Classification & Localization of Inpainted Regions

Deep Learning | MSc Artificial Intelligence

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Outline

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Problem Definition

- The goal is to train a model that detects an artificial region in an image.
- An artificial region refers to a part of the image that has been generated by AI.
- Each image may or may not have been edited, which leads us to approach the problem as an object detection task, consisting of Classification and Localization subtasks.
- Most publicly available datasets primarily consist of fully generated images. Therefore, we have generated our own dataset, which includes images that may or may not contain an artificial region.

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Image Inpainting

- Image Inpainting refers to the process of filling in missing or corrupted parts of an image based on the surrounding context.
- GANs can be trained to generate realistic and visually coherent content to fill in missing or damaged areas of an image.
- We perform Image Inpating in the Places365 (a small subset of) dataset in order to create data for our task.
- "Free-Form Image Inpainting with Gated Convolution" proposes a novel model architecture, that demonstrates excellent performance on this task.

Dataset generation

- The model requires two images as inputs. An image with the region to be inpainted covered by a mask and an image that includes just this mask. Then, it outputs the inpainted image.
- We created a python script that creates such boxes. Their position and size are distributed uniformly.
- We mixed inpainted and non-inpainted images in a dataset that sums up to 36500 images.
- Each image corresponds to a 5-dimensional ground truth vector (inpainted? , xmin, ymin, xmax,ymax).

Dataset generation

(a) Original

(b) Mask

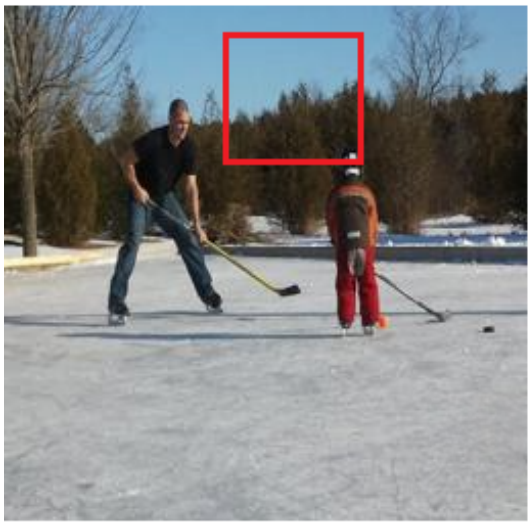
(c) Masked

(d) Inpainted image

Dataset generation

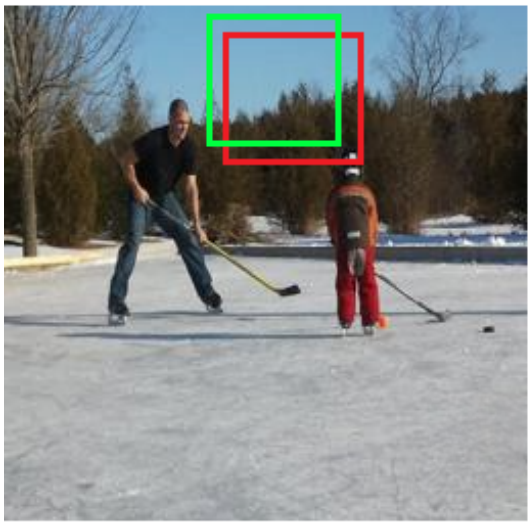
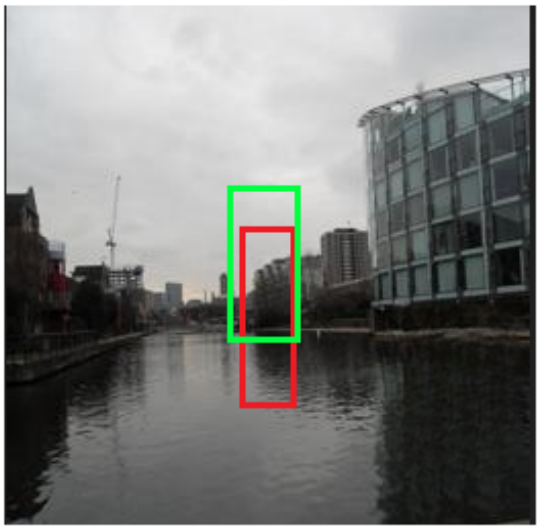



Dataset generation



Dataset generation



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Classification & Localization

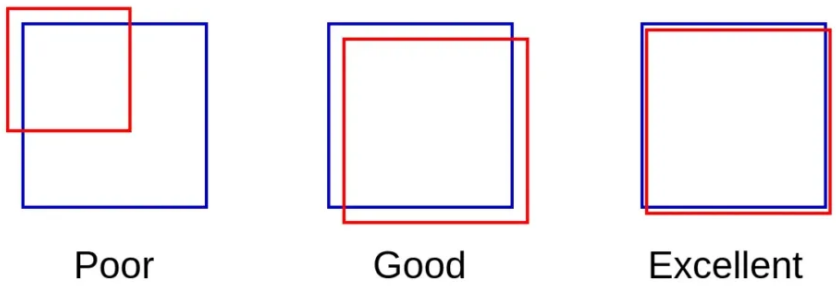
- We used pretrained (on ImageNet) state of the art CNN models.
- We finetuned them after changing their last layer to match our representation, so they consist of one sigmoid and 4 linear units. The fist one will address the binary classification task and the rest will perform the bounding box regression.
- Both tasks have to be solved simultaneously, so we need one common loss function:

$$\text{Total Loss} = \alpha \cdot \text{Classification Loss} + \beta \cdot \text{Localization Loss}$$

How to measure performance?

- For the binary classification part we have some pretty standard options like Precision, Recall, f1 etc.
- Intersection Over Union (IoU) $\in [0, 1]$ is a *scale invariant* metric for the assessment of the bounding box regression.

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



Scale Invariant property

Pair 1:

$$\text{Ground Truth Bbox:} \quad (x_{\text{min}} = 10, y_{\text{min}} = 10, x_{\text{max}} = 80, y_{\text{max}} = 80)$$
$$\text{Prediction Bbox:} \quad (x_{\text{min}} = 15, y_{\text{min}} = 15, x_{\text{max}} = 85, y_{\text{max}} = 85)$$

Pair 2:

$$\text{Ground Truth Bbox:} \quad (x_{\text{min}} = 10, y_{\text{min}} = 10, x_{\text{max}} = 180, y_{\text{max}} = 180)$$
$$\text{Prediction Bbox:} \quad (x_{\text{min}} = 15, y_{\text{min}} = 15, x_{\text{max}} = 200, y_{\text{max}} = 200)$$

IoU(Pair 1) $\approx$ IoU(Pair 2) ≈ 0.75

MSE loss(Pair 1): $= \frac{(10-15)^2+(10-15)^2+(80-85)^2+(80-85)^2}{4} = 25$

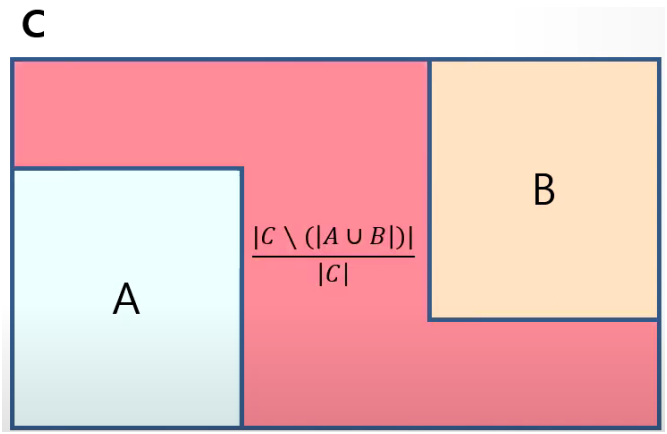
MSE loss(Pair 2): $= \frac{(10-15)^2+(10-15)^2+(200-185)^2+(200-185)^2}{4} = 225$

Loss Functions

- Standard Binary Cross Entropy Loss for classification.
- IoU cannot be used as localization loss directly, because it suffers from zero gradient computations.
- MSE, mean L2/L1 distance and Smooth-L1 are common choices.
- Generalized-IoU is a derivation of IoU that has non-zero gradient everywhere.

$$\text{smooth L1}_\beta(\hat{y}, y) = \begin{cases} 0.5 \cdot (\hat{y} - y)^2 & \text{if } |\hat{y} - y| < \beta \\ |\hat{y} - y| - 0.5 \cdot \beta^2 & \text{otherwise} \end{cases}$$

$$\text{GIoU} = \text{IoU} - \frac{|\text{C}/(A \bigcup B)|}{|C|}$$



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Experiments

Table: Models' Performance on Test set (6500 images)

Model	Precision	Recall	F1	Mean IoU
AlexNet	0.878	0.852	0.8657	0.531
VGG11	0.882	0.897	0.8955	0.545
ResNet18	0.902	0.913	0.908	0.688
ResNet50	**0.928**	**0.99**	**0.958**	**0.713**

Best model

Table: ResNet50 best model hyperparameters

Hyperparameter	**Value**
NUM_EPOCHS	7
BATCH_SIZE	512
LEARNING_RATE	0.001
ALPHA	100
BETA	0.8

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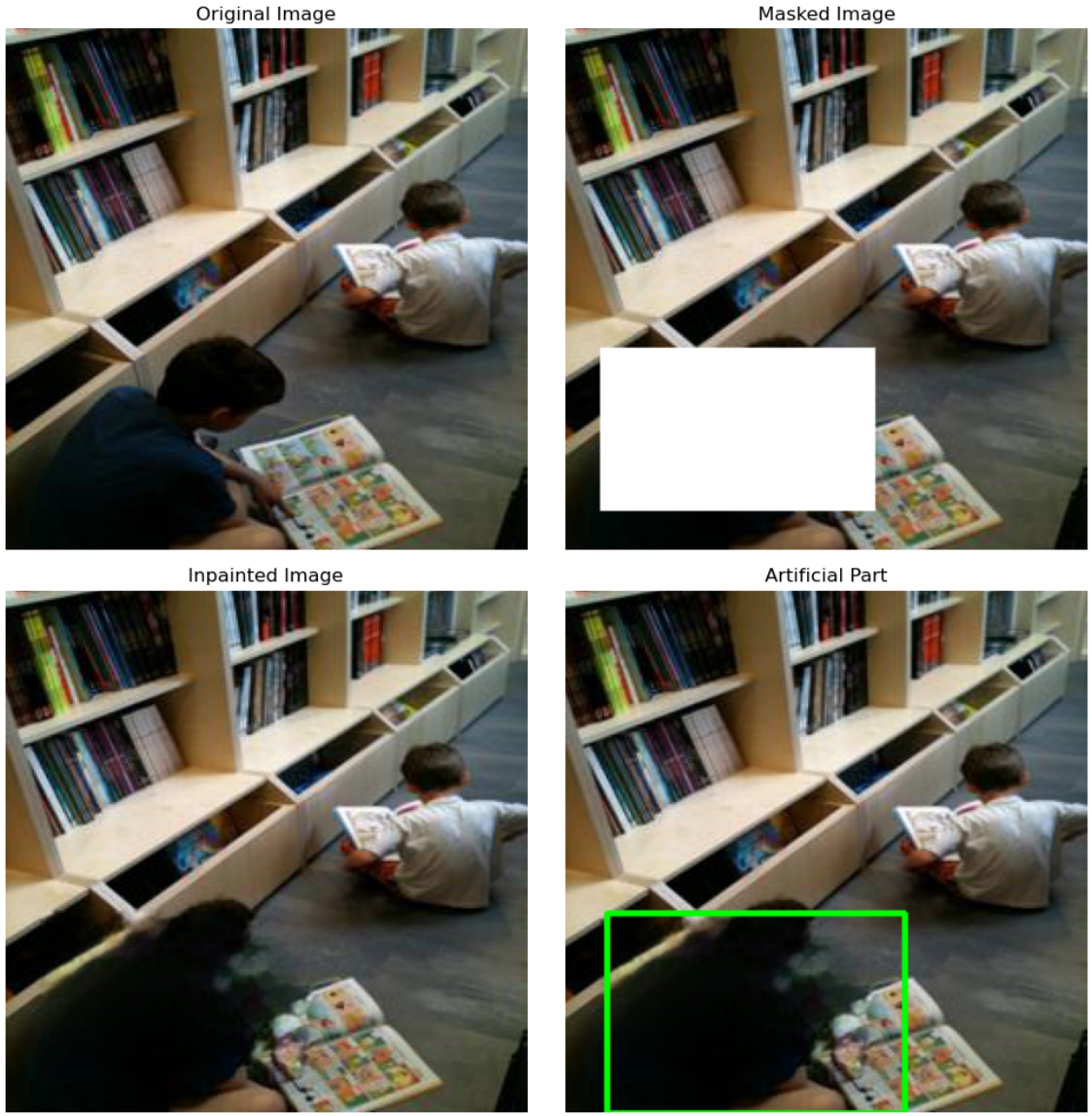
Performance analysis

- The Classification task were very easy for the models, localization proved harder.
- All the models have exhibited high accuracy in cases where the GAN network generated blurry outputs (and discontinuities). Even in instances of minimal blurriness, imperceptible to the human eye, a neural network can effortlessly detect it.
- By artificially generating regions with a fixed rectangular shape, we introduce a strong bias that the models are capable of capturing. Within these rectangles, the pixels generated by the GAN, may exhibit similar value distributions.
- These steep horizontal and vertical transitions may be challenging for the human eye to distinguish, but neural networks find them relatively easy to detect.
- Idea: Transform the problem into Classification & Segmentation.

An easy result



A good result

Thank you!