Ungraded Lab Part 1 - Deploying a Machine Learning Model

Welcome to this ungraded lab! If you are reading this it means you did the setup properly, nice work!

This lab is all about deploying a real machine learning model, and checking what doing so feels like. More concretely, you will deploy a computer vision model trained to detect common objects in pictures. Deploying a model is one of the last steps in a prototypical machine learning lifecycle. However, we thought it would be exciting to get you to deploy a model right away. This lab uses a pretrained model called `YOLOV3` (https://pjreddie.com/darknet/yolo/). This model is very convenient for two reasons: it runs really fast, and for object detection it yields accurate results.

The sequence of steps/tasks to complete in this lab are as follow:

1. Inspect the image data set used for object detection
2. Take a look at the model itself
3. Deploy the model using `fastAPI` (https://fastapi.tiangolo.com/)

Object Detection with YOLOV3

Inspecting the images

Let's take a look at the images that will be passed to the YOLOV3 model. This will bring insight on what type of common objects are present for detection. These images are part of the `ImageNet` (http://www.image-net.org/index) dataset.

In [1]:
```python
from IPython.display import Image, display
```

In [2]:
```
# Some example images
image_files = [
    'apple.jpg',
    'clock.jpg',
    'oranges.jpg',
    'car.jpg'
]

for image_file in image_files:
    print(f"\nDisplaying image: {image_file}")
    display(Image(filename=f"images/{image_file}"))
```

```
Displaying image: apple.jpg
```

```
Displaying image: clock.jpg
```

```
Displaying image: oranges.jpg
```

```
Displaying image: car.jpg
```

Overview of the model

Now that you have a sense of the image data and the objects present, let's try and see if the model is able to detect and classify them correctly.

For this you will be using `cvlib` (https://www.cvlib.net/), which is a very simple but powerful library for object detection that is fueled by `OpenCV` (https://docs.opencv.org/4.5.1/) and `Tensorflow` (https://www.tensorflow.org/).

More concretely, you will use the `detect_common_objects` (https://docs.cvlib.net/object_detection/) function, which takes an image formatted as a `numpy array` (https://numpy.org/doc/stable/reference/generated/numpy.array.html) and returns:

- `bbox` : list of list containing bounding box coordinates for detected objects.

  ```
  Example:

      [[32, 76, 128, 192], [130, 83, 220, 185]]
  ```

- `label` : list of labels for detected objects.

  ```
  Example:

      ['apple', 'apple']
  ```

- `conf` : list of confidence scores for detected objects.

  ```
  Example:
  ```

```
[0.6187325716018677, 0.42835739254951477]
```

In the next section you will visually see these elements in action.

Creating the detect_and_draw_box function

Before using the object detection model, create a directory where you can store the resulting images:

In [3]:
```
import os

dir_name = "images_with_boxes"
if not os.path.exists(dir_name):
    os.mkdir(dir_name)
```

Let's define the `detect_and_draw_box` function which takes as input arguments: the **filename** of a file on your system, a **model**, and a **confidence level**. With these inputs, it detects common objects in the image and saves a new image displaying the bounding boxes alongside the detected object.

You might ask yourself why does this function receive the model as an input argument? What models are there to choose from? The answer is that `detect_common_objects` uses the `yolov3` model by default. However, there is another option available that is much tinier and requires less computational power.

It is the `yolov3-tiny` version. As the model name indicates, this model is designed for constrained environments that cannot store big models. With this comes a natural tradeoff: the results are less accurate than the full model. However, it still works pretty well. Going forward, we recommend you stick to it since it is a lot smaller than the regular `yolov3` and downloading its pretrained weights takes less time.

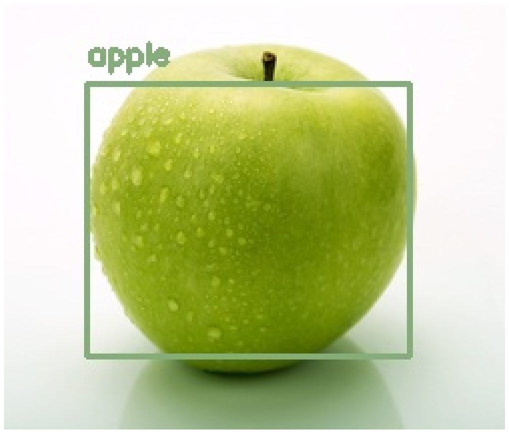
The model output is a vector of probabilities for the presence of different objects on the image. The last input argument, confidence level, determines the threshold that the probability needs to surpass to report that a given object is detected on the supplied image. By default, `detect_common_objects` uses a value of 0.5 for this.

In [4]:
```
import cv2
import cvlib as cv
from cvlib.object_detection import draw_bbox


def detect_and_draw_box(filename, model="yolov3-tiny", confidence=0.5):
    """Detects common objects on an image and creates a new image with b

    Args:
        filename (str): Filename of the image.
        model (str): Either "yolov3" or "yolov3-tiny". Defaults to "yolo
        confidence (float, optional): Desired confidence level. Defaults
    """

    # Images are stored under the images/ directory
    img_filepath = f'images/{filename}'

    # Read the image into a numpy array
    img = cv2.imread(img_filepath)

    # Perform the object detection
    bbox, label, conf = cv.detect_common_objects(img, confidence=confide

    # Print current image's filename
    print(f"========================\nImage processed: {filename}\n")

    # Print detected objects with confidence level
    for l, c in zip(label, conf):
        print(f"Detected object: {l} with confidence level of {c}\n")

    # Create a new image that includes the bounding boxes
    output_image = draw_bbox(img, bbox, label, conf)

    # Save the image in the directory images_with_boxes
    cv2.imwrite(f'images_with_boxes/{filename}', output_image)

    # Display the image with bounding boxes
    display(Image(f'images_with_boxes/{filename}'))
```

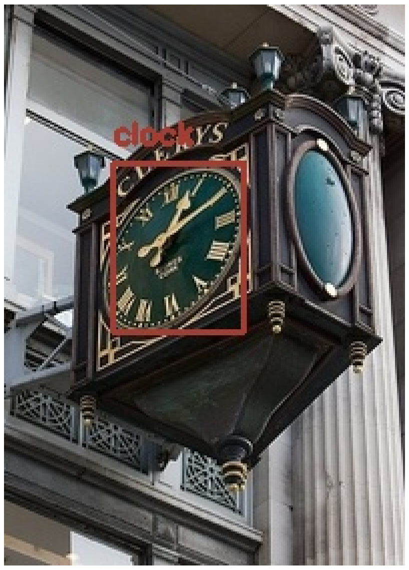
Let's try it out for the example images.

In [5]:
```
for image_file in image_files:
    detect_and_draw_box(image_file)
```

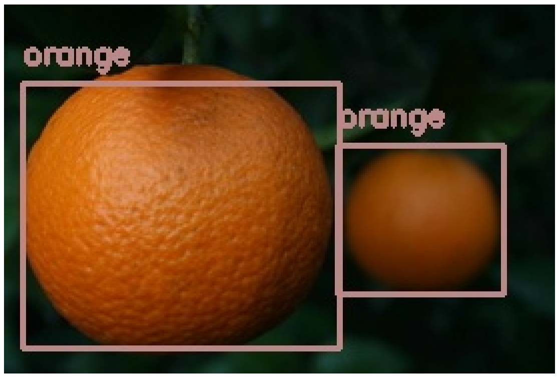
```
Downloading yolov3-tiny.cfg from https://github.com/pjreddie/darknet/r
aw/master/cfg/yolov3-tiny.cfg (https://github.com/pjreddie/darknet/ra
w/master/cfg/yolov3-tiny.cfg)

100% |
|

Downloading yolov3-tiny.weights from https://pjreddie.com/media/files/
yolov3-tiny.weights (https://pjreddie.com/media/files/yolov3-tiny.weig
hts)

 99% |################################################################
####### |

Downloading yolov3_classes.txt from https://github.com/arunponnusamy/o
bject-detection-opencv/raw/master/yolov3.txt (https://github.com/arunp
onnusamy/object-detection-opencv/raw/master/yolov3.txt)

100% |
|

========================
Image processed: apple.jpg

Detected object: apple with confidence level of 0.5717206597328186
```



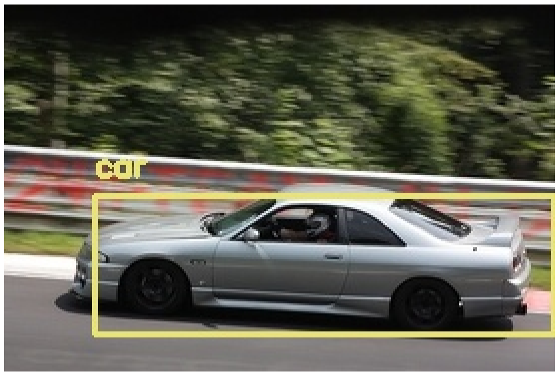
```
========================
Image processed: clock.jpg

Detected object: clock with confidence level of 0.9683184623718262
```



```
========================
Image processed: oranges.jpg

Detected object: orange with confidence level of 0.6185588836669922

Detected object: orange with confidence level of 0.5561690330505371
```



```
========================
Image processed: car.jpg

Detected object: car with confidence level of 0.6325406432151794
```

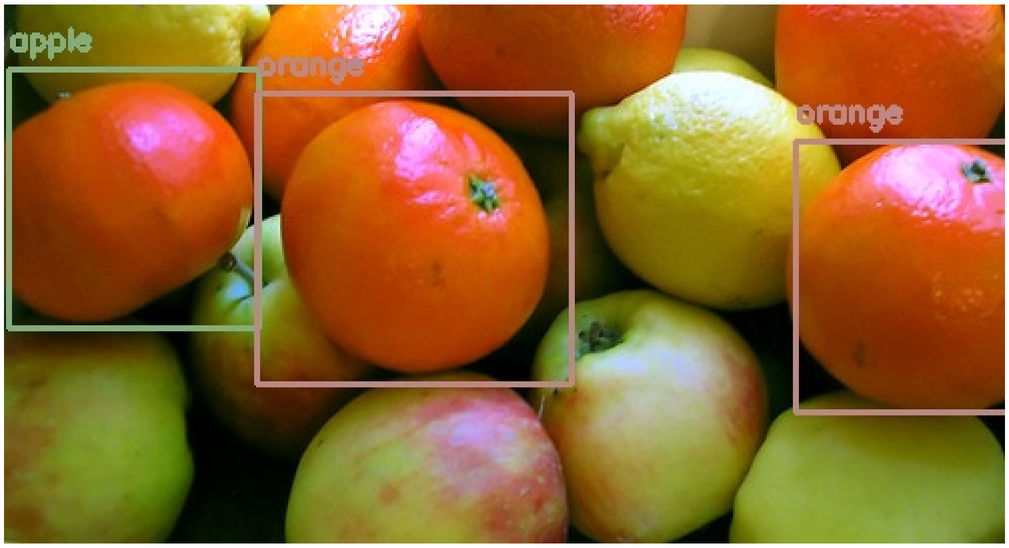


Changing the confidence level

Looks like the object detection went fairly well. Let's try it out on a more difficult image containing several objects:

In [6]:
```
detect_and_draw_box("fruits.jpg")
```

```
========================
Image processed: fruits.jpg

Detected object: apple with confidence level of 0.5818482041358948

Detected object: orange with confidence level of 0.5346484184265137

Detected object: orange with confidence level of 0.515099287033081
```

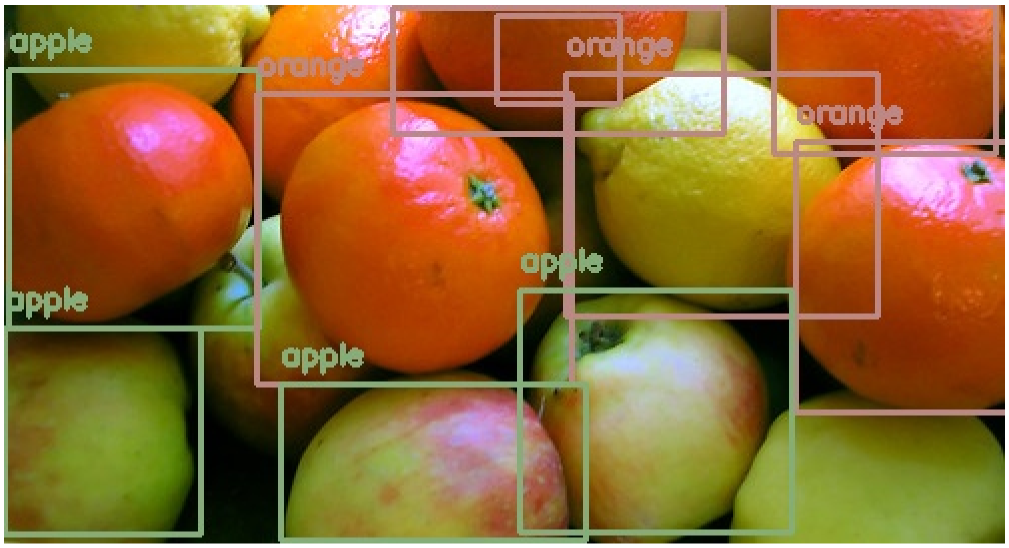


The **model failed to detect** several fruits and **misclassified** an orange as an apple. This might seem strange since it was able to detect one apple before, so one might think the model has a fair representation on how an apple looks like.

One possibility is that the model **did** detect the other fruits but with a confidence level lower than 0.5. Let's test if this is a valid hypothesis:

```
In [7]: detect_and_draw_box("fruits.jpg", confidence=0.2)
```

```
========================
Image processed: fruits.jpg

Detected object: apple with confidence level of 0.5818482041358948

Detected object: orange with confidence level of 0.5346484184265137

Detected object: orange with confidence level of 0.515099287033081

Detected object: apple with confidence level of 0.34759870171546936

Detected object: orange with confidence level of 0.32876086235046387

Detected object: apple with confidence level of 0.31244686245918274

Detected object: orange with confidence level of 0.27986079454421997

Detected object: orange with confidence level of 0.2749977707862854

Detected object: apple with confidence level of 0.2744504511356354

Detected object: orange with confidence level of 0.21419058740139008
```



By lowering the confidence level the model successfully detects most of the fruits. However, in order to correctly detect the objects present, we had to set the confidence level really low. In general, you should be careful when decreasing or increasing these kinds of parameters, as changing them might yield undesired results.

As for this concrete example when an orange was misclassified as an apple, it serves as a reminder that these models are not perfect and this should be considered when using them for tasks in production.

Deploying the model using fastAPI

Placing your object detection model in a server

Now that you know how the model works it is time for you to deploy it! Aren't you excited? :)

Before diving into deployment, let's quickly recap some important concepts and how they translate to `fastAPI`. Let's also create a directory to store the images that are uploaded to the server.

In [8]:
```
dir_name = "images_uploaded"
if not os.path.exists(dir_name):
    os.mkdir(dir_name)
```

Some concept clarifications

Client-Server model

When talking about **deploying**, what is usually meant is to put all of the software required for predicting in a `server`. By doing this, a `client` can interact with the model by sending `requests` to the server.

This client-server interaction is out of the scope of this notebook but there are a lot of resources on the internet that you can use to understand it better.

The important thing you need to focus on, is that the Machine Learning model lives in a server waiting for clients to submit prediction requests. The client should provide the required information that the model needs in order to make a prediction. Keep in mind that it is common to batch many predictions in a single request. The server will use the information provided to return predictions to the client, who can then use them at their leisure.

Let's get started by creating an instance of the `FastAPI` class:

```
app = FastAPI()
```

The next step is using this instance to create endpoints that will handle the logic for predicting (more on this next). Once all the code is in place to run the server you only need to use the command:

```
uvicorn.run(app)
```

Your API is coded using fastAPI but the serving is done using `uvicorn` (https://www.uvicorn.org/), which is a really fast Asynchronous Server Gateway Interface (ASGI) implementation. Both technologies are closely interconnected and you don't need to understand the implementation details. Knowing that uvicorn handles the serving is sufficient for the purpose of this lab.

Endpoints

You can host multiple Machine Learning models on the same server. For this to work, you can assign a different `endpoint` to each model so you always know what model is being used. An endpoint is represented by a pattern in the `URL`. For example, if you have a website called `myawesomemodel.com` you could have three different models in the following endpoints:

- `myawesomemodel.com/count-cars/`
- `myawesomemodel.com/count-apples/`
- `myawesomemodel.com/count-plants/`

Each model would do what the name pattern suggests.

In fastAPI you define an endpoint by creating a function that will handle all of the logic for that endpoint and decorating (https://www.python.org/dev/peps/pep-0318/) it with a function that contains information on the HTTP method allowed (more on this next) and the pattern in the URL that it will use.

The following example shows how to allow a HTTP GET request for the endpoint "/my-endpoint":

```python
@app.get("/my-endpoint")
def handle_endpoint():
    ...
    ...
```

HTTP Requests

The client and the server communicate with each other through a protocol called `HTTP`. The key concept here is that this communication between client and server uses some verbs to denote common actions. Two very common verbs are:

- `GET` -> Retrieves information from the server.
- `POST` -> Provides information to the server, which it uses to respond.

If your client does a `GET request` to an endpoint of a server you will get some information from this endpoint without the need to provide additional information. In the case of a `POST request` you are explicitly telling the server that you will provide some information for it that must be processed in some way.

Interactions with Machine Learning models living on endpoints are usually done via a `POST request` since you need to provide the information that is required to compute a prediction.

Let's take a look at a POST request:

```
@app.post("/my-other-endpoint")
def handle_other_endpoint(param1: int, param2: str):
    ...
    ...
```

For POST requests, the handler function contains parameters. In contrast with GET, POST requests expect the client to provide some information to it. In this case we supplied two parameters: an integer and a string.

Why fastAPI?

With fastAPI you can create web servers to host your models very easily. Additionally, this platform is extremely fast and it **has a built-in client that can be used to interact with the server**. To use it you will need to visit the "/docs" endpoint, for this case this means to visit http://localhost:8000/docs (http://localhost:8000/docs). Isn't that convenient?

Enough chatter, let's get going!

In [9]:
```
import io
import uvicorn
import numpy as np
import nest_asyncio
from enum import Enum
from fastapi import FastAPI, UploadFile, File, HTTPException
from fastapi.responses import StreamingResponse
```

In [10]:
```
# Assign an instance of the FastAPI class to the variable "app".
# You will interact with your api using this instance.
app = FastAPI(title='Deploying a ML Model with FastAPI')

# List available models using Enum for convenience. This is useful when
class Model(str, Enum):
    yolov3tiny = "yolov3-tiny"
    yolov3 = "yolov3"


# By using @app.get("/") you are allowing the GET method to work for the
@app.get("/")
def home():
    return "Congratulations! Your API is working as expected. Now head o


# This endpoint handles all the logic necessary for the object detection
# It requires the desired model and the image in which to perform object
@app.post("/predict")
def prediction(model: Model, file: UploadFile = File(...)):

    # 1. VALIDATE INPUT FILE
    filename = file.filename
    fileExtension = filename.split(".")[-1] in ("jpg", "jpeg", "png")
    if not fileExtension:
        raise HTTPException(status_code=415, detail="Unsupported file pr

    # 2. TRANSFORM RAW IMAGE INTO CV2 image

    # Read image as a stream of bytes
    image_stream = io.BytesIO(file.file.read())

    # Start the stream from the beginning (position zero)
    image_stream.seek(0)

    # Write the stream of bytes into a numpy array
    file_bytes = np.asarray(bytearray(image_stream.read()), dtype=np.uin

    # Decode the numpy array as an image
    image = cv2.imdecode(file_bytes, cv2.IMREAD_COLOR)


    # 3. RUN OBJECT DETECTION MODEL

    # Run object detection
    bbox, label, conf = cv.detect_common_objects(image, model=model)

    # Create image that includes bounding boxes and labels
    output_image = draw_bbox(image, bbox, label, conf)

    # Save it in a folder within the server
    cv2.imwrite(f'images_uploaded/{filename}', output_image)


    # 4. STREAM THE RESPONSE BACK TO THE CLIENT
    # Open the saved image for reading in binary mode
    file_image = open(f'images_uploaded/{filename}', mode="rb")

    # Return the image as a stream specifying media type
    return StreamingResponse(file_image, media_type="image/jpeg")
```

By running the following cell you will spin up the server!

This causes the notebook to block (no cells/code can run) until you manually interrupt the kernel. You can do this by clicking on the `Kernel` tab and then on `Interrupt` . You can also enter Jupyter's command mode by pressing the `ESC` key and tapping the `I` key twice.

In [*]:
```
# Allows the server to be run in this interactive environment
nest_asyncio.apply()

# Host depends on the setup you selected (docker or virtual env)
host = "0.0.0.0" if os.getenv("DOCKER-SETUP") else "127.0.0.1"

# Spin up the server!
uvicorn.run(app, host=host, port=8000)
```

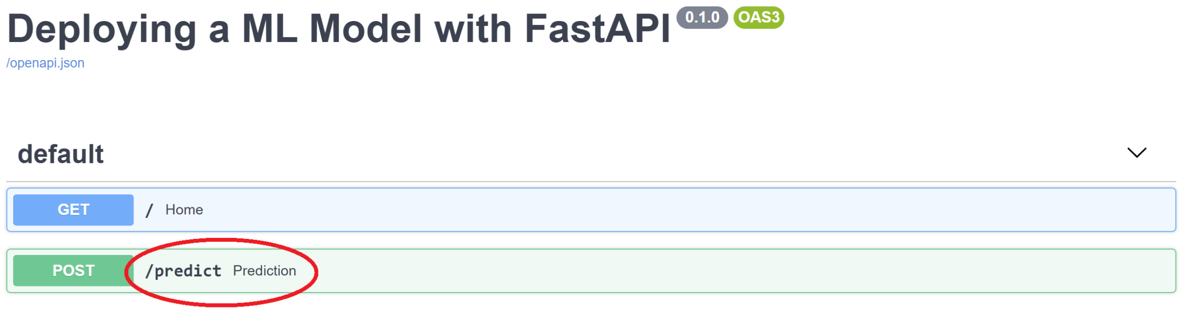
```
INFO:     Started server process [29]
INFO:     Waiting for application startup.
INFO:     Application startup complete.
INFO:     Uvicorn running on http://0.0.0.0:8000 (http://0.0.0.0:8000)
(Press CTRL+C to quit)

INFO:     172.17.0.1:39618 - "GET / HTTP/1.1" 200 OK
INFO:     172.17.0.1:39618 - "GET /favicon.ico HTTP/1.1" 404 Not Found
INFO:     172.17.0.1:39620 - "GET /docs HTTP/1.1" 200 OK
INFO:     172.17.0.1:39620 - "GET /openapi.json HTTP/1.1" 200 OK
INFO:     127.0.0.1:40156 - "POST /predict?model=yolov3-tiny HTTP/1.1"
200 OK
INFO:     127.0.0.1:40158 - "POST /predict?model=yolov3-tiny HTTP/1.1"
200 OK
INFO:     127.0.0.1:40160 - "POST /predict?model=yolov3-tiny HTTP/1.1"
200 OK
INFO:     127.0.0.1:40162 - "POST /predict?model=yolov3-tiny HTTP/1.1"
200 OK
```

The server is now running! Head over to http://localhost:8000/ (http://localhost:8000/) to see it in action.

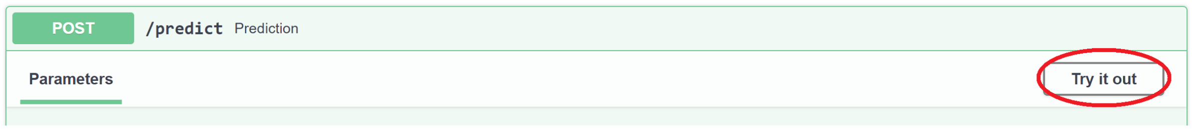
Try submitting an image and see how your API is able to detect objects within it and return a new image containing the bounding boxes alongside the labels of the detected objects. **You can do this by visiting http://localhost:8000/docs (http://localhost:8000/docs) to open fastAPI's built-in client.**

When doing so you will get a screen that should look like the one below, follow the instructions next:

Click on top of the `/predict` endpoint and more options will become visible:

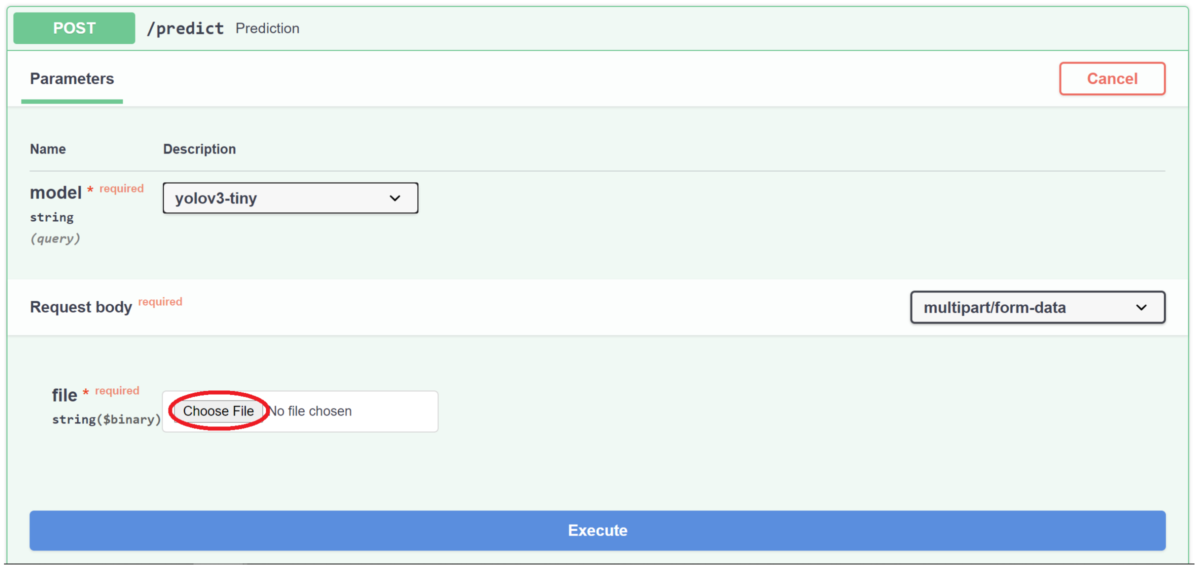


To test your server click on the **Try it out** button.



You can choose a model from the **model** field (if you select the full YOLO model the server will be stuck until the weights for this model are downloaded) and a **file** which should be the image in which you want the server to detect objects.

Submit an image from your local filesystem by clicking the **Choose File** button, then click on the blue **Execute** button to send an HTTP request to the server. After doing so, **scroll down and you will see the response from it**. Pretty cool, right?



Try different images! You can use the ones we provided with this lab or some of your own. Since the model is using the default confidence level of 0.5 it might not always succeed to detect some objects.

Also, try submitting non-image files and see how the server reacts to it.

Consuming your model from another client

It is awesome that fastAPI allows you to interact with your API through its built-in client. However, you might wonder how you can interact with your API using regular code and not some UI.

To do so, we have also provided a notebook in which you can check how a minimal client in Python looks like. For this, **leave the server running (don't interrupt the kernel or close this window)** and open the `client.ipynb` notebook. To do so you can open the File Browser tab on the sidebar located on the left of the window and double click on `client.ipynb` . If you cannot see a different tab for each file (which is very useful for moving between them) then it is possible you have the "Simple Interface" (aka Single-Document) mode enabled. To disable it you can go to the View tab and do so.

There is also an optional challenge ahead!