ExploratoryDataAnalysis-2

March 19, 2025

1 Exploratory Data Analysis

1.1 1. Personal Information

Name: Rosa Keuss

Student ID: 12690589

E-mail address: rosa.keuss@student.uva.nl

Submitted on: 18-03-2025

Github repository: https://github.com/rkeuss/toxic-cloud-segmentation

1.2 2. Data Context

In this study, both video-labeled data and pixel-labeled data is used.

IJmond (Video-Labeled) To include local data, the IJmond (https://github.com/MultiX-Amsterdam/ijmond-camera-monitor/tree/main/dataset/2024-01-22) video dataset (IJmond-VID) is used. IJmond-VID has a limited size as it consists of 879 video clips. These clips originate from three camera angles of the Tata Steel site.

IJmond (Pixel-Labeled) The video frames of the IJmond dataset discussed were manually annotated on pixel-level in RoboFlo2, an online tool facilitating image annotation. Therefore, around 900 segmented video frames are available. Additionally, the IJmond video frames discussed previously were cropped and these cropped images were segmented resulting in another pixel-level dataset of about 900 images. These two datasets will be combined and hereafter they will be called 'IJmond-SEG'.

1.3 3. Data Description

1.3.1 Imports

This cell imports the necessary libraries and modules for our analysis. It includes data manipulation tools such as Pandas and NumPy, visualization libraries like Matplotlib.

[30]:
```
import os
import json
import pandas as pd
import cv2
import glob
```

```
import random
import torch
import torch.nn as nn
import torch.optim as optim
import torch.multiprocessing as mp
from torch.utils.data import DataLoader
import segmentation_models_pytorch as smp
from sklearn.metrics import jaccard_score, f1_score
import albumentations as A
from albumentations.pytorch import ToTensorV2
from collections import Counter
from tqdm import tqdm
from IPython.display import Markdown
from pycocotools.coco import COCO
import coco_dataset
import ssl
```

1.3.2 Load data

IJMOND-VID In this section, notice that the algorithm used to pick one frame from each video does not always pick the good frame. The frame may not contain smoke (but the video contains smoke). Data cleaning is needed to exclude those frames not containing any smoke.

[2]:
```
base_path = "data/dataset/IJMOND_VID/bbox_batch_2"
image_files = []

for root, dirs, files in os.walk(base_path):
    # Check if the current directory is a frame directory (numeric folder name)
    if os.path.basename(root).isdigit():
        for file in files:
            if file.endswith(".png"):
                image_files.append(os.path.join(root, file))
```

[3]:
```
# Create a DataFrame
df = pd.DataFrame(image_files, columns=["image_path"])

# Display first few paths as text
print(df.head(10))  # Print first 10 paths

# Function to display images
def show_images(image_list, num_images=4):
    sample_images = random.sample(image_list, min(num_images, len(image_list)))␣
↪ # Select random images
    fig, axes = plt.subplots(1, len(sample_images), figsize=(15, 5))

    for i, img_path in enumerate(sample_images):
        image = cv2.imread(img_path)
```

```
        image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
        axes[i].imshow(image)
        axes[i].axis("off")
        axes[i].set_title(os.path.basename(img_path))

    plt.show()

# Show a few images from the dataset
show_images(image_files)
```

```
                                          image_path
0  data/dataset/IJMOND_VID/bbox_batch_2/B6goTCxdT...
1  data/dataset/IJMOND_VID/bbox_batch_2/B6goTCxdT...
2  data/dataset/IJMOND_VID/bbox_batch_2/cXROio3tc...
3  data/dataset/IJMOND_VID/bbox_batch_2/cXROio3tc...
4  data/dataset/IJMOND_VID/bbox_batch_2/9srWEqkUa...
5  data/dataset/IJMOND_VID/bbox_batch_2/9srWEqkUa...
6  data/dataset/IJMOND_VID/bbox_batch_2/XufZFo45V...
7  data/dataset/IJMOND_VID/bbox_batch_2/XufZFo45V...
8  data/dataset/IJMOND_VID/bbox_batch_2/wDEDMiQes...
9  data/dataset/IJMOND_VID/bbox_batch_2/wDEDMiQes...
```

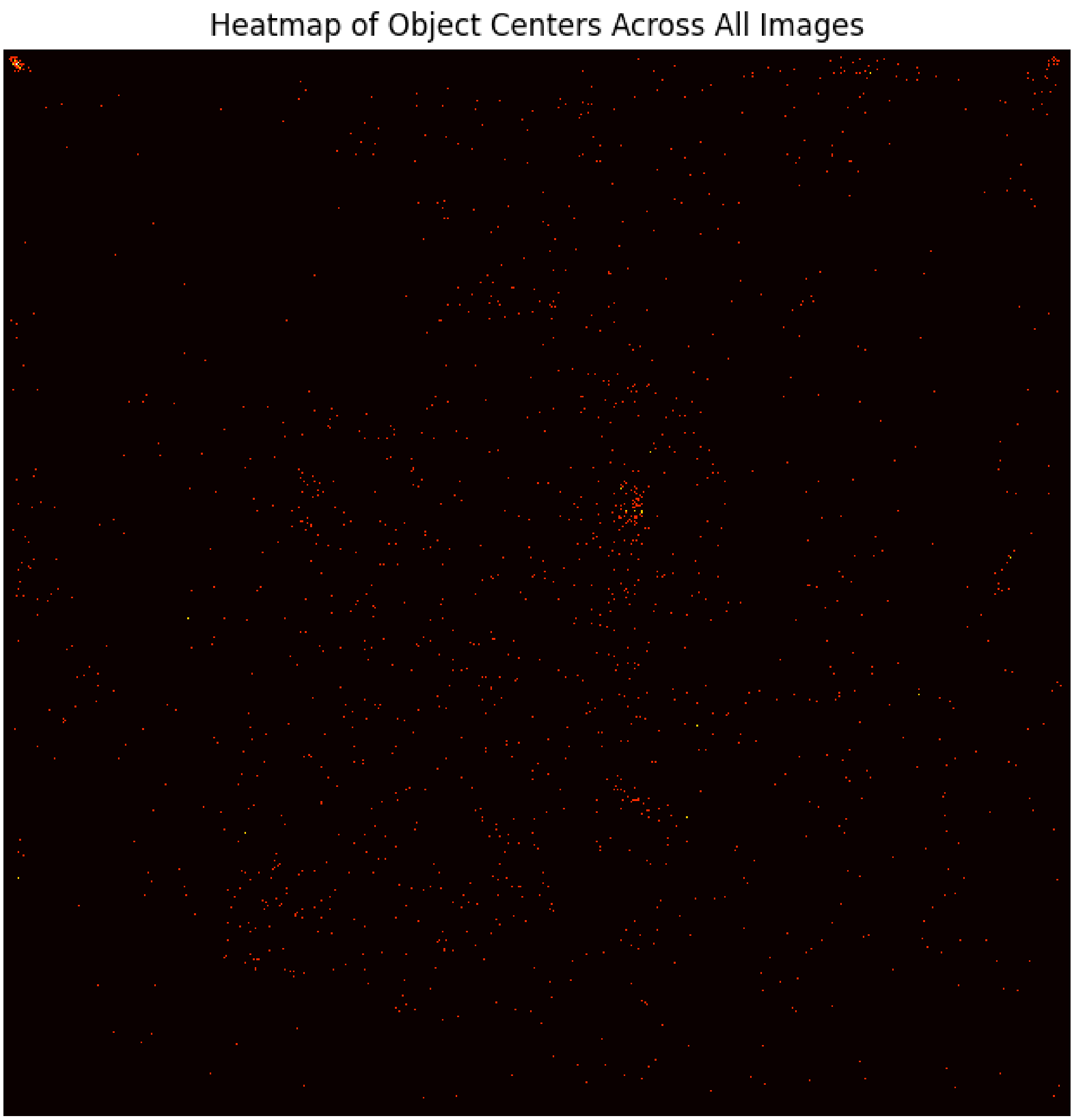
[4]:
```
# Lists to store extracted data
n_ijmond_img_images = len(image_files)
n_ijmond_img_boxes = len(image_files)
n_ijmond_img_categ = 1
ijmond_img_heights = []    # Image heights
ijmond_img_widths = []     # Image widths

for img_path in image_files:
    image = cv2.imread(img_path)
    if image is not None:
        h, w, _ = image.shape
        ijmond_img_heights.append(h)
        ijmond_img_widths.append(w)
    else:
```

```
        ijmond_img_heights.append(None)
        ijmond_img_widths.append(None)
```

Let's look at the spatial distribution of object annotations across images.

[5]:
```
import os
import json
import numpy as np
import matplotlib.pyplot as plt

# Define the base path of the dataset
base_path = "data/dataset/IJMOND_VID/bbox_batch_2"

# Initialize heatmap
heatmap_data = np.zeros((640, 640))

# Traverse dataset to find metadata.json files
for root, dirs, files in os.walk(base_path):
    if "metadata.json" in files:
        metadata_path = os.path.join(root, "metadata.json")

        # Load metadata.json
        with open(metadata_path, "r") as f:
            metadata = json.load(f)

        # Extract bounding box and image size information
        bbox = metadata["boxes"]
        img_width = metadata["image_width"]
        img_height = metadata["image_height"]

        # Compute the center of the bounding box
        center_x = int((bbox["x"] + bbox["w"] / 2) * (640 / img_width))
        center_y = int((bbox["y"] + bbox["h"] / 2) * (640 / img_height))

        # Ensure coordinates are within bounds
        center_x = max(0, min(639, center_x))
        center_y = max(0, min(639, center_y))

        # Update heatmap
        heatmap_data[center_y, center_x] += 1

# Plot the heatmap
plt.figure(figsize=(8, 8))
plt.imshow(np.log1p(heatmap_data), cmap='hot', interpolation='nearest')  # Log␣
 ↪scale for visibility
plt.axis('off')
plt.title('Heatmap of Object Centers Across All Images')
```

```
plt.show()
```



IJMOND-SEG Let's first load the data and look at the general structure.

[6]:
```
json_path = "data/dataset/IJMOND_SEG/test/_annotations.coco.json"
with open(json_path, "r") as f:
    coco_data = json.load(f)

coco = COCO(json_path)
imgIds = coco.getImgIds()
images = coco.loadImgs(imgIds)
```

```
loading annotations into memory…
Done (t=0.01s)
creating index…
index created!
```

[7]:
```
print("IJMOND-SEG Keys: ", coco_data.keys())
print("Dataset Info:", coco_data["info"])
print("Categories:", coco_data["categories"])
print("Total Images:", len(coco_data["images"]))
print("Images Keys: ", coco_data['images'][0].keys())
print("Total Annotations:", len(coco_data["annotations"]))
print("Licences Keys: ", coco_data['licenses'][0].keys())

# Count occurrences of "hoogovens" vs "kooks"
image_filenames = [img["file_name"] for img in coco_data["images"]]
category_counts = Counter(["hoogovens" if "hoogovens" in fname else "kooks" for␣
↪fname in image_filenames])
print(f"Dataset Split: {category_counts}")

n_ijmond_seg_images = len(coco_data['images'])
n_ijmond_seg_boxes = len(coco_data['annotations'])
n_ijmond_seg_categ = len(coco_data['categories'])
ijmond_seg_heights = [x['height'] for x in coco_data['images']]
ijmond_seg_widths = [x['width'] for x in coco_data['images']]
```

```
IJMOND-SEG Keys:  dict_keys(['info', 'licenses', 'categories', 'images',
'annotations'])
Dataset Info: {'year': '2025', 'version': '5', 'description': 'Exported from
roboflow.com', 'contributor': '', 'url': 'https://public.roboflow.com/object-
detection/undefined', 'date_created': '2025-02-13T22:21:42+00:00'}
Categories: [{'id': 0, 'name': 'smoke', 'supercategory': 'none'}, {'id': 1,
'name': 'high-opacity-smoke', 'supercategory': 'smoke'}, {'id': 2, 'name': 'low-
opacity-smoke', 'supercategory': 'smoke'}]
Total Images: 900
Images Keys:  dict_keys(['id', 'license', 'file_name', 'height', 'width',
'date_captured'])
Total Annotations: 1209
Licences Keys:  dict_keys(['id', 'url', 'name'])
Dataset Split: Counter({'kooks': 891, 'hoogovens': 9})
```

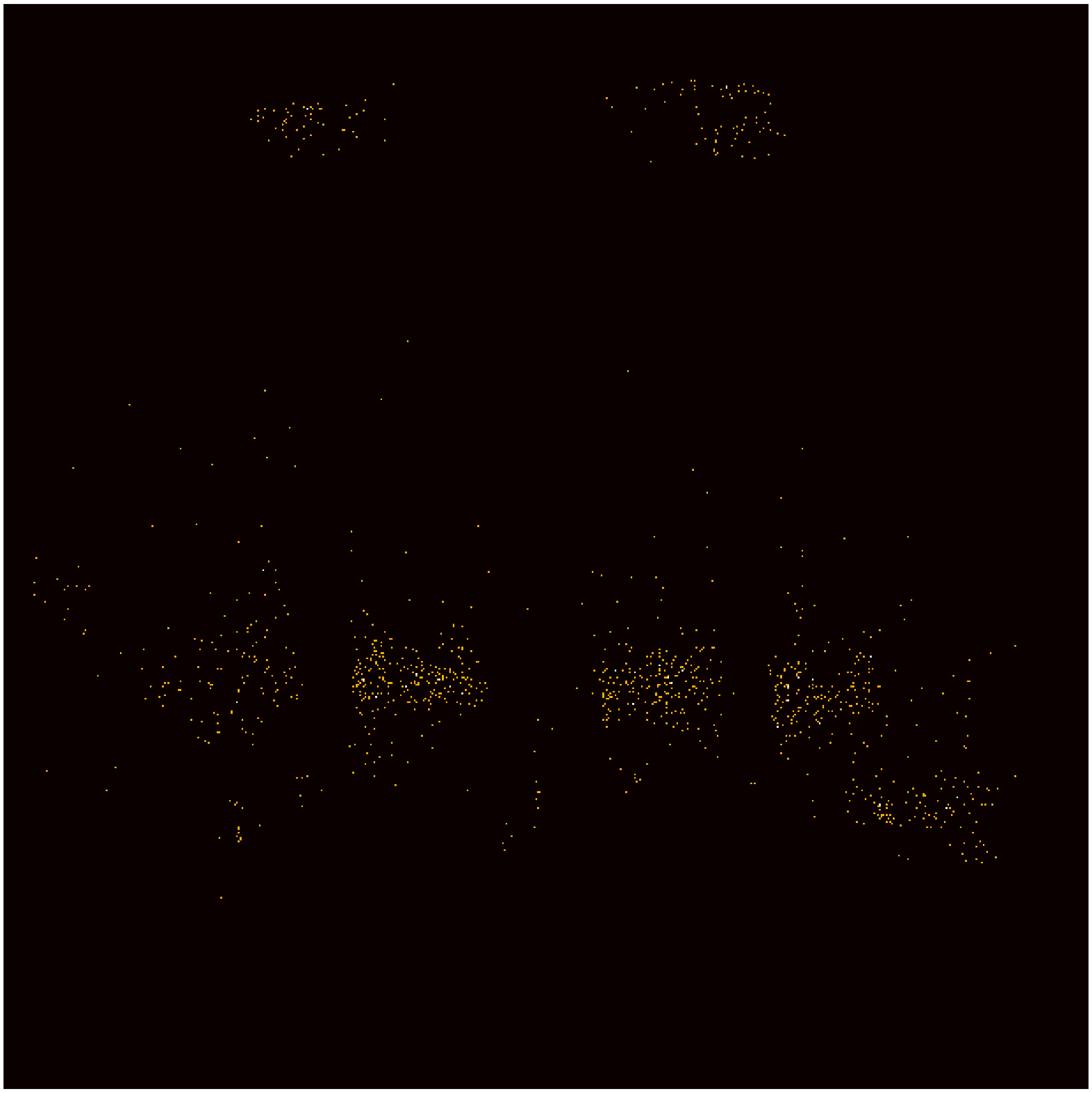
So the pixels are labeled as 'background' or 'smoke'. If a pixel has label 'smoke' a distinction is made between 'high opacity smoke' and 'low-opacity-smoke'. Furthermore, the total number of annotations is 1209.

Now, we will look at the spatial distribution of object annotations across images.

[8]:
```
heatmap_data = np.zeros((640, 640))
for img_id in imgIds:
    img = coco.loadImgs(img_id)[0]
```

```
    annIds = coco.getAnnIds(imgIds=img['id'])
    anns = coco.loadAnns(annIds)
    for ann in anns:
        # Normalize x and y to the heatmap resolution
        bbox = ann['bbox']
        center_x = int((bbox[0] + bbox[2] / 2) * (640 / img['width']))
        center_y = int((bbox[1] + bbox[3] / 2) * (640 / img['height']))
        heatmap_data[center_y, center_x] += 1

plt.figure(figsize=(8, 8))
plt.imshow(np.log1p(heatmap_data), cmap='hot', interpolation='nearest') # Use␣
 ↪log scale for better visibility
plt.axis('off')
plt.title('Heatmap of Object Centers Across All Images')
plt.show()
```

Heatmap of Object Centers Across All Images



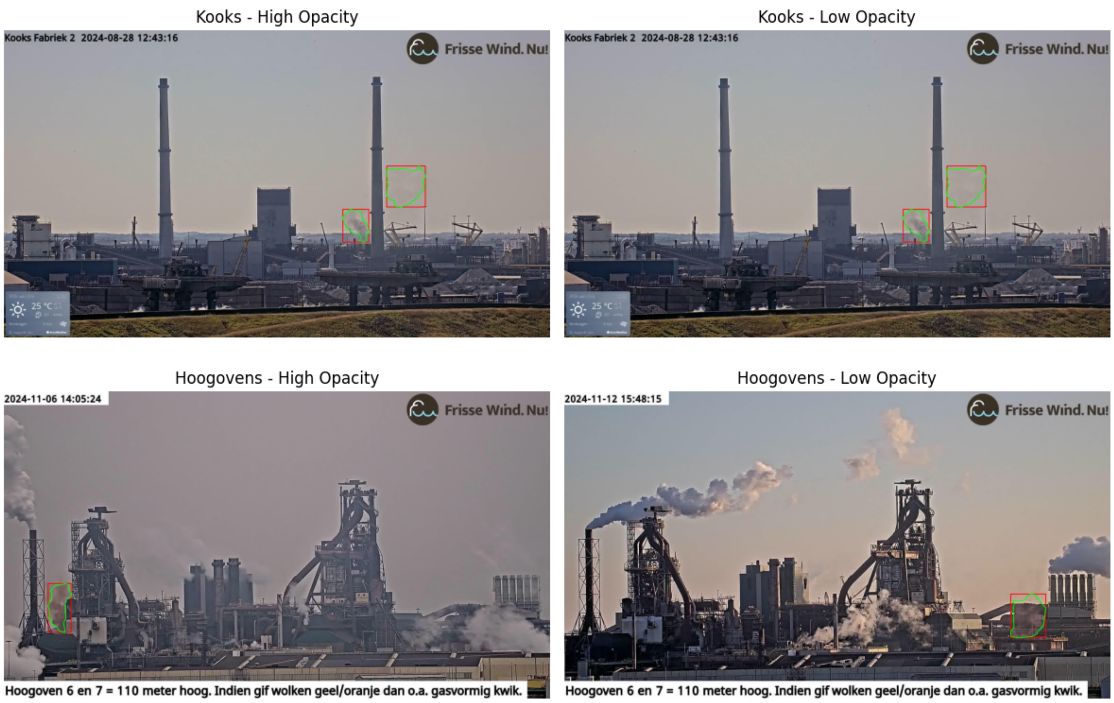
There are roughly 6 'heat islands' visable. This means most centers of smoke are located around one of those. This is ofcourse logical as the steal factories are not moving objects.

Next, example visualizations from the dataset are given.

[9]:
```
# Organize images by category ('kooks' or 'hoogovens') and smoke type
selected_images = {
    "kooks": {"high-opacity-smoke": None, "low-opacity-smoke": None},
    "hoogovens": {"high-opacity-smoke": None, "low-opacity-smoke": None}
}

# Find suitable images
```

```
for img in images:
    img_id = img["id"]
    anns = coco.loadAnns(coco.getAnnIds(imgIds=img_id))

    # Determine category (kooks or hoogovens)
    category = "hoogovens" if "hoogovens" in img["file_name"] else "kooks"

    # Check for smoke types
    smoke_types = {ann["category_id"]: ann for ann in anns}
    if 1 in smoke_types and selected_images[category]["high-opacity-smoke"] is␣
 ↪None:
        selected_images[category]["high-opacity-smoke"] = img
    if 2 in smoke_types and selected_images[category]["low-opacity-smoke"] is␣
 ↪None:
        selected_images[category]["low-opacity-smoke"] = img

    # Stop if we found all required images
    if all(v is not None for v in selected_images["kooks"].values()) and \
       all(v is not None for v in selected_images["hoogovens"].values()):
        break

# Function to draw bounding boxes and segmentation masks
def draw_annotations(image_path, anns):
    image = cv2.imread(image_path)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

    for ann in anns:
        x, y, w, h = ann["bbox"]
        cv2.rectangle(image, (int(x), int(y)), (int(x + w), int(y + h)), (255,␣
 ↪0, 0), 2)

        for seg in ann["segmentation"]:
            seg = np.array(seg, dtype=np.int32).reshape((-1, 2))
            cv2.polylines(image, [seg], isClosed=True, color=(0, 255, 0),␣
 ↪thickness=2)

    return image

# Display selected images
fig, axes = plt.subplots(2, 2, figsize=(12, 8))
axes = axes.ravel()
titles = ["Kooks - High Opacity", "Kooks - Low Opacity", "Hoogovens - High␣
 ↪Opacity", "Hoogovens - Low Opacity"]

for i, (category, smoke_dict) in enumerate(selected_images.items()):
    for j, (smoke_type, img) in enumerate(smoke_dict.items()):
        if img is not None:
```

```
            image_path = f"data/dataset/IJMOND_SEG/test/{img['file_name']}"
            anns = coco.loadAnns(coco.getAnnIds(imgIds=img['id']))
            image = draw_annotations(image_path, anns)
            axes[i * 2 + j].imshow(image)
            axes[i * 2 + j].set_title(titles[i * 2 + j])
            axes[i * 2 + j].axis("off")

plt.tight_layout()
plt.show()
```



Lastly, let's compare IJmond-VID to IJmond-SEG.

[10]:
```
data = [
    {
        "Split": "IJmond-VID",
        "Number of images": n_ijmond_img_images,
        "Number of bounding boxes": n_ijmond_img_boxes,
        "Number of classes": n_ijmond_img_categ,
        "Height-Max": max(ijmond_img_heights),
        "Height-Min": min(ijmond_img_heights),
        "Height-Avg": int(sum(ijmond_img_heights) / len(ijmond_img_heights)),
        "Width-Max": max(ijmond_img_widths),
        "Width-Min": min(ijmond_img_widths),
        "Width-Avg": int(sum(ijmond_img_widths) / len(ijmond_img_widths))
    },
```

```
    {
        "Split": "IJmond-SEG",
        "Number of images": n_ijmond_seg_images,
        "Number of bounding boxes": n_ijmond_seg_boxes,
        "Number of classes": n_ijmond_seg_categ,
        "Height-Max": max(ijmond_seg_heights),
        "Height-Min": min(ijmond_seg_heights),
        "Height-Avg": int(sum(ijmond_seg_heights) / len(ijmond_seg_heights)),
        "Width-Max": max(ijmond_seg_widths),
        "Width-Min": min(ijmond_seg_widths),
        "Width-Avg": int(sum(ijmond_seg_widths) / len(ijmond_seg_widths))
    }
]

markdown_table = "|| Split | Number of images | Number of bounding boxes |␣
↪Number of classes | Height Max | Height Min | Height Avg | Width Max | Width␣
↪Min | Width Avg |\n"
markdown_table += "|---|---|---|---|---|---|---|---|---|---|---|\n"
for i, row in enumerate(data, start=1):
    markdown_table += (f"| {i} | {row['Split']} | {row['Number of images']} | "
                       f"{row['Number of bounding boxes']} | {row['Number of␣
↪classes']} |"
                       f"{row['Height-Max']} | {row['Height-Min']} |␣
↪{row['Height-Avg']} |"
                       f"{row['Width-Max']} | {row['Width-Min']} |␣
↪{row['Width-Avg']} |\n")

display(Markdown(markdown_table))
```

	Split	Number of images	Number of bounding boxes	Number of classes	Height Max	Height Min	Height Avg	Width Max	Width Min	Width Avg
1	IJmond-VID	940	940	1	900	600	720	900	600	720
2	IJmond-SEG	900	1209	3	1080	1080	1080	1920	1920	1920

1.4 4. Backup dataset (SMOKE5K)

The SMOKE5K dataset consists of both synthetic images and real images. It contains 5,400 images, where 400 real smoke images from it is used for testing, and the remaining 5,000 images are for training. The dataset is thus already split into a test and train set. Each set consists of the folders 'gt_' and 'img' containing the annotations and images respectively. The files in the 'gt_' folders are named like '1234567890_+12345.png'. The same holds for the images, but they are in .jpg format.

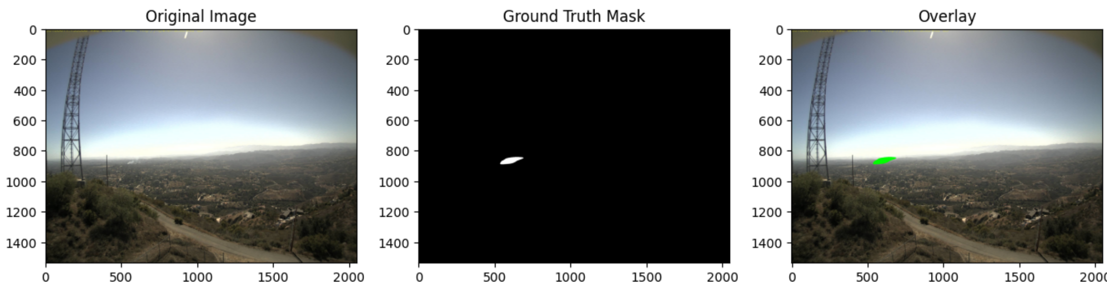
Below, both the train and test set will be loaded and some examples will be shown. However, as this is a backup dataset, it will not be analyzed as extensively as the IJmond data.

[27]:
```
train_img_dir = "data/dataset/SMOKE5K/train/img"
train_gt_dir = "data/dataset/SMOKE5K/train/gt"
test_img_dir = "data/dataset/SMOKE5K/test/img"
test_gt_dir = "data/dataset/SMOKE5K/test/gt_"

train_images = sorted(glob.glob(os.path.join(train_img_dir, "*.jpg")))
train_gt = sorted(glob.glob(os.path.join(train_gt_dir, "*.png")))

test_images = sorted(glob.glob(os.path.join(test_img_dir, "*.jpg")))
test_gt = sorted(glob.glob(os.path.join(test_gt_dir, "*.png")))

print(f"Train Images: {len(train_images)}, Train GT: {len(train_gt)}")
print(f"Test Images: {len(test_images)}, Test GT: {len(test_gt)}")

# Ensure matching filenames
for img_path, gt_path in zip(train_images[:5], train_gt[:5]):  # Checking first␣
↪5 pairs
    print("Image:", os.path.basename(img_path), "-> GT:", os.path.
↪basename(gt_path))
```

```
Train Images: 5058, Train GT: 5058
Test Images: 400, Test GT: 400
Image: 1528757586_+00180.jpg -> GT: 1528757586_+00180.png
Image: 1528757766_+00360.jpg -> GT: 1528757766_+00360.png
Image: 1528757946_+00540.jpg -> GT: 1528757946_+00540.png
Image: 1528758306_+00900.jpg -> GT: 1528758306_+00900.png
Image: 1528758486_+01080.jpg -> GT: 1528758486_+01080.png
```

[28]:
```
def show_sample(image_path, gt_path):
    # Load image and ground truth mask
    image = cv2.imread(image_path)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)  # Convert BGR to RGB
    gt_mask = cv2.imread(gt_path, cv2.IMREAD_GRAYSCALE)  # Load mask in␣
↪grayscale

    # Resize GT mask to match image (if needed)
    if gt_mask.shape != image.shape[:2]:
        gt_mask = cv2.resize(gt_mask, (image.shape[1], image.shape[0]))

    # Create overlay (green mask)
    overlay = image.copy()
    overlay[gt_mask > 0] = (0, 255, 0)

    # Display images
    fig, ax = plt.subplots(1, 3, figsize=(15, 5))
```

```python
    ax[0].imshow(image)
    ax[0].set_title("Original Image")
    ax[1].imshow(gt_mask, cmap="gray")
    ax[1].set_title("Ground Truth Mask")
    ax[2].imshow(overlay)
    ax[2].set_title("Overlay")
    plt.show()

# Show an example
show_sample(train_images[0], train_gt[0])
```



To convert the SMOKE5K dataset to COCO format, the following code should be executed. Conversion to COCO format allows usage with standard ML frameworks.

[31]:
```python
coco_data_5k = {
    "images": [],
    "annotations": [],
    "categories": [{"id": 0, "name": "smoke", "supercategory": "none"}]
}

def get_image_size(image_path):
    """Returns (height, width) of an image"""
    image = cv2.imread(image_path)  # Read image
    if image is None:
        return None  # Skip if the image is missing or unreadable
    height, width = image.shape[:2]  # Extract dimensions
    return height, width

def get_bbox(mask_path):
    """Computes bounding box from binary mask"""
    mask = cv2.imread(mask_path, cv2.IMREAD_GRAYSCALE)
    if mask is None:
        return None  # Skip if mask is missing

    # Find all non-zero pixels
    ys, xs = np.where(mask > 0)
```

```python
    # Compute bounding box (x, y, width, height)
    if len(xs) > 0 and len(ys) > 0:
        x_min, y_min = xs.min(), ys.min()
        x_max, y_max = xs.max(), ys.max()
        w, h = x_max - x_min, y_max - y_min
        return [int(x_min), int(y_min), int(w), int(h)]
    return None  # Return None if no mask is found


def get_segmentation(mask_path):
    """Computes segmentation polygons from binary mask"""
    mask = cv2.imread(mask_path, cv2.IMREAD_GRAYSCALE)
    if mask is None:
        return []  # Return empty if no mask

    # Find contours (external only)
    contours, _ = cv2.findContours(mask, cv2.RETR_EXTERNAL, cv2.
 ↪CHAIN_APPROX_SIMPLE)

    segmentation = []
    for contour in contours:
        # Flatten contour coordinates into a single list
        segmentation.append(contour.flatten().tolist())

    return segmentation


# Iterate over images and masks
for idx, (img_path, gt_path) in enumerate(zip(train_images, train_gt)):
    file_name = os.path.basename(img_path)

    height, width = get_image_size(img_path)
    bbox = get_bbox(gt_path)

    coco_data_5k["images"].append({
        "id": idx,
        "file_name": file_name,
        "height": height,
        "width": width
    })

    coco_data_5k["annotations"].append({
        "id": idx,
        "image_id": idx,
        "category_id": 0,
        "bbox": bbox,
```

```
        "segmentation": get_segmentation(gt_path),
        "iscrowd": 0,
        "area": bbox[2] * bbox[3]
    })


# Save as JSON
with open("data/dataset/SMOKE5K/smoke5k_coco.json", "w") as f:
    json.dump(coco_data_5k, f)

print("COCO Dataset Created!")
```

```
COCO Dataset Created!
```

1.5 5. Baseline model

Implementation using DeepLabV3+ with ResNet50 as a backbone, which is a common and strong baseline. For now, I switched to FPN MobilenetV2 to make it much lighter and faster.

[9]:
```
# Load Pretrained DeepLabV3+ Model

ssl._create_default_https_context = ssl._create_unverified_context
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = smp.FPN(
    encoder_name="mobilenet_v2",
    encoder_weights="imagenet",
    in_channels=3,
    classes=4
).to(device)
```

[10]:
```
# Define Loss and Optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=1e-4)

# Define Training and Validation Loops
def train(model, loader, optimizer, criterion):
    model.train()
    running_loss = 0.0

    for batch_idx, (images, masks) in enumerate(loader):
        print(f"  Training batch {batch_idx+1}/{len(loader)}")  #   Debug print

        images, masks = images.to(device), masks.to(device)

        optimizer.zero_grad()
        outputs = model(images)
        loss = criterion(outputs, masks)
```

```
        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    return running_loss / len(loader)


def validate(model, loader, criterion):
    model.eval()
    running_loss = 0.0
    with torch.no_grad():
        for images, masks in tqdm(loader):
            images, masks = images.to(device), masks.to(device)
            outputs = model(images)
            loss = criterion(outputs, masks)
            running_loss += loss.item()

    return running_loss / len(loader)
```

[11]:
```
train_transform = A.Compose([
    A.Resize(256, 256),
    A.HorizontalFlip(p=0.5),
    A.RandomBrightnessContrast(p=0.2),
    A.Normalize(mean=(0.485, 0.456, 0.406), std=(0.229, 0.224, 0.225)),
    ToTensorV2(),
])

val_transform = A.Compose([
    A.Resize(256, 256),
    A.Normalize(mean=(0.485, 0.456, 0.406), std=(0.229, 0.224, 0.225)),
    ToTensorV2(),
])
```

[ ]:
```
if __name__ == "__main__":
    mp.set_start_method("spawn", force=True)  # Ensure spawn method is used

    # Define path
    coco_annotations = "data/dataset/IJMOND_SEG/test/_annotations.coco.json"
    coco_images = "data/dataset/IJMOND_SEG/test/"

    # Load COCO dataset
    coco = COCO(coco_annotations)
    imgIds = coco.getImgIds()

    # Split dataset
    train_size = int(0.8 * len(imgIds))
```

```
    train_imgIds = imgIds[:train_size]
    val_imgIds = imgIds[train_size:]

    # Define dataset
    train_dataset = coco_dataset.COCOSegmentationDataset(coco, train_imgIds,␣
↪coco_images, transform=train_transform)
    val_dataset = coco_dataset.COCOSegmentationDataset(coco, val_imgIds,␣
↪coco_images, transform=val_transform)

    # Define data loaders
    train_loader = DataLoader(train_dataset, batch_size=8, shuffle=True,␣
↪num_workers=0)
    val_loader = DataLoader(val_dataset, batch_size=8, shuffle=False,␣
↪num_workers=0)

    num_epochs = 25
    best_loss = float("inf")
    scheduler = torch.optim.lr_scheduler.StepLR(optimizer, step_size=10,␣
↪gamma=0.1)

    for epoch in range(num_epochs):
        train_loss = train(model, train_loader, optimizer, criterion)
        val_loss = validate(model, val_loader, criterion)

        print(f"Epoch [{epoch+1}/{num_epochs}], Train Loss: {train_loss:.4f},␣
↪Val Loss: {val_loss:.4f}")

        if val_loss < best_loss:
            best_loss = val_loss
            torch.save(model.state_dict(), "best_model.pth")
            print("Model saved!")

        scheduler.step()
```

Now that the model is trained we perform inference and evaluate the model.

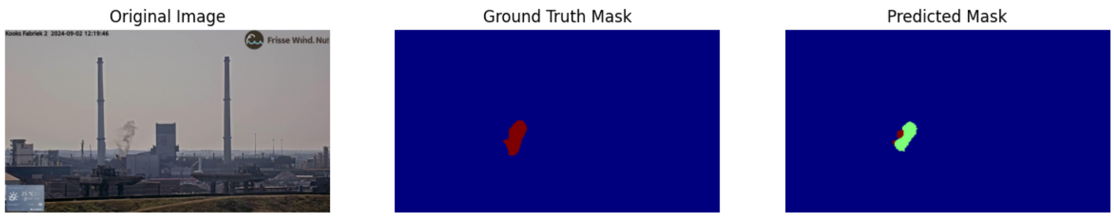
[22]:
```
# perform inference

def predict_coco(model, coco, image_id, image_dir, transform):
    model.eval()

    # Load image
    img_info = coco.loadImgs(image_id)[0]
    img_path = os.path.join(image_dir, img_info['file_name'])
    image = cv2.imread(img_path)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
```

```
    # Transform
    augmented = transform(image=image)
    image = augmented["image"].unsqueeze(0).to(device)

    with torch.no_grad():
        output = model(image)
        output = torch.argmax(output.squeeze(), dim=0).cpu().numpy()

    output_resized = cv2.resize(output, (img_info['width'],␣
↪img_info['height']), interpolation=cv2.INTER_NEAREST)

    return output_resized
```

[23]:

```
# Visualization of a predicted mask

import matplotlib.pyplot as plt
import numpy as np

# Example inference
image_id = val_imgIds[1]
predicted_mask = predict_coco(model, coco, image_id, coco_images, val_transform)

# Load original image
img_info = coco.loadImgs(image_id)[0]
img_path = os.path.join(coco_images, img_info['file_name'])
image = cv2.imread(img_path)
image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

# Load ground truth mask
ann_ids = coco.getAnnIds(imgIds=image_id)
anns = coco.loadAnns(ann_ids)
true_mask = np.zeros((img_info['height'], img_info['width']), dtype=np.uint8)

for ann in anns:
    true_mask += coco.annToMask(ann) * ann['category_id']

# Plot the image, ground truth mask, and predicted mask
fig, ax = plt.subplots(1, 3, figsize=(15, 5))

ax[0].imshow(image)
ax[0].set_title("Original Image")
ax[0].axis("off")

ax[1].imshow(true_mask, cmap="jet")
ax[1].set_title("Ground Truth Mask")
ax[1].axis("off")
```

```python
ax[2].imshow(predicted_mask, cmap="jet")
ax[2].set_title("Predicted Mask")
ax[2].axis("off")

plt.show()
```



[24]:
```python
print("True mask shape:", true_mask.shape)
print("Predicted mask shape:", predicted_mask.shape)
```

```
True mask shape: (1080, 1920)
Predicted mask shape: (1080, 1920)
```

[25]:
```python
# Evaluate the model

# Flatten masks to 1D arrays
true_mask_flat = true_mask.flatten()
predicted_mask_flat = predicted_mask.flatten()

# IoU Score: IoU = (Intersection of masks) / (Union of masks). So, higher IoU (~1.0) means better segmentation quality.
iou_score = jaccard_score(true_mask_flat, predicted_mask_flat, average='macro')

# Dice Score: Higher Dice Score (~1.0) means better segmentation
dice_score = f1_score(true_mask_flat, predicted_mask_flat, average='macro')

print(f"IoU Score: {iou_score:.4f}")
print(f"Dice Score: {dice_score:.4f}")
```

```
IoU Score: 0.5579
Dice Score: 0.6019
```

[26]:
```python
# Evaluate on entire validation set

iou_scores = []
dice_scores = []

for img_id in val_imgIds[:20]:  # Evaluate on first 20 images
```

```
    predicted_mask = predict_coco(model, coco, img_id, coco_images,␣
↪val_transform)

    # Load ground truth mask
    ann_ids = coco.getAnnIds(imgIds=img_id)
    anns = coco.loadAnns(ann_ids)
    true_mask = np.zeros((img_info['height'], img_info['width']), dtype=np.
↪uint8)

    for ann in anns:
        true_mask += coco.annToMask(ann) * ann['category_id']

    # Compute IoU and Dice scores
    true_mask_flat = true_mask.flatten()
    predicted_mask_flat = predicted_mask.flatten()

    iou_scores.append(jaccard_score(true_mask_flat, predicted_mask_flat,␣
↪average='macro'))
    dice_scores.append(f1_score(true_mask_flat, predicted_mask_flat,␣
↪average='macro'))

# Print average scores
print(f"Mean IoU Score: {np.mean(iou_scores):.4f}")
print(f"Mean Dice Score: {np.mean(dice_scores):.4f}")
```

```
Mean IoU Score: 0.5691
Mean Dice Score: 0.6099
```

1.6 Conclusion

This analysis shows that both IJmond datasets can be used for my research on semantic segmentation. However, the IJmond-VID dataset still needs to be cleaned to exclude frames without smoke. Additionally, a baseline model has been already trained and evaluated using the IJmond-SEG dataset. It shows that the model does not perform good segmentation yet and could be improved significantly. In case any significant problem arises, a backup dataset is introduced.

1.7 7. References

IJmond dataset

1. MultiX-Amsterdam. 2024. IJmond Camera Monitor Dataset (2024-01-22). https://github.com/MultiX-Amsterdam/ijmond-camera-monitor/tree/main/dataset/2024-01-22 Accessed: 14-02-2025

SMOKE5K

2. Siyuan Yan, Jing Zhang, and Nick Barnes. 2023. Transmission-Guided Bayesian Generative Model for Smoke Segmentation. https://github.com/SiyuanYan1/Transmission-BVM/blob/main/sampling-based-BVM/data.py arXiv:2303.00900 [cs].