A SSD study for Object Detection in Open Images Dataset v5

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Abstract

This project is a study in the computer vision field, more specifically, the object detection area. The project presents a study in a very disseminated solution called Single Shot Detection, which designed a solution using a deep neural network that intends to classify and find as many bounding boxes it can on an image. The central concept of this approach is the performance of the model, making it possible to be used in many different solutions, delivering a more feasible result. This project also proposes some simple changes using different architectures plugged in the SSD design, such as, MobileNet, ResNet and Xception.

1 Definition

1.1 Project Overview

The main challenge in this project is to create a model that identifies objects in images. This challenge involves two main tasks. The former is to identify object positions in a picture, and the latter is to classify those objects correctly.

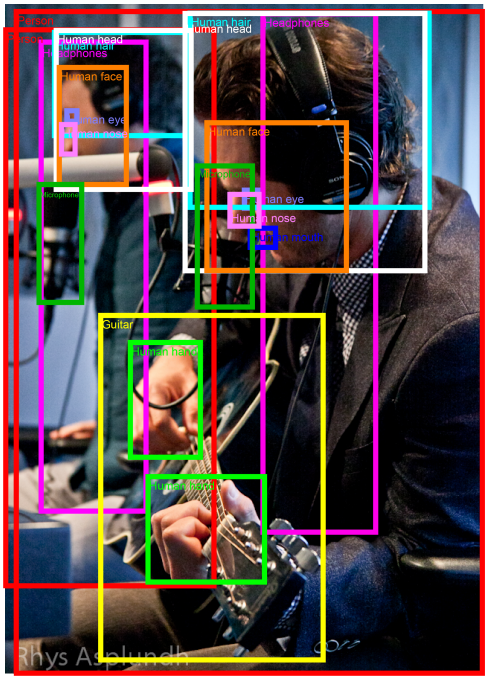


Figure 1: Mark Paul Gosselaar plays the guitar by Rhys A. [1]

The Kaggle competition created by Google [2] using a recently announced dataset is called Open Images 2019 - Object Detection[1], and it motivates this work. This project implements a strategy, using Deep Learning to solve the problem, which is grounded in some researches that this paper is going to present.

This project is a result of 3 months of research and hard work made in the area of computer vision and deep learning architecture. More than to solve the Kaggle problem, the main objective was learning about computer vision and more about Deep Learning.

1.2 Problem Statement

I want to start discussing the main difference between the proposal of the project and the final project delivered. When I wrote the proposal, I did not have the full context of the area, besides that, I proposed a possible and relevant architecture. The idea was to create a simple pipeline with two models concatenated, and each model would optimize one technique (classification and localization of bounding boxes). However, during more studying, it was clear that this architecture was burdensome and inefficient, which is not a problem for some circumstances, but this is not the case. Given that I have limited resources and time, and the dataset has around 1.7 million images, my proposal to use more than one models concatenated, knowing that I had to running the training process a few times, sounds very overwhelming, so I had to change my initial design.

We could define the object detection research area in two big sets about how to predict objects in an image. The first goes to path of pass the image for the model more than once to return one prediction. The computer vision area believed for much time that this was the only way. In the very beginning, there were very complex architectures using SVMs (Support Vector Machines) and regressors [3][4] to draw bounding boxes. Nowadays, there are more robust architectures using deep learning like R-CNNs [5], Fast R-CNNs [6] and Faster R-CNNs[7]. The second one goes to a performance path and limits the model to pass the image just once to predict both, the bounding box localization and the classification, at the same time. Examples of this approach are YOLO (You Only Look Once)[8] and SSD (Single Shot Detection) [9].

This project uses SSD structure, which will

be detailed discussed in the next sections. At the very end, I am going to present the changes that were made in the architecture to use new networks (like Resnet and Xception) to extract more accurate data from the images.

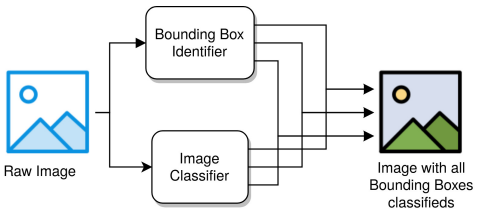


Figure 2: High level Model based on SSD idea

1.3 Metrics

The metric proposed by Google in the competition is the mean Average Precision (mAP) [10], a very didactic explanation about the metric could be found in here [11] and [12].

The mAP metric could be defined as

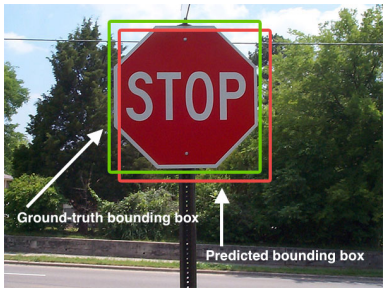
$$mAP = \frac{\sum_{c=1}^{C} AP_c}{C}$$

where C value is the number of all categories (classes).

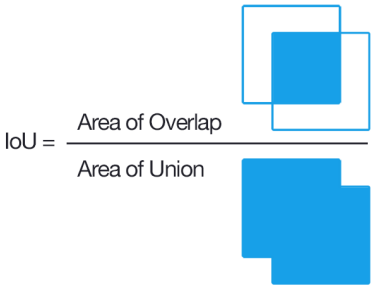
To understand AP_c, it must comprehend first what is IoU. IoU is the Intersection over Union. It is equal to the ratio of the $Area\ of\ Overlap$ and the $Area\ of\ Union$, considering the Predict bounding box (created by the model) and the Ground-truth bounding box (previously annotated).

Here, it is going to define:

$$TruePositive \doteq IoU > 0.5$$
$$FalsePositive \doteq IoU < 0.5$$
$$or\ DuplicatedPredictBoundingBox$$
$$FalseNegative \doteq IoU > 0.5$$
$$and\ WrongClassification$$



(a) Difference between a Predict bounding box with a Ground-truth bouding box [13]



(b) IoU visual represented [13]

With the concept of True Positive (TP), True Negatives (TN), and False Positives (FN) defined, it is possible to create a Precision-Recall Curve, which defines a function that gives a precision based on the recall.

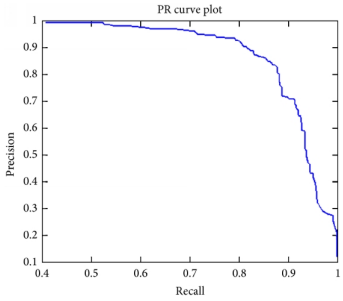


Figure 3: Precision-Recall curve [11]

So by definition, AP_c (Average Precision of some category c), is defined as an Area Under the Curve (AUC) of the Precision-Recall curve.

$$AP_c = \int_0^1 p(r)dr$$

where $p(r)$ is the precision defined in function of recall.

It is essential to retain that in this project it is going to be used AP_{50} (which uses a threshold of 0.5 in IoU to define TP), but other average precision metrics could be used, like, AP_{75} (with IoU threshold of 0.75) or AP_{90} (with IoU threshold of 0.90).

2 Analysis

2.1 Data Exploration

For the problem itself, there are two datasets (Image-level and bounding boxes), plus two files that describe each class used in the labeling process, and the relation among them.

About the classes, there are 600 unique classes, and they are represented as a graph. So they have inheritances. All classes start from a class that I called "Entity" (it has no name, in fact), and all other classes derive from it or from the classes that derive from it on some level. In the appendix A, I expose all connections at each level (the deepest level is five).

The Train, Cross-Validation and Test set are already given by Google. This project intends to use the same distribution given. However, during the analysis it was possible to notice that there are some classes presented in Train set that are not presented in Test and Cross-Validation sets. The following table shows how much unique classes are present in each data set.

Besides that, the distribution of each class is not uniform. 30 classes are responsible for 80% of bounding boxes labels, and 300 classes are responsible for less than 1% of bounding boxes. Of course, this affects how the final model performs in a random image.

Table 1: Unique classes in each Dataset and amount of Bounding Boxes

	Unique Classes	Count of Boubing Boxes
Train	599	14,609,671
Cross-Validation	570	303,980
Test	583	937,327

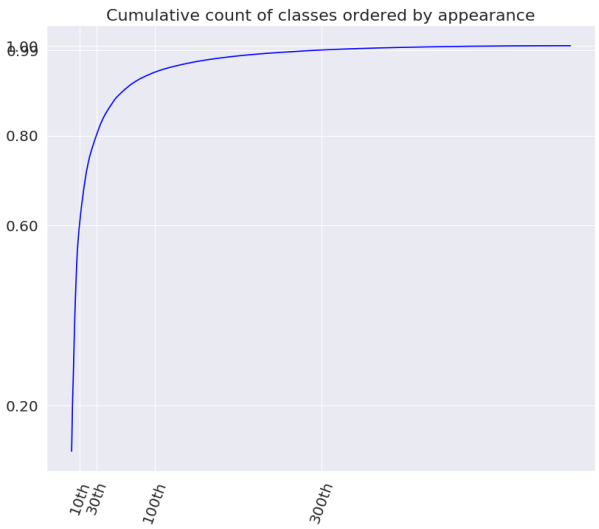


Figure 4: Cumulative count of classes order by appearance

The two datasets, image-level label and bounding boxes, both are divided in three (train, test, cross-validation). Google explains in the blog [14] how they create the Image-level dataset and how, with it, they create the bounding boxes dataset. The label-image set was created, and a little part of it (around 1.7 million images) were chosen to have more granular work. The labels previously created were relabeled and transformed in bounding boxes that identify, not only what is the object, but the position of those objects. This work uses only the bounding boxes dataset.

About Bounding Box Dataset, some points must be concerned. The labels in the original data set are encoded (probably to avoid mis-

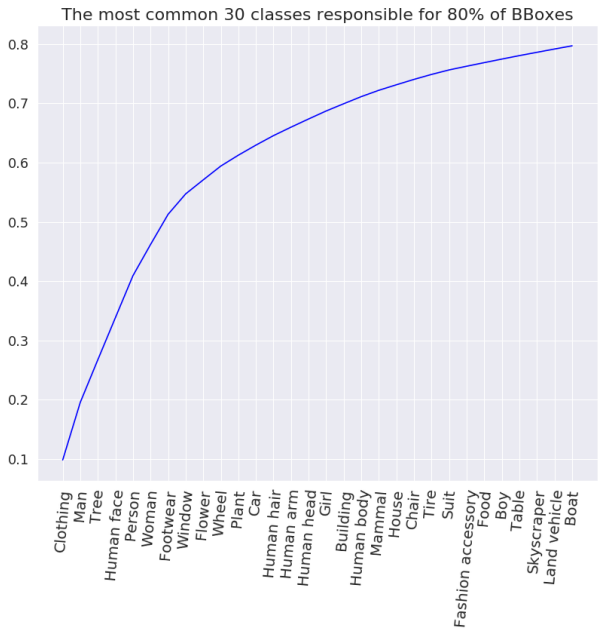


Figure 5: The thirty classes with most appearance

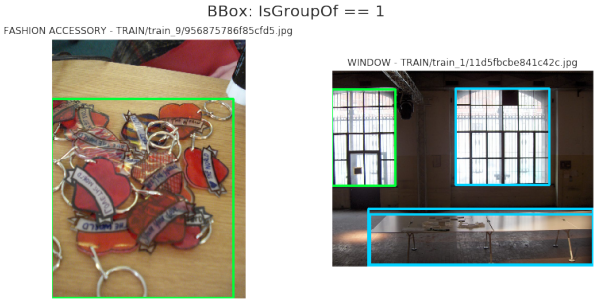


Figure 6: Bounding Box Green represents IsGroupOf True

match and homonyms). In the analysis process they were converted to semantic labels (using a support dataset provided by Google). However, in modeling, it is going to use the encoded version.

Beyond the label and the bounding boxes position, the dataset also has some flags (IsOccluded, IsTruncated, IsGroupOf, IsDepiction, IsInside). These flags are very helpful to debug the decisions that a model does.

"IsOccluded" points a Bounding Box that has a type of obstruction in it, making it more difficult to be understandable.

"IsTruncated" points a Bounding Box that ends or starts in some edges of the image.

"IsGroupOf" means that the label given is about a group of things, and the bounding box is around all of those things.

"IsDepiction" represents bounding boxes that do not label the object itself, but a representation of the object. Draws, representation, costumes, are some examples.

"IsInside" is about the Bounding Boxes labeled inside rooms or buildings, with artificial light.

As stated, the distributions of classes are not uniform, and this is a big concern about how good the model will be. There is a more accurate and complete analysis made by me, with a study of the correlations between flags and many other topics in all datasets. It can be checked in here [15] on my github.

2.2 Techniques

This project is about how to design and to create deep neural networks. More than that, it is going to deep dive into how Convolutional Neural Networks (CNNs) work and how to extract more value of them.

Neural networks could have complex architectures made over some of straightforward ideas. First of all, there is the function; the loss function is the measure of the error of some neural network, in this project it designs a tailor-made loss function (proposed by SSD paper), which I am going to discuss more further.

In the training process, we have to define a batch size. Batch size is a number which specifies how many examples we are going to use in the feed-forward process (the predict itself), and how many targets we are going to compare with the results. With the predictions in hand, we compare with targets previously la-

Table 2: Amount of each flag in Bounding Box dataset

	IsOccluded	IsTruncated	IsGroupOf	IsDepiction	IsInside
Train	9,629,150	3,643,883	852,641	774,485	13,718
Cross-Validation	134,497	69,698	26,360	14,181	2,200
Test	417,398	211,732	81,037	44,038	6,964

belled using the loss function. Then, in the process called backpropagation, it is used an optimizer to update the weights of the neural network.

To converge neural networks, for most of the times, we have to pass the same train set in the model, doing the feed-forward and backpropagation. The Epoch number defines how many times we are doing this. Besides running many epochs, sometimes, there is not enough data or data with quality to train a Neural Network. For that reason, we also have to do a process called data augmentation, which consists of augmenting the dataset with more useful examples created with the original ones.

Convolutional Neural Networks (CNNs)[16] are neural networks with convolutional layers. These are layers that identify patterns in the images. In the first levels, they find the most common patterns, as edges, and in the deep levels, they identify the most specific patterns, as the form of a cat. These patterns are identified creating many filters and applying filters over filters to classify more complex patterns, we call this filters, kernels. Besides that, we condense the filters information applied in convolutional layers with pooling layers, which have the purpose of considering only the core information for the deeper layers. [17] AlexNet [18] was the first famous CNN architecture to classify images. Many others come later derived from it and newer ones, like VGG [19], ResNET [20], Inception [21] or Xception [22].

2.3 Benchmark

This project was inspired by the Kaggle competition launched by Google, given that, It is going to use as a benchmark the leaderboard itself, [23] and the goal is to achieve the best score that I can do, with the resources and the time that I have available.

The Score evaluated is the same discussed in the metric topic of the first part of this project.

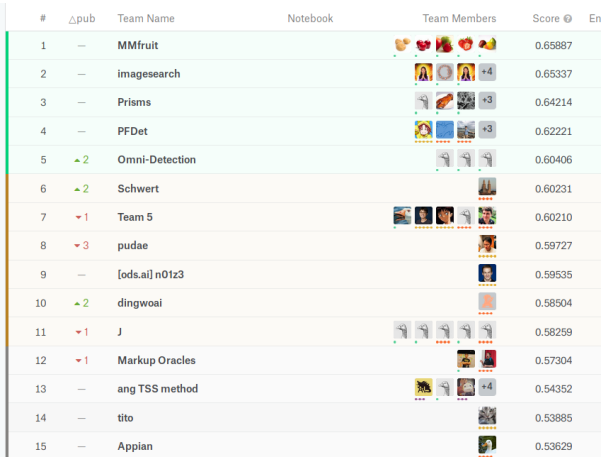


Figure 7: Leaderboard Image Dection Kaggle Competition - 2019

3 Methodology

3.1 Data Preprocessing

There are three processes made in the data of this project. The first one is a simple One Hot Encode in the categorical feature that defines the class of the bounding box. One Hot Encode is a technique that maps a categorical variable to many boolean features, as many of the numbers of the categories. Each class is recorded as True in the category column created.

The second one is data augmentation. Because this dataset is hugely unbalanced, this project uses this approach to reduce the problem. It is defined five levels of data augmentations, as described below, and it is applied only one of that in each image of the dataset, based on how frequent is a class - more frequent is the class, lesser is the level. Each level creates newly enhanced images.

1st level - Image flip horizontally 2nd level - 1st level + randomly change the saturation 3rd level - 2nd level + randomly change the contrast + flip horizontally with randomly change of saturation 4th level - 3rd level + nine slight zooms in the image 5th level - 4th level + nine large zooms in the image

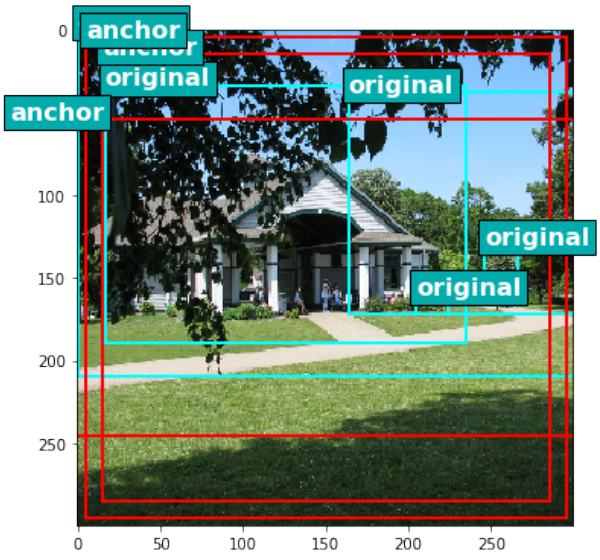


Figure 8: Original Image with anchors (red) and original bboxes (blue)

The SSD paper proposes the image flips and the zooms to augment the data. However, the saturation and contrast changes was an approach inspired by much reading on data augmentation process. By transforming the image with the contrast and saturation, the hypothesis was that the neural network would have different conditions to identify the objects.

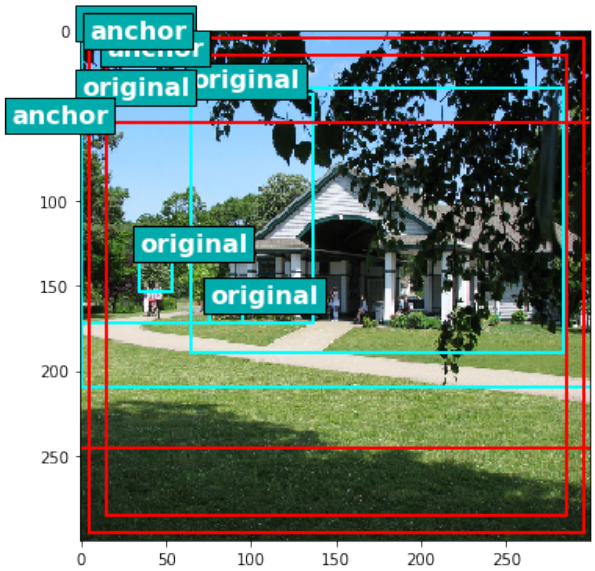


Figure 9: Flip Image (data augmentation) with anchors (red) and original bboxes (blue)

The third and last process is data selection to train. The initial train dataset contains more than 1.7 million images, with more than 14 million bounding boxes. After data augmentation, this training dataset reaches 2.7 million images with more than 23 millions bounding boxes, which is more balanced, but it is enormous. This project created a subset of train dataset trying to preserve the proportions of the more balanced data, but making it possible to train each epoch in the available time. The data selection is described next. The train augmented dataset was divided into batches (around 50 images each), and by analysing them, the top 650 ones that contained the most balanced dataset were chosen.

All these processes comprehend many steps, and they are available in the GitHub [24].

3.2 Implementation

SSD is a technique which incorporates in the VGG16 a capability to find bounding boxes. To do so, it uses the concept of the convo-

lutional layers. In the paper, they propose to remove the fully connected and final layers (which classifies the image overall) and to plug a new architecture. This architecture takes the last feature maps and applies into them a sequence of convolutions (actually, a set of two convolutions, which I am going to describe as a convolutional set). Each convolutional set reduces the features map and passes it to the next level. Also, it is used to predict an object in each kernel application of the present convolutional layer. Given that each set reduces the feature map, it increases for the next ones the length of the possible bounding box that could be predicted. So in the first levels of this architecture, the network predicts smaller bounding boxes, and in the final levels, the network predicts bigger bounding boxes.

For each kernel application, we also define some forms of bounding boxes, changing the proportion of the width and size based on the kernel. The paper defines these "default bounding boxes" as Anchors.

All kernels are squares, with 3x3 pixels of the feature map, and depending on the level there are 4 or 6 anchors inside this kernel. Two of them are squares with the proportion of height per width equals 1. The other two consider the proportion of height and width equals 2 and 1/2. And for the case of 6 anchors, another 2 proportions of height and width equals 3 and 1/3 are considered. With an input image with 300x300 pixels, the SSD predicts 8732 bounding boxes (one for each Anchor defined).

The shape of the predicted tensor for each of 8732 outputs is a tensor with n class + 4 position metrics of the bounding boxes (which SSD paper states to use the position x of the centre, the position y of the centre, width and height). In this project, the output tensor of this architecture have 3-rank, and its shape is (batch-size, 8732, (600+4)). 600 is the number of the classes in the Open Images dataset.

To evaluate this, the SSD paper proposes

$$L(x,c,l,g) = \frac{1}{N}(L_{conf}(x,c) + \alpha L_{loc}(x,l,g))$$

$$L_{loc}(x,l,g) = \sum_{i\in Pos}^{N}\sum_{m\in\{cx,cy,w,h\}} x_{ij}^{k}\text{smooth}_{\text{L1}}(l_i^m - \hat{g}_j^m)$$

$$\hat{g}_j^{cx} = (g_j^{cx} - d_i^{cx})/d_i^w \qquad \hat{g}_j^{cy} = (g_j^{cy} - d_i^{cy})/d_i^h$$

$$\hat{g}_j^w = \log\left(\frac{g_j^w}{d_i^w}\right) \qquad \hat{g}_j^h = \log\left(\frac{g_j^h}{d_i^h}\right)$$

$$L_{conf}(x,c) = -\sum_{i\in Pos}^{N} x_{ij}^p log(\hat{c}_i^p) - \sum_{i\in Neg} log(\hat{c}_i^0) \quad \text{where} \quad \hat{c}_i^p = \frac{\exp(c_i^p)}{\sum_p \exp(c_i^p)}$$

Figure 10: The tailor-made implementation [25]

a loss function which mixes the classification loss, using log loss function in softmax of each class and a regressor error metric, summing both.

After that, it was designed a custom Keras layer to the network for when it operates in the inference mode. This layer intends to suppress these 8732 bounding boxes using non-max-suppression with IOU threshold of 0.45, keeping the 200th most relevant bounding boxes with the higher evaluated metrics.

The first part of the research I spent designing the SSD as is, using Keras and Tensorflow. The architecture developed is the same proposed in the paper. The full code is available on Github [24].

3.3 Refinement

After implementing the SDD with VGG16 as the paper proposes, I decided to change it and plugged three other networks at the start of the SSD structure, substituting VGG. The other ones are Mobilenet-v2, Resnet50 and Xception.

Each network used weights optimized in the training of the Imagenet dataset as an initial state, and the training process iterated over them, instead of entirely initial randomly weights.

In the Evaluation Section are the metrics collected in the cross-validation dataset for each architecture. Still, I decided to show and

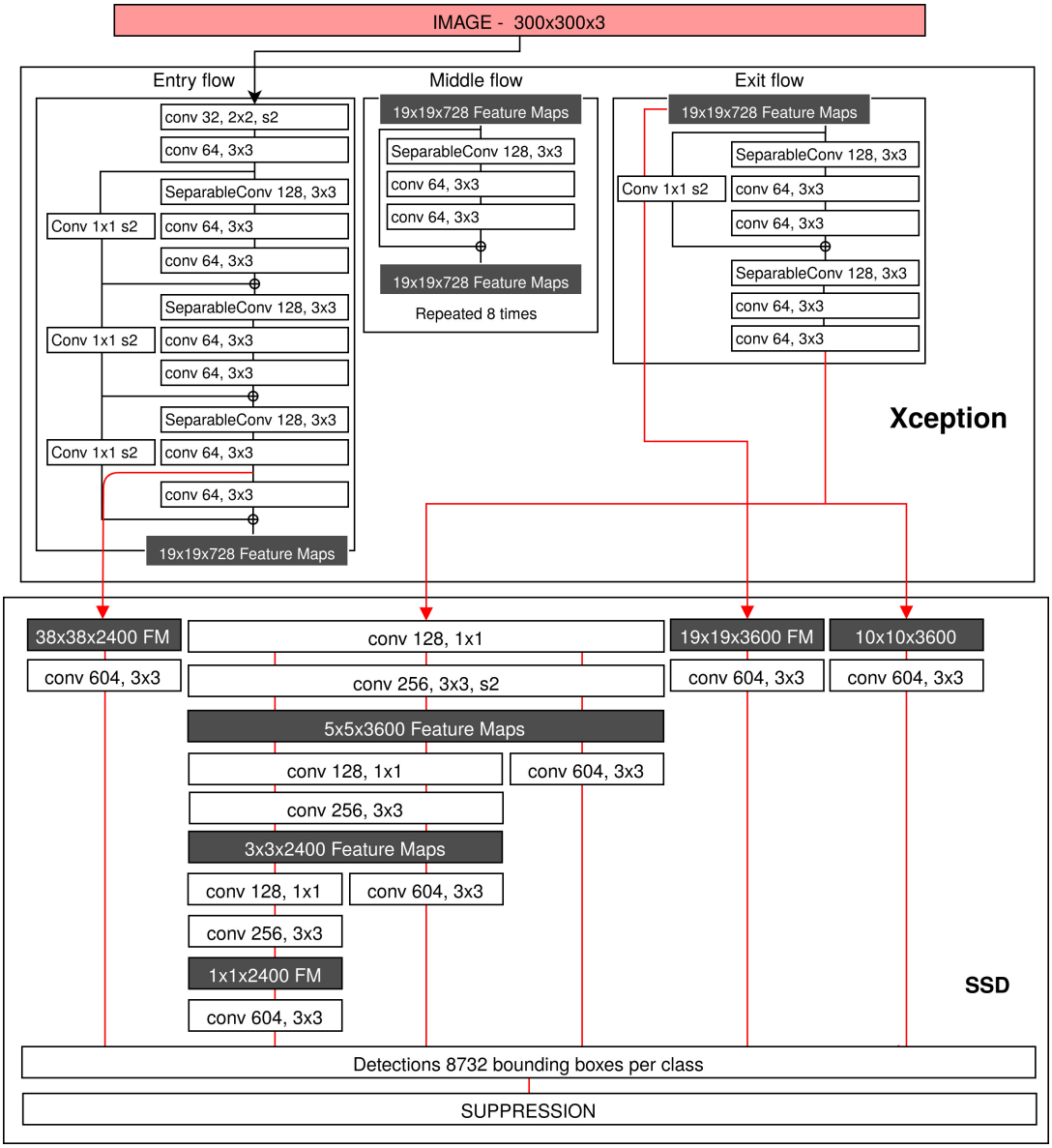


Figure 11: Final Model - SSD + Xception

explain more about the winner, that was the Xception with SSD model.

To understand Xception, we have to understand depthwise separable convolution, which is simply the concept of a channel-wise spatial convolution (which is a convolution not only in the feature map but among the channels) concatenated with a 1x1 convolution called pointwise convolution. These 1x1 convolutions could be understood as a type of pooling over the channels, and they intend to reduce the number of channels. The Xception proposes to revert the order of the depthwise convolution with the 1x1 convolution. The main argument is that this reduces the weights of the model considerably with the same accuracy.

11 illustrates what this project implements, plugging the first architecture proposed in Xception with its depthwise-pointwise.

4 Results

4.1 Model Evaluation and Validation

To the final results, many models were trained. All of them followed the same pattern, they used the partial train dataset created, the 35k images (650 batches of 50 images), and they were evaluated in the cross-validation dataset. The hyper-parameters used to train the models were: the amount of epoch was 30, with a batch size of 24, SGD (Stochastic Gradient Descent) as the optimizer, with momentum of 0.9, decay of 0.0005 and a learning rate scheduler that uses $10^{-}3$ in first 15 epochs, $10^{-}4$ in the epochs 16 to 25, and $10^{-}5$ in the last five epochs.

This work presents the best four models created with this evaluation model. The cross-validation dataset has 570 classes, table 3 are the mAP achieved for each model, I also considered the weighted mAP, which is the weighted mean AP, and the weights are the amount of the bounding boxes of each class. The weighted mAP is calculated because the dataset is very unbalanced [26].

Architectures	Standard	Weighted
VGG16+SSD	0.0012	0.0002
Mobilenet+SSD	0.0036	0.0020
Resnet+SSD	0.0091	0.0308
Xception+SSD	0.0174	0.1199

Table 3: mAP and weighted mAP for each final model

The two best architectures, Resnet50 and Xception, were reloaded with the weights obtained and retrained for more 30 epochs. And the table 5 shows the final results in the cross-validation

Architectures	Standard	Weighted
Resnet+SSD v2	0.0067	0.0353
Xception+SSD v2	0.0229	0.1788

Table 4: mAP and weighted mAP for the final two trained with more 30 epochs

According to the evaluation made on cross-validation the Xception architecture with the SSD is the best model. A final evaluation in test set is made and REF show the final metric.

Architectures	Standard	Weighted
Xception+SSD v2	0.0256	0.0823

Table 5: mAP and weighted mAP for the final model chosen with test dataset

At the end model performs a 8.3% for weighted mAP and 2.56% for standard mAP. The weighted is about 12% the first Kaggle submission and the Standard mAP is about 3.5% of its achieved metric.

4.2 Justification

The final model, considering the weighted mAP tell us that it predicts correctly 8.3% of the bounding boxes presented. The ultimate metric is a reasonable result, even predicting very poor for some classes, which is easy to conclude with the difference between weighted and standard mAP. The main reason for this is the unbalanced dataset.

After all, this reflects the types of pictures that this model is going to evaluate. How many are the images with crabs passing to the model in comparison with images of people?

I believe that filtering the dataset and working with fewer classes and balanced occurrences results in a much better model.

It is not recommended to use a model with this mAP on a critical system, like self-driving cars. But for a mobile application used to identify objects in user photos, it is an acceptable MVP (Minimum Viable Product), even more, if the project reduces the classes scope to recognize fewer categories.

5 Conclusion

5.1 Free-Form Visualization

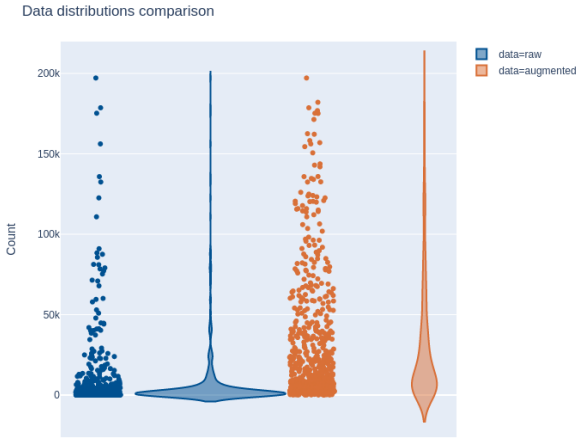


Figure 12: Count amount of distribution for each class

As mentioned, the main challenge of the project is the unbalanced data. In this notebook, I demonstrated the criteria of the data augmentation. A good visualization that emphasis the distribution before and after data augmentation are 15 and 12. The raw data has a more skewed distribution and clearly the data augmentation helped to fixed that as much as it could, the impact in the final model is expressive because of that.

The data augmentation itself is also a great part of the project. All the code to do the transformation are tailor-made and they could be found in github [27]. More examples of data augmentation made for 8 are 13 and 14 applying zoom and control saturation.

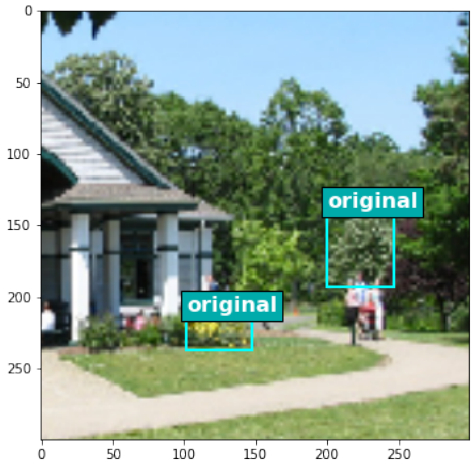


Figure 13: Zoom in data augmentation, transforming also the bounding boxes

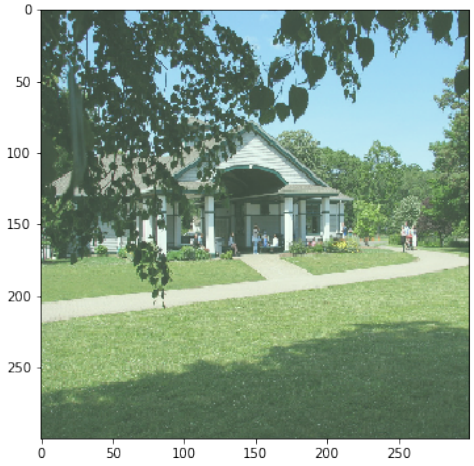


Figure 14: An example of saturation change

5.2 Reflection

In the very end, the final results are far from the top 50's Kaggle submissions, even the weighted mAP in the Xception with SSD.

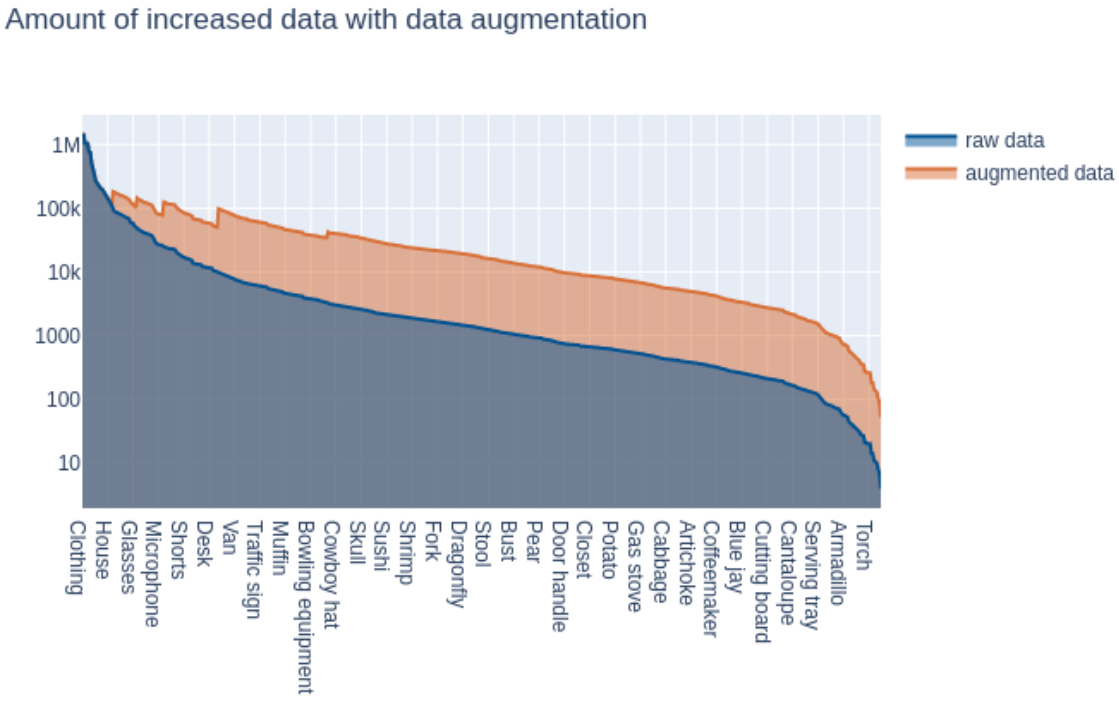


Figure 15: Amount of data before/after data augmentation

The first reason is that the area of computer vision and object detection have a massive amount of knowledge and papers to read, and I am a rookie person is this area yet.

Another point that must be mentioned is the volume of data. The data is massive, and the impact of that is it needs many computer resources. To achieve these results, I created a lot of intermediates preprocess data, but also I filtered and removed a lot of data trying to evaluate and iterate faster. In the very end, I had 2.5 terabytes of hard drive used on my machine.

The final models were trained with a few parts of the dataset, around 35000 images (650 batches with approximately 50 55 images per batch). However, each one trained with 30 epochs spent more than 30 hours in Geforce 1080TI with 11Gb GDDR6. It is possible to estimate that this same train in the CPU would spend more than 120 hours.

More than one model was created. And each model created, each design proposed, each concept tested to fully understand the Networks consumed resources and time. It was three months on this project, and if I could, I would spend three more months improving it (and I probably will). To deliver a result in the due date, I decided on a strategy and followed it until the end.

Even the low score, I am very proud of this work. All code was designed by me and can be found in my Github, and a lot of knowledge from object detection to TensorFlow 2.0 and Keras was learnt.

5.3 Improvement

As previously stated, the dataset provided in the Kaggle competition is very unbalanced. This project used data augmentation technique to reduce this problem. However, there is plenty of room for more improvements in this aspect. The dataset has some flags, discussed in the data exploration section. These flags describe images that have objects with obstruction, images that are related to groups of objects and even images that are depictions, for example, a statue as a depiction of a human body. During the selection of the data to compose the subset for training the networks, these flags can be used to guarantee a more balanced data. The impact of this in the model would be better predictions since the network is trained with more data for the classes that have fewer bounding boxes.

Another improvement would be running the training process for more epochs. In this project, the models trained with a maximum of 60 epochs, because the time is limited. Though, the SSD paper proposes around 200 epochs. This improvement would impact directly on the mAP metric, increasing how much the model learned to predict.

Last, but not least, as discussed before, there are other types of Convolutional Neural Networks. YOLO can be used to attempt to solve the problem. It uses an entirely different architecture but could be a compelling approach to compare YOLO and SSD using this dataset since the papers related to this project compare them using much smaller datasets. The idea behind this change in the architecture would be increasing the object detections in the images as well.

References

[1] Google AI Blog. Introducing the open images dataset. https://ai.googleblog.com/2016/09/introducing-open-images-dataset.html, 2016.

[2] Google Research. Open images 2019 - object detection. https://www.kaggle.com/c/open-images-2019-object-detection/overview, jun 2019.

[3] Andrew Zisserman Andrea Vedaldi, Matthew Blaschko. Learning equivariant structured output svm regressors. Nov 2011. https://ieeexplore.ieee.org/document/6126339.

[4] Christopher J.C. Burges. A tutorial on support vector machines for pattern recognition. Jun 1998. https://link.springer.com/article/10.1023/A:1009715923555.

[5] Ross Girshick Jeff Donahue Trevor Darrell Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. Oct 2014. https://arxiv.org/pdf/1311.2524.pdf.

[6] Ross Girshick. Fast r-cnn. Sep 2015. https://arxiv.org/pdf/1504.08083v2.pdf.

[7] Ross Girshick Shaoqing Ren, Kaiming He and Jian Sun. Faster r-cnn: Towards real-time objectdetection with region proposal networks. Jan 2016. https://arxiv.org/pdf/1506.01497.pdf.

[8] Ross Girshick Ali Farhadi Joseph Redmon, Santosh Divvala. You only look once: Unified, real-time object detection. May 2016. https://arxiv.org/abs/1506.02640.

[9] Dumitru Erhan Christian Szegedy Scott Reed Cheng-Yang Fu Alexander C. Berg Wei Liu, Dragomir Anguelov. Ssd: Single shot multibox det. dec 2016. https://arxiv.org/abs/1512.02325.

[10] wikipedia. Mean average precision. https://en.wikipedia.org/wiki/Evaluation_measures_(information_retrieval)#Mean_average_precision.

[11] Jonathan Hui. map (mean average precision) for object detection. https://medium.com/@jonathan_hui/map-mean-average-precision-for-object-detection-45c121a31173.

[12] Ren Jie Tan. Breaking down mean average precision (map). https://towardsdatascience.com/breaking-down-mean-average-precision-map-ae462f623a52#d439.

[13] Adrian Rosebrock. Intersection over union (iou) for object detection. https://www.pyimagesearch.com/2016/11/07/intersection-over-union-iou-for-object-detection/.

[14] Google Research. Overview of open images v5. https://storage.googleapis.com/openimages/web/factsfigures.html.

[15] Bruno de Almeida Silveira. Eda - object detection - open images v5. http://htmlpreview.github.io/?https://github.com/BAlmeidaS/capstone-udacity-mle/blob/master/project/notebooks/HTML/EDA.html.

[16] Raimi Karim. Illustrated: 10 cnn architectures. https://towardsdatascience.com/illustrated-10-cnn-architectures-95d78ace614d, jul 2019.

[17] Paramartha Dutta Farhana Sultana, A. Sufian. Advancements in image classification using convolutional neural network. May 2019. https://arxiv.org/pdf/1905.03288.pdf.

[18] Geoffrey E. Hinton Alex Krizhevsky, Ilya Sutskever. Imagenet classification with deep convolutionalneural networks. 2012. https://arxiv.org/pdf/1905.03288.pdf.

[19] Andrew Zisserman Karen Simonyan. Very deep convolutional networks ffor large-scale image recognition. Apr 2015. https://arxiv.org/pdf/1409.1556.pdf.

[20] Shaoqing Ren Jian Sun Kaiming He, Xiangyu Zhang. Deep residual learning for image recognition. Dec 2015. https://arxiv.org/abs/1512.03385.

[21] Vincent Vanhoucke Alex Alemi Christian Szegedy, Sergey Ioffe. Inception-v4, inception-resnet and the impact of residual connections on learning. Feb 2016. https://arxiv.org/abs/1602.07261.

[22] François Chollet. Xception: Deep learning with depthwise separable convolutions. Oct 2016. https://arxiv.org/abs/1610.02357.

[23] Leaderboard. Leaderboard - open images 2019 - object detection. https://www.kaggle.com/c/open-images-2019-object-detection/leaderboard.

[24] Bruno de Almeida Silveira. github. http://htmlpreview.github.io/?https://github.com/BAlmeidaS/capstone-udacity-mle/blob/master/project/notebooks/HTML/EDA.html.

[25] Bruno de Almeida Silveira. github. https://github.com/BAlmeidaS/capstone-udacity-mle/blob/master/project/model/loss.py.

[26] Bruno de Almeida Silveira. github. http://htmlpreview.github.io/?https://github.com/BAlmeidaS/capstone-udacity-mle/blob/master/project/notebooks/HTML/model-evaluating.html.

[27] Bruno de Almeida Silveira. github. https://github.com/BAlmeidaS/capstone-udacity-mle/blob/master/project/utils/data_augmentation.py.

A Class hierarchy

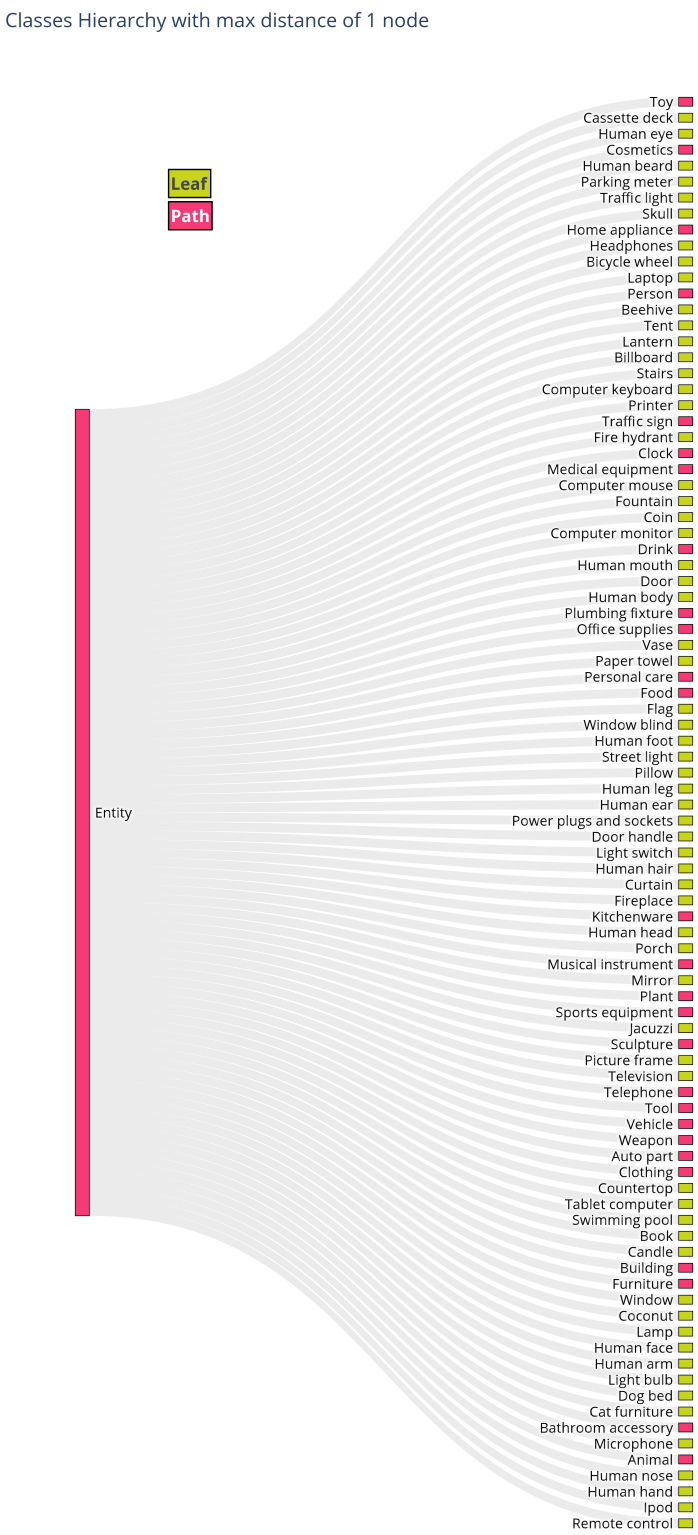


Figure 16: Class Hierarchy - First Level

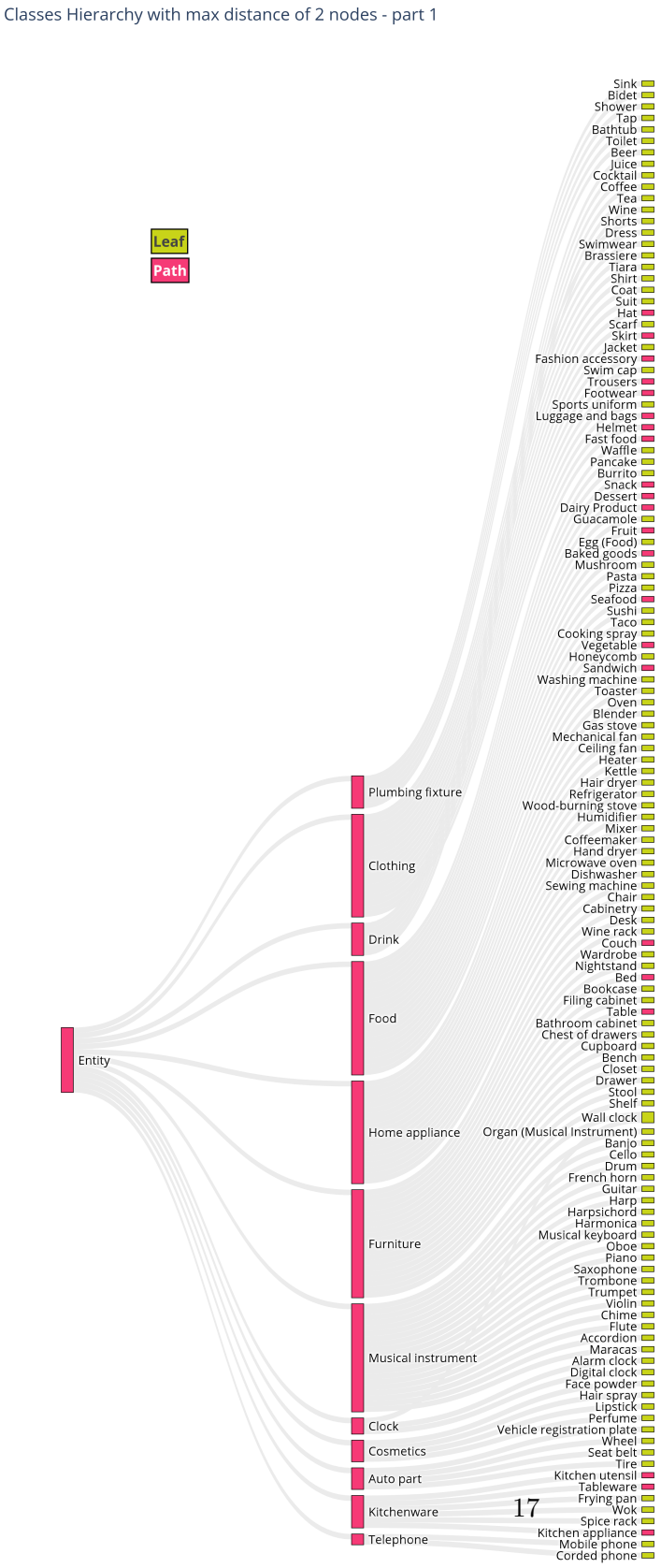


Figure 17: Class Hierarchy - Second Level first part

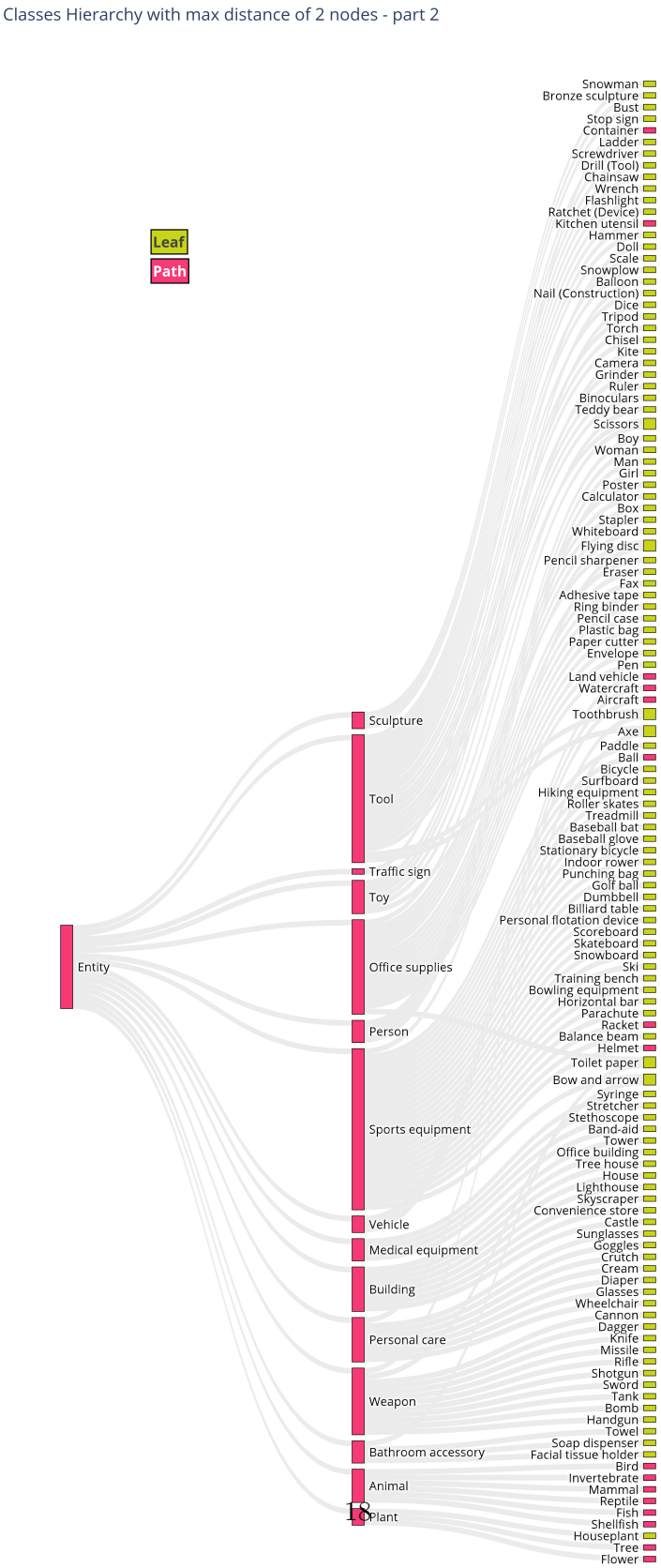


Figure 18: Class Hierarchy - Second Level second part

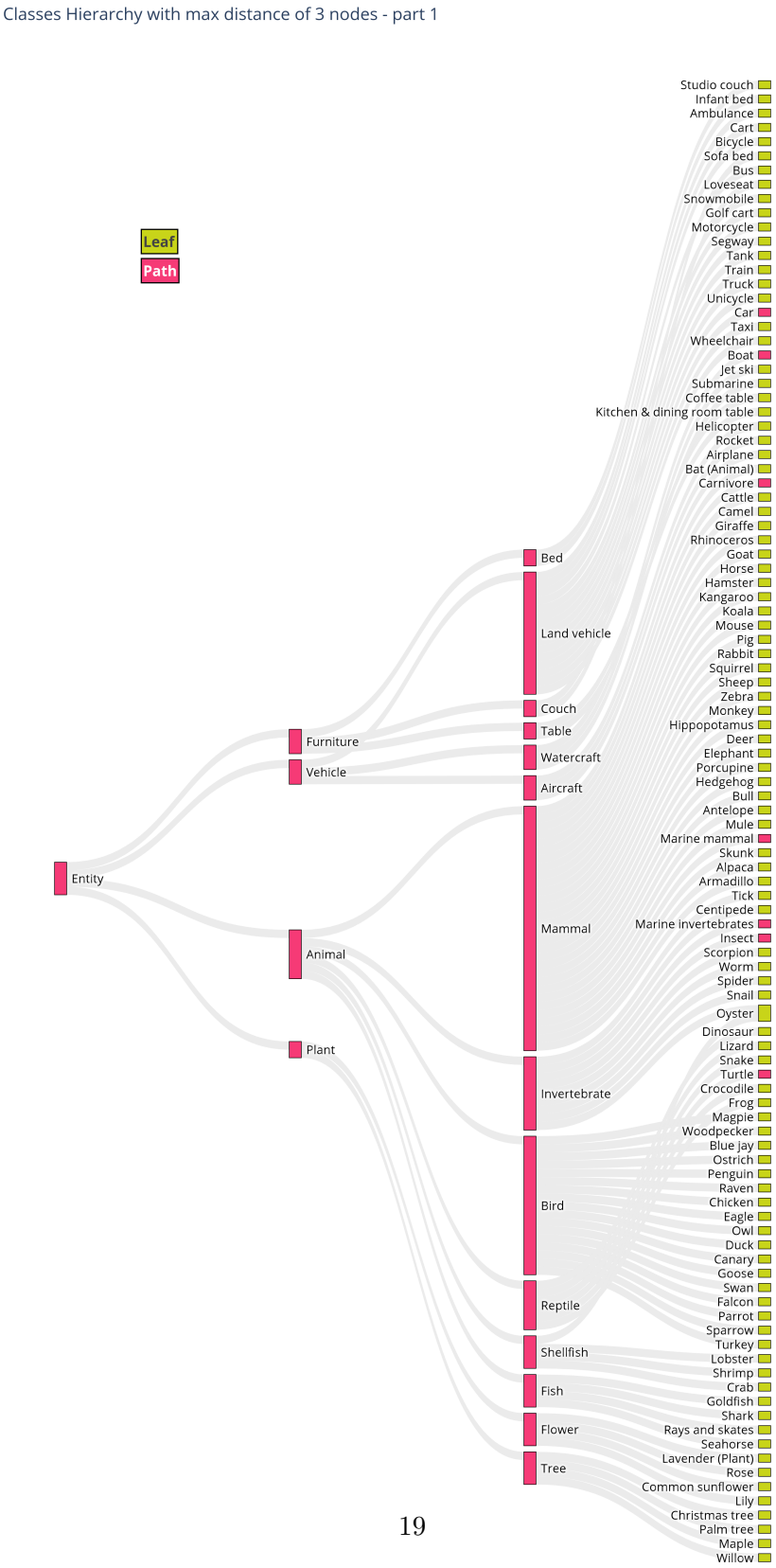


Figure 19: Class Hierarchy - Third Level first part

Classes Hierarchy with max distance of 3 nodes - part 2

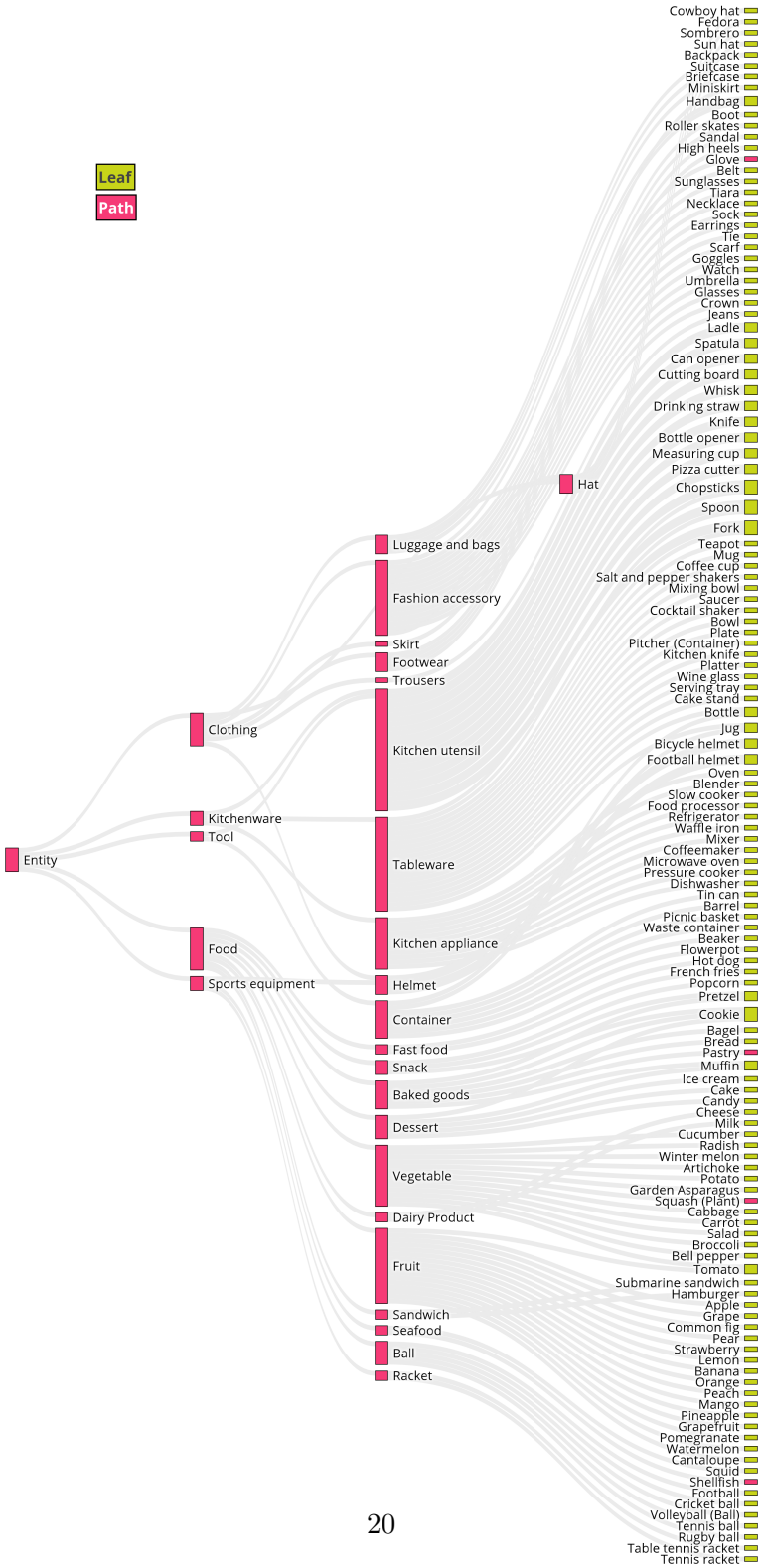


Figure 20: Class Hierarchy - Third Level second part

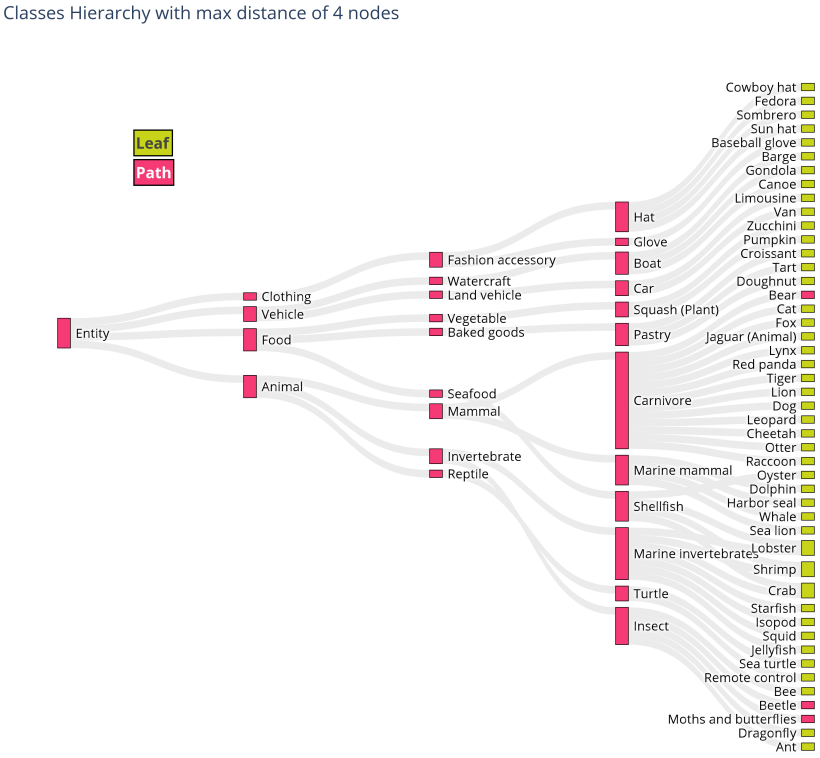


Figure 21: Class Hierarchy - Fourth Level

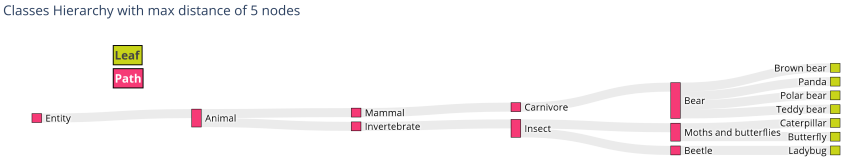


Figure 22: Class Hierarchy - Fifth Level