FACULTY OF SCIENCE
UNIVERSITY OF COPENHAGEN

Bachelor Thesis

2D Articulated Human Pose Estimation

Using Explainable Artificial Intelligence

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Contents

1 Machine Learning Theory

Throughout this section, the theory of machine learning that will be used in this thesis is described and explained.

1.1 Motivation

It can be difficult for humans to recognize certain patterns and trends in data. This becomes more difficult the greater the quantity of the data is, which is becomming more and more common with the rapidly growing topic of *Big Data*. For this reason, computers are often used instead of humans to recognize patterns and trends in the data by analyzing the data, which is what is called *Machine Learning*. In this thesis, we will use machine learning in section **MANGLER REFERENCE** to develop a model to estimate the 2D pose of a single human in an image. Later, in section **MANGLER REFERENCE**, we will use machine learning to improve our understanding of the model.

1.2 Machine Learning Paradigms

Machine learning usually consists of the three following paradigms

- *Supervised learning* where the data consists of features and labels. By analyizing the data the algorithm learns to predict the labels given the features [3].
- *Unsupervised learning* where the data only consists of features. The algorithm then learns properties of the data, without any provided labels [3].
- *Reinforcement learning* where the algorithm learns to perform the action in a given environment that yields the highest reward [1].

Throughout this thesis both supervised and unsupervised learning will be used, both of which will be explain further.

1.2.1 Supervised Machine Learning

1.2.2 Unsupervised Machine Learning

Understanding K-Means Clustering
Understanding Principal Components Analysis

1.3 Evaluation of Machine Learning Models

1.3.1 Evaluation Metrics for Supervised Machine Learning

1.3.2 Evaluation Metrics for Unsupervised Machine Learning

1.4 Neural Networks

1.5 Convolutional Neural Networks

1.6 Stacked Hourglass

1.6.1 The Residual Modules

1.6.2 The Hourglass

1.6.3 The Stacked Hourglass

2 The Dataset

To perform the pose estimation, we need some data to train, validate and test our model. Throughout this section the used data is described and preprocessed.

2.1 The COCO Dataset

Figure 1: Example of image from the COCO dataset with labels

Notice how the image contains multiple people, each with their own keypoints and amount of joints labeled

The data needed for our model has to fit to our problem and has to be annotated, as our model will perform supervised learning. There are multiple datasets that fits these requirements, one of these datasets is the Common Objects in Context (COCO) dataset [4], which we will use. The dataset contains annotations for different purposes, however, for our pose-estimation-task, only the keypoint sannotations of human bodies are needed. An example of such a picture with the keypoints labeled can be seen in Figure 1.

The annotation of each person consists of an array with a length of 51. Each joint corresponds to three sequential elements in the array, where the first index tells the x-location of the joint in the image, the second index tells the y-location of the joint in the image, and the third index is a flag, v, telling the visibility of the joint in the image. v has three outcomes; if $v = 0$, then the joint is not labeled, if $v = 1$, then the joint is labeled but not visible, and if $v = 2$, then the joint is visible and labeled.

The dataset is split into three parts; a part used for training the model, a part used for validating the model and a part used for testing the model. However, the part used for testing the model is unlabel, hence, why it is unusable for our purpose, as our model will be doing supervised learning, where the labels are needed. As both the training dataset and the validation dataset will be used for training and tuning the model, we will need to create our own hold-out dataset for testing to provide an unbiased evaluation of the final model.

The training and validation sets contains a total of about 123.000 various images. As we only need the images that contain humans, we will be discarding the images without any humans, leaving us with a total of about 66.808 images of humans doing various tasks. Each image can contain multiple people, which we need to handle before training our model, as we will be focusing on single-human pose estimation. Besides this, each image also has different resolution and aspect ration, which we also need to handle, as our model requires the images to have a fixed resolution. Lastly, we should also do some handling of the labels before training the model for two reasons

1. There could have been some inaccuracies, when the joints were labeled. This especially applies when $v = 1$, that is, when the joint is labeled but not visible, as there are more inaccuracies or uncertainty when labeling a non-visible joint than a when labeling a visible joint.

2. Each joint could correspond to multiple pixels in the image, hence why it is not correct to only use a single pixel as the location of the joint in the image, which is the current case.

2.2 Data Preprocessing

2.2.1 Creating the test dataset

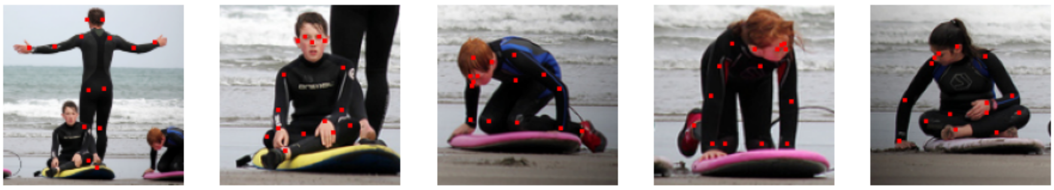
To create the dataset which will be used for testing, we take the training set, since it is the larger of the training set and the validation set, and sample 5.064 images randomly without replacement, to create a test set. This ensures that the test-set and validation-set is of the same size. This new test set will not be used when training the model, nor used when tuning the parameters. Instead, it will only be used to evaluate the final model.

2.2.2 Preprocessing the images

Figure 2: Data distribution

	Amount of images	Percentage
Training set	5.064	x
Validation set	5.064	x
Testing set	0	x
Total	**x**	**x**

Figure 3: The results of processing the image from Figure 1 with the corresponding labels

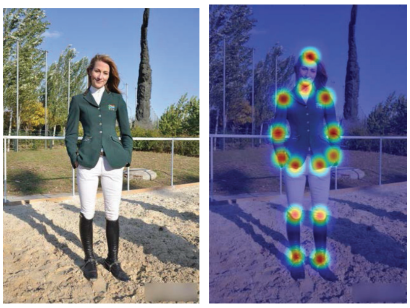


We start the preprocessing of the images, by creating multiple bounding boxes, where each bounding box surrounds a single person, which is done by making use of the boundig box annotations provided by COCO. Then, each bounding box is transformed into a square by making the shorter sides have the same length as the longer sides - this is done to ensure that the aspect ratio of the image is kept, when it is later resized.
An issues can happen, where the bounding box still contains multiple people, which will confuse our model, since it does not know which person it should annotate. To fix this we center the bounding box around the person it should annotate, making the model annotate the person in the center of the input image. This is done by centering the bounding box with respect to the outermost keypoints of the person.
Since each keypoint does not necessarily lie on the edge of the person, the current bounding boxes would result in not all of the pixels of the corresponding person being in the bounding box. For this reason, each bounding box is expanded with 10% in the height and width. If, however, the image cannot contain the expanded bounding box, the bounding box is then expanded as much as possible, while still being a square. If it is the case, that one of the corners of the bounding box lies outside of the image, then the bounding box is moved either up or down, keeping the annotated person centered along the x-axis.
When all of the above is done, the image is then croped to each bounding box, resulting in multiple squared images, each containing an unique person. Each of these squared images are then resized to a 256×256 image, which is then saved as a `png`-file. Doing all of these steps

results in the distribution of images displayed in Figure 2. In Figure 3 the results of processing the image from Figure 1 is shown with the corresponding labels.

2.2.3 Handling the labels

Figure 4: An example of the heatmaps of a single image fused together and put over the original image [2]



Left: The original image. Right: The heatmaps of all the keypoints, fused together to a single image.

For each image of a single person, our model outputs 17 heatmaps, one for each possible joint in the image, which tells the probability of the joint being in each pixel. An example of a heatmaps can be seen in Figure 4.
The heatmap of a single joint is created firstly, by initializing an all-zero 2D array with size 256×256 for each of the 17 heatmaps. Next, in the ith 2D array at position (x_i, y_i), corresponding to the position of the ith joint, a 1 is placed - this 1 now corresponds to where the ith joint is placed in the image according to the keypoint annotation of the image.
Next, a Gaussian filter is used to smear out the image, where the standard deviation depends on the visibility of the joint; if the joint is visible, then the standard deviation is 0.5, whereas the standard deviation is 1 if the joint is not visible, since we are more unsure if the joint has been labeled correctly.
Lastly, as the model outputs 17 64×64 heatmaps, our heatmaps are resizes from a dimension of 256×256 to a dimension of 64×64.
We do all of this for all of the 17 joints for each image, resulting in the keypoints which will be used for developing our model.

References

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