



Object Recognition Practical Sessions

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Date	Theory title	teacher	Practical session)	
02/22	Presentation and CNN basics	Sergio	CNN basics I		
03/01	Backbone architectures	Meysam	CNN basics II		
03/08/2022	Recurrent architectures	Sergio	CNN advanced architectures		
03/15/2022	Object detection and segmentation	Meysam	Object detection I		
03/22/2022	Human pose estimation	Meysam	Object detection II		8 sessions
03/29/2022	Human behaviour	Sergio	Human pose I		3 blocks
04/05/2022	Exams week (31/03 - 06/04)	-	-		
04/12/2022	Easter holidays (11/04 - 18/04)	-27	-		
04/19/2022	Presentation I	Sergio			
04/26/2022	Transformers	Meysam	Human pose II		
05/03/2022	Graph neural networks	Meysam	Object recognition		
05/10/2022	Master seminar (09/05 - 13/05)		-		
05/17/2022	Presentation II	Sergio			
05/24/2022	Exam				

Deliverables

- 1. Contextual data augmentation, deadline 21/03/2022 23:59
- 2. Fashion parsing (segmentation), deadline 25/04/2022 23:59
- 3. Body and clothes depth estimation, deadline 03/06/2022 23:59

Contextual data augmentation

- 1. Select one of the networks studied in the class,
- 2. Train the network on Pascal VOC dataset for multi-label classification,
- 3. During the training corrupt the training images with contextual data augmentation,
 - a. Select random objects and put them on random locations in the training image.
- 4. Study the results. What happens if
 - a. No contextual data augmentation is applied,
 - b. objects overlap vs no overlapping,
 - c. objects appear in random scales and orientation,
 - d. objects are selected such that the whole dataset is balanced, i.e. the number of labels in the whole dataset is equal,









Contextual data augmentation

- The report and code/s must be uploaded to the virtual campus before the deadline.
- The report must be short. Maximum 2 pages with font size 11.
- The report must at least contain the following information:
 - Which network has been used and why,
 - How the network has been trained: hyperparameters, optimizer, loss, training strategy, etc,
 - A thorough discussion of the results.

It can be defined as one of these problems:

- Fashion attributes classification,
- Fashion description by caption,
- Semantic segmentation,
- Hierarchical segmentation and attribute detection

Fashion attributes classification



Fashion description by caption



LOS ANGELES, CA

466 FANS 288 VOTES 62 FAVOURITES

TAGS

CHIC EVERDAY FALL

COLOURS

WHITE-BOOTS

NOVEMBER 10, 2014

GARMENTS

White Cheap Monday Boots Chilli Beans Sunglasses Missguided Romper

Daniel Wellington Watch

COMMENTS

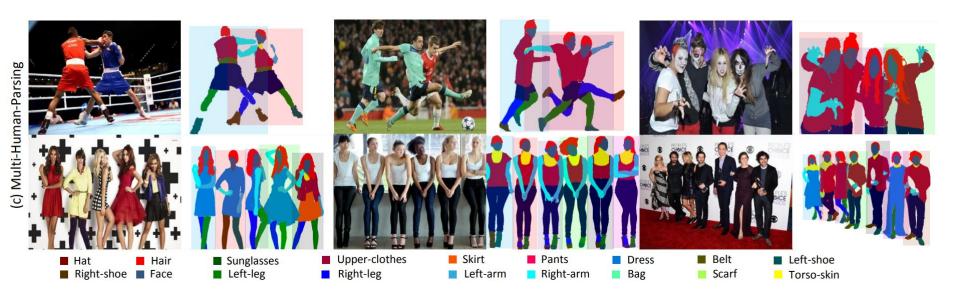
Nice!!

Love the top!

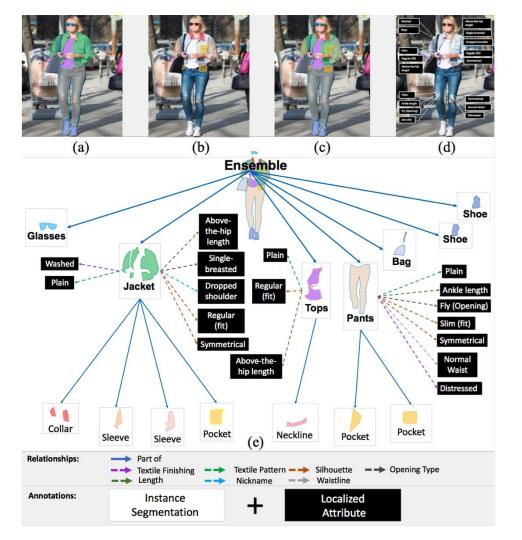
cute

. . .

Fashion parsing Semantic segmentation



Fashion parsing Hierarchical segmentation and attribute detection



What do you need to do in this task?

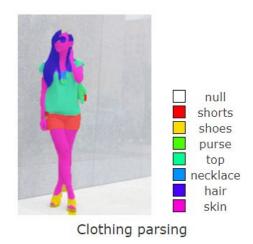
Fashion semantic segmentation

On which dataset?

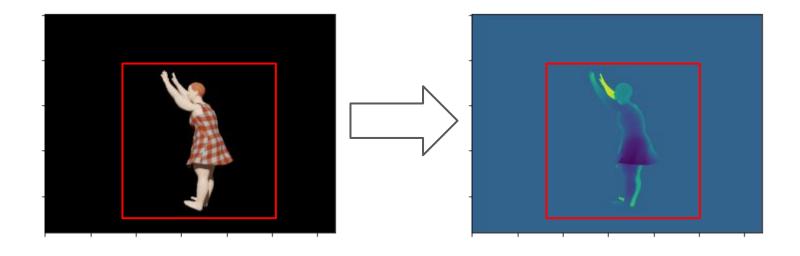
Fashionpedia: https://fashionpedia.github.io/home/

How?

 Select a segmentation algorithm from <u>https://paperswithcode.com/task/semantic-segmentation</u>



- The report and code/s must be uploaded to the virtual campus before the deadline.
- Students must confirm the selected algorithm by email before APR 5th. It is recommended to assure the code is stable and works properly before this date.
- The report must be short. Maximum 3 pages with font size 11.
- The report must at least contain the following information:
 - A short summary of the selected algorithm and justification why it is selected,
 - How the network has been trained: hyperparameters, optimizer, loss, training strategy, etc,
 - A short summary and statistics of the dataset,
 - A thorough discussion of the results.



Dataset:

A subset of the CLOTH3D++ dataset (https://chalearnlap.cvc.uab.cat/dataset/38/description/).
 Randomly select 4K images as the test data. The link to download the data: cloth3d++_subset.zip

Depth rendering:

Based on the code given for PR7.

Preprocessing:

Crop and save the images such that 1) the center of the subject and cropping to be the same,
 2) leave 10px margin between cropping and subject boundaries, and 3) apply square cropping. Note: in some frames the subject may go out of the scene. You can ignore these frames.

Training model:

UNET based on this code: https://keras.io/examples/vision/depth_estimation/

- The report and code/s must be uploaded to the virtual campus before the deadline.
- The report must be short. Maximum 3 pages with font size 11.
- The report must at least contain the following information:
 - How the network has been trained: hyperparameters, optimizer, loss, training strategy, etc,
 - A short summary of the dataset,
 - A thorough discussion of the results including:
 - The impact of image resolution on the results (256 vs 128),
 - The impact of contextual data augmentation, using PASCAL VOC 2007 objects with at most two random objects per image, random rotation and scale, and overlapping allowed.
 - Tuning the loss functions.

Tips and modifications required on the code

In the python notebook of PR7:

```
thresh = max_depth - 1

mask = depth<thresh

dmin = depth.min()

dmean = depth[mask].mean()

dmax = depth[mask].max()

depth[mask] = depth[mask] - dmean

depth[~mask] = 0.0

thresh = max_depth - 1

mask = depth<thresh

dmin = depth.min()

dmean = depth[mask].mean()

dmax = depth[mask].max()

depth[mask] = (depth[mask] - dmin) * 1000 + 1

depth[~mask] = 0.0
```

Tips and modifications required on the code

```
def load(self, image path, depth map, mask):
    """Load input and target image."""
   image_ = cv2.imread(image_path)
   image = cv2.cvtColor(image , cv2.COLOR BGR2RGB)
   image = cv2.resize(image , self.dim)
   image = tf.image.convert image dtype(image , tf.float32)
                                                                             Remember to save the depth images as numpy
   depth_map = np.load(depth_map).squeeze()
                                                                              arrays.
   mask = np.load(mask)
   mask = mask > 0
   max_depth = min(300, np.percentile(depth_map, 99))
   depth map = np.clip(depth map, self.min depth, max depth)
                                                                              Remove the red box
   depth map = np.log(depth map, where=mask)
   depth map = np.ma.masked where(~mask, depth map)
   depth_map = np.clip(depth_map, 0.1, np.log(max_depth))
   depth map = cv2.resize(depth map, self.dim)
   depth map = np.expand dims(depth map, axis=2)
   depth map = tf.image.convert image dtype(depth map, tf.float32)
   return image, depth map
```

Tips and modifications required on the code

```
def call(self, x):
   c1, p1 = self.downscale blocks[0](x)
   c2, p2 = self_downscale blocks[1](p1)
   c3, p3 = self_downscale blocks[2](p2)
   c4, p4 = self_downscale_blocks[3](p3)
   bn = self.bottle neck block(p4)
   u1 = self.upscale_blocks[0](bn, c4)
   u2 = self.upscale blocks[1](u1, c3)
   u3 = self.upscale_blocks[2](u2, c2)
   u4 = self.upscale_blocks[3](u3, c1)
   return self conv layer(u4)
```

Multiply the output with the groundtruth subject mask

Tips and modifications required on the code

For a faster I/O operation, you may

1- Train with multiple workers, e.g. model.fit(....., workers=4), or

2- (optional) Save the whole data in a tfrecord file and iterate over it, an example here:

https://keras.io/examples/keras_recipes/tfrecord/