_conv1               (BatchNorm)
res2a_branch2a         (Conv2D)
bn2a_branch2a          (BatchNorm)
res2a_branch2b         (Conv2D)
bn2a_branch2b          (BatchNorm)
res2a_branch2c         (Conv2D)
res2a_branch1          (Conv2D)
bn2a_branch2c          (BatchNorm)
bn2a_branch1           (BatchNorm)
res2b_branch2a         (Conv2D)
bn2b_branch2a          (BatchNorm)
res2b_branch2b         (Conv2D)
bn2b_branch2b          (BatchNorm)
res2b_branch2c         (Conv2D)
bn2b_branch2c          (BatchNorm)
res2c_branch2a         (Conv2D)
bn2c_branch2a          (BatchNorm)
res2c_branch2b         (Conv2D)
bn2c_branch2b          (BatchNorm)
res2c_branch2c         (Conv2D)
bn2c_branch2c          (BatchNorm)
res3a_branch2a         (Conv2D)
bn3a_branch2a          (BatchNorm)
res3a_branch2b         (Conv2D)
bn3a_branch2b          (BatchNorm)
res3a_branch2c         (Conv2D)
res3a_branch1          (Conv2D)
bn3a_branch2c          (BatchNorm)
bn3a_branch1           (BatchNorm)
res3b_branch2a         (Conv2D)
bn3b_branch2a          (BatchNorm)
res3b_branch2b         (Conv2D)
bn3b_branch2b          (BatchNorm)
res3b_branch2c         (Conv2D)
bn3b_branch2c          (BatchNorm)
```

```
res3c_branch2a          (Conv2D)
bn3c_branch2a           (BatchNorm)
res3c_branch2b          (Conv2D)
bn3c_branch2b           (BatchNorm)
res3c_branch2c          (Conv2D)
bn3c_branch2c           (BatchNorm)
res3d_branch2a          (Conv2D)
bn3d_branch2a           (BatchNorm)
res3d_branch2b          (Conv2D)
bn3d_branch2b           (BatchNorm)
res3d_branch2c          (Conv2D)
bn3d_branch2c           (BatchNorm)
res4a_branch2a          (Conv2D)
bn4a_branch2a           (BatchNorm)
res4a_branch2b          (Conv2D)
bn4a_branch2b           (BatchNorm)
res4a_branch2c          (Conv2D)
res4a_branch1           (Conv2D)
bn4a_branch2c           (BatchNorm)
bn4a_branch1            (BatchNorm)
res4b_branch2a          (Conv2D)
bn4b_branch2a           (BatchNorm)
res4b_branch2b          (Conv2D)
bn4b_branch2b           (BatchNorm)
res4b_branch2c          (Conv2D)
bn4b_branch2c           (BatchNorm)
res4c_branch2a          (Conv2D)
bn4c_branch2a           (BatchNorm)
res4c_branch2b          (Conv2D)
bn4c_branch2b           (BatchNorm)
res4c_branch2c          (Conv2D)
bn4c_branch2c           (BatchNorm)
res4d_branch2a          (Conv2D)
bn4d_branch2a           (BatchNorm)
res4d_branch2b          (Conv2D)
bn4d_branch2b           (BatchNorm)
res4d_branch2c          (Conv2D)
bn4d_branch2c           (BatchNorm)
res4e_branch2a          (Conv2D)
bn4e_branch2a           (BatchNorm)
res4e_branch2b          (Conv2D)
bn4e_branch2b           (BatchNorm)
res4e_branch2c          (Conv2D)
bn4e_branch2c           (BatchNorm)
res4f_branch2a          (Conv2D)
bn4f_branch2a           (BatchNorm)
res4f_branch2b          (Conv2D)
bn4f_branch2b           (BatchNorm)
```

```
res4f_branch2c          (Conv2D)
bn4f_branch2c           (BatchNorm)
res4g_branch2a          (Conv2D)
bn4g_branch2a           (BatchNorm)
res4g_branch2b          (Conv2D)
bn4g_branch2b           (BatchNorm)
res4g_branch2c          (Conv2D)
bn4g_branch2c           (BatchNorm)
res4h_branch2a          (Conv2D)
bn4h_branch2a           (BatchNorm)
res4h_branch2b          (Conv2D)
bn4h_branch2b           (BatchNorm)
res4h_branch2c          (Conv2D)
bn4h_branch2c           (BatchNorm)
res4i_branch2a          (Conv2D)
bn4i_branch2a           (BatchNorm)
res4i_branch2b          (Conv2D)
bn4i_branch2b           (BatchNorm)
res4i_branch2c          (Conv2D)
bn4i_branch2c           (BatchNorm)
res4j_branch2a          (Conv2D)
bn4j_branch2a           (BatchNorm)
res4j_branch2b          (Conv2D)
bn4j_branch2b           (BatchNorm)
res4j_branch2c          (Conv2D)
bn4j_branch2c           (BatchNorm)
res4k_branch2a          (Conv2D)
bn4k_branch2a           (BatchNorm)
res4k_branch2b          (Conv2D)
bn4k_branch2b           (BatchNorm)
res4k_branch2c          (Conv2D)
bn4k_branch2c           (BatchNorm)
res4l_branch2a          (Conv2D)
bn4l_branch2a           (BatchNorm)
res4l_branch2b          (Conv2D)
bn4l_branch2b           (BatchNorm)
res4l_branch2c          (Conv2D)
bn4l_branch2c           (BatchNorm)
res4m_branch2a          (Conv2D)
bn4m_branch2a           (BatchNorm)
res4m_branch2b          (Conv2D)
bn4m_branch2b           (BatchNorm)
res4m_branch2c          (Conv2D)
bn4m_branch2c           (BatchNorm)
res4n_branch2a          (Conv2D)
bn4n_branch2a           (BatchNorm)
res4n_branch2b          (Conv2D)
bn4n_branch2b           (BatchNorm)
```

```
res4n_branch2c         (Conv2D)
bn4n_branch2c          (BatchNorm)
res4o_branch2a         (Conv2D)
bn4o_branch2a          (BatchNorm)
res4o_branch2b         (Conv2D)
bn4o_branch2b          (BatchNorm)
res4o_branch2c         (Conv2D)
bn4o_branch2c          (BatchNorm)
res4p_branch2a         (Conv2D)
bn4p_branch2a          (BatchNorm)
res4p_branch2b         (Conv2D)
bn4p_branch2b          (BatchNorm)
res4p_branch2c         (Conv2D)
bn4p_branch2c          (BatchNorm)
res4q_branch2a         (Conv2D)
bn4q_branch2a          (BatchNorm)
res4q_branch2b         (Conv2D)
bn4q_branch2b          (BatchNorm)
res4q_branch2c         (Conv2D)
bn4q_branch2c          (BatchNorm)
res4r_branch2a         (Conv2D)
bn4r_branch2a          (BatchNorm)
res4r_branch2b         (Conv2D)
bn4r_branch2b          (BatchNorm)
res4r_branch2c         (Conv2D)
bn4r_branch2c          (BatchNorm)
res4s_branch2a         (Conv2D)
bn4s_branch2a          (BatchNorm)
res4s_branch2b         (Conv2D)
bn4s_branch2b          (BatchNorm)
res4s_branch2c         (Conv2D)
bn4s_branch2c          (BatchNorm)
res4t_branch2a         (Conv2D)
bn4t_branch2a          (BatchNorm)
res4t_branch2b         (Conv2D)
bn4t_branch2b          (BatchNorm)
res4t_branch2c         (Conv2D)
bn4t_branch2c          (BatchNorm)
res4u_branch2a         (Conv2D)
bn4u_branch2a          (BatchNorm)
res4u_branch2b         (Conv2D)
bn4u_branch2b          (BatchNorm)
res4u_branch2c         (Conv2D)
bn4u_branch2c          (BatchNorm)
res4v_branch2a         (Conv2D)
bn4v_branch2a          (BatchNorm)
res4v_branch2b         (Conv2D)
bn4v_branch2b          (BatchNorm)
```

```
res4v_branch2c         (Conv2D)
bn4v_branch2c          (BatchNorm)
res4w_branch2a         (Conv2D)
bn4w_branch2a          (BatchNorm)
res4w_branch2b         (Conv2D)
bn4w_branch2b          (BatchNorm)
res4w_branch2c         (Conv2D)
bn4w_branch2c          (BatchNorm)
res5a_branch2a         (Conv2D)
bn5a_branch2a          (BatchNorm)
res5a_branch2b         (Conv2D)
bn5a_branch2b          (BatchNorm)
res5a_branch2c         (Conv2D)
res5a_branch1          (Conv2D)
bn5a_branch2c          (BatchNorm)
bn5a_branch1           (BatchNorm)
res5b_branch2a         (Conv2D)
bn5b_branch2a          (BatchNorm)
res5b_branch2b         (Conv2D)
bn5b_branch2b          (BatchNorm)
res5b_branch2c         (Conv2D)
bn5b_branch2c          (BatchNorm)
res5c_branch2a         (Conv2D)
bn5c_branch2a          (BatchNorm)
res5c_branch2b         (Conv2D)
bn5c_branch2b          (BatchNorm)
res5c_branch2c         (Conv2D)
bn5c_branch2c          (BatchNorm)
fpn_c5p5               (Conv2D)
fpn_c4p4               (Conv2D)
fpn_c3p3               (Conv2D)
fpn_c2p2               (Conv2D)
fpn_p5                 (Conv2D)
fpn_p2                 (Conv2D)
fpn_p3                 (Conv2D)
fpn_p4                 (Conv2D)
In model:  rpn_model
    rpn_conv_shared        (Conv2D)
    rpn_class_raw          (Conv2D)
    rpn_bbox_pred          (Conv2D)
mrcnn_mask_conv1       (TimeDistributed)
mrcnn_mask_bn1         (TimeDistributed)
mrcnn_mask_conv2       (TimeDistributed)
mrcnn_mask_bn2         (TimeDistributed)
mrcnn_class_conv1      (TimeDistributed)
mrcnn_class_bn1        (TimeDistributed)
mrcnn_mask_conv3       (TimeDistributed)
mrcnn_mask_bn3         (TimeDistributed)
```

```
mrcnn_class_conv2      (TimeDistributed)
mrcnn_class_bn2        (TimeDistributed)
mrcnn_mask_conv4       (TimeDistributed)
mrcnn_mask_bn4         (TimeDistributed)
mrcnn_bbox_fc          (TimeDistributed)
mrcnn_mask_deconv      (TimeDistributed)
mrcnn_class_logits     (TimeDistributed)
mrcnn_mask             (TimeDistributed)
```

```
C:\anaconda3\envs\mask_rcnn\lib\site-packages\tensorflow\python\ops\gradients_impl.py:110: UserW
  "Converting sparse IndexedSlices to a dense Tensor of unknown shape. "
```

In [33]:
```
# Save weights
# Typically not needed because callbacks save after every epoch
# Uncomment to save manually
# model_path = os.path.join(MODEL_DIR, "mask_rcnn_fashion.h5")
# model.keras_model.save_weights(model_path)
```

1.7 Detection

In [34]:
```
class InferenceConfig(FashionConfig):
    GPU_COUNT = 1
    IMAGES_PER_GPU = 1

inference_config = InferenceConfig()

# Recreate the model in inference mode
model = modellib.MaskRCNN(mode="inference",
                          config=inference_config,
                          model_dir=MODEL_DIR)

# Get path to saved weights
# Either set a specific path or find last trained weights
# model_path = os.path.join(ROOT_DIR, ".h5 file name here")
model_path = model.find_last()

# Load trained weights
print("Loading weights from ", model_path)
model.load_weights(model_path, by_name=True)
```

```
Loading weights from  C:\Training\DeepLearningGit\virtualFitting\mask_rcnn\logs\fashion20190514T
Re-starting from epoch 1
```

In [35]:
```
# Test on a random image
# image_id = random.choice(dataset_val.image_ids)
# image_ids = dataset_val.image_ids
```

```python
image_ids = [0]
for image_id in image_ids:
    original_image, image_meta, gt_class_id, gt_bbox, gt_mask =\
        modellib.load_image_gt(dataset_val, inference_config,
                               image_id, use_mini_mask=False)

    log("original_image", original_image)
    log("image_meta", image_meta)
    log("gt_class_id", gt_class_id)
    log("gt_bbox", gt_bbox)
    log("gt_mask", gt_mask)

    visualize.display_instances(original_image, gt_bbox, gt_mask, gt_class_id,
                                dataset_train.class_names, figsize=(8, 8))
```

```
original_image           shape: (128, 128, 3)         min:    0.00000  max:  255.00000  int32
image_meta               shape: (26,)                 min:    0.00000  max:  600.00000  float64
gt_class_id              shape: (5,)                  min:    2.00000  max:   11.00000  int32
gt_bbox                  shape: (5, 4)                min:   28.00000  max:  124.00000  int32
gt_mask                  shape: (128, 128, 5)         min:    0.00000  max:    1.00000  bool
```

```
In [36]: results = model.detect([original_image], verbose=1)

         r = results[0]
         visualize.display_instances(original_image, r['rois'], r['masks'], r['class_ids'],
                                     dataset_val.class_names, r['scores'], ax=get_ax())
```

```
Processing 1 images
image                    shape: (128, 128, 3)        min:    0.00000  max:  255.00000  int32
molded_images            shape: (1, 128, 128, 3)     min: -123.70000  max:  151.10000  float64
image_metas              shape: (1, 26)              min:    0.00000  max:  128.00000  int32
anchors                  shape: (1, 4092, 4)         min:   -0.71267  max:    1.20874  float32
```

1.8 Evaluation

In [37]:
```
# Compute VOC-Style mAP @ IoU=0.5
# Running on 10 images. Increase for better accuracy.
image_ids = np.random.choice(dataset_val.image_ids, 10)
APs = []
for image_id in image_ids:
    # Load image and ground truth data
    image, image_meta, gt_class_id, gt_bbox, gt_mask =\
        modellib.load_image_gt(dataset_val, inference_config,
                               image_id, use_mini_mask=False)
    molded_images = np.expand_dims(modellib.mold_image(image, inference_config), 0)
    # Run object detection
```

```
        results = model.detect([image], verbose=0)
        r = results[0]
        # Compute AP
        AP, precisions, recalls, overlaps =\
            utils.compute_ap(gt_bbox, gt_class_id, gt_mask,
                             r["rois"], r["class_ids"], r["scores"], r['masks'])
        APs.append(AP)

    print("mAP: ", np.mean(APs))
```

```
mAP:  0.5800000101327896
```

1.9 Applications once get the mask

Here is one simple example: if we know the pixel region of the skirt and top, we can change the textures or perform any other operations in those regions.

```
In [152]: # skirt is 11
          print(r['masks'].shape)
          print(r['class_ids'])
          skirt = np.where(r['class_ids']==11)
          skirt_idx = skirt[0][0]
          mask_skirt = r['masks'][:,:,skirt_idx]
          mask_top = r['masks'][:,:,np.where(r['class_ids']==9)[0][0]]
```

```
(128, 128, 18)
[ 9 11  4  4  4  4  4  4  4  2  4  4  4  4  4  4  4  4]
```

```
In [160]: import matplotlib.pyplot as plt
          %matplotlib inline
          import pylab
          import numpy as np

          image = original_image
          out = np.array(image, np.int32)
          # mask out skirt
          other = out * (mask_skirt[:,:,None] == 0)
          skirt = out * (mask_skirt[:,:,None]!=0)
          change = (out-90) * (mask_skirt[:,:,None]!=0)
          mix = other + skirt

          plt.figure(1)
          plt.subplot(1,2,1).axis('off')
          plt.imshow(mask_skirt)
          plt.subplot(1,2,2).axis('off')
          plt.imshow(mix)
```

```python
plt.figure(2)
plt.subplot(1,2,1).axis('off')
plt.imshow(skirt)
plt.subplot(1,2,2).axis('off')
plt.imshow(other+change)

out = other + change
other = out * (mask_top[:,:,None] == 0)
top = out * (mask_top[:,:,None]!=0)
change = (out+100) * (mask_top[:,:,None]!=0)
mix = other + top

plt.figure(3)
plt.subplot(1,2,1).axis('off')
plt.imshow(mask_top)
plt.subplot(1,2,2).axis('off')
plt.imshow(mix)

plt.figure(4)
plt.subplot(1,2,1).axis('off')
plt.imshow(top)
plt.subplot(1,2,2).axis('off')
plt.imshow(other+change)
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] f
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] f
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] f
```

Out[160]: <matplotlib.image.AxesImage at 0x1ff54a130b8>