NYU FRE 7773 - Week 13

Machine Learning in Financial Engineering

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Serving predictions

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Welcome to the jungle

If your work needs to have an impact, it needs to RUN OUTSIDE YOUR LAPTOP:

1. Your code can be **inspected, modified, understood** by others, typically your technical colleagues: you need to write clean, modular, testable code and make your pipeline fully reproducible.
2. Your model can be **trusted** by others, typically, other stakeholders, who may or may not be technical folks: you need to “make sure” the model behaved as designed before pushing it in front of end-users.
3. Predictions can be **consumed** by others, typically anybody with an internet connection: you need to expose your model as an endpoint which returns predictions when supplied with the appropriate parameters.

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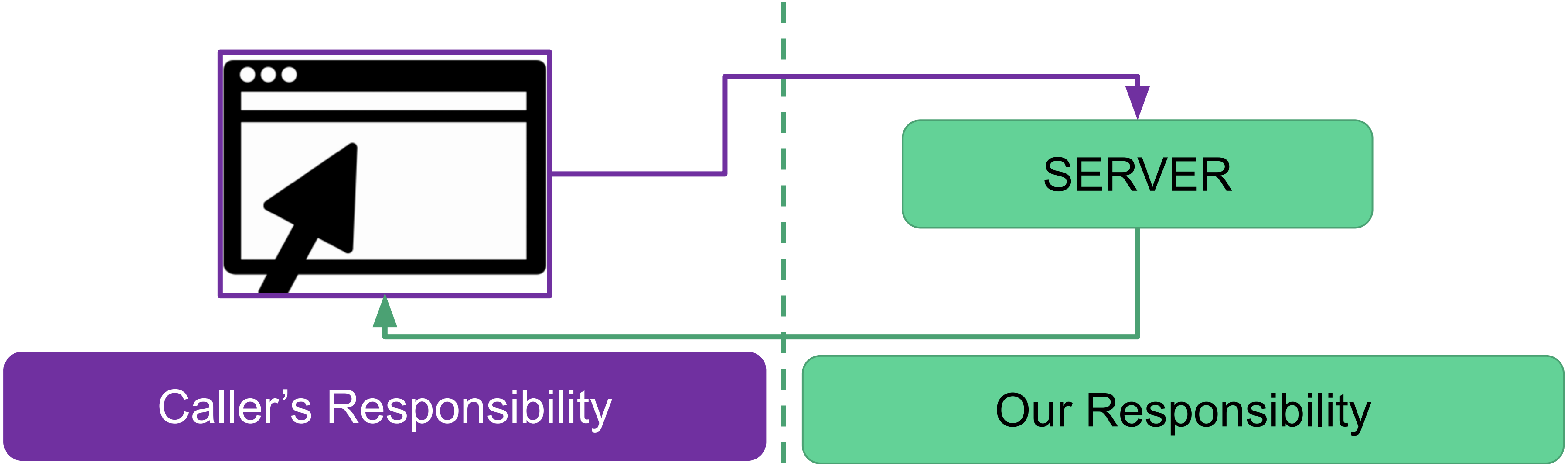
Part 3: Serving predictions

- If our model stays on our laptop, nobody will be able to use it!
- **Client-server architecture**: our model interacts with *many* remote clients through an API (also called “endpoint”) - we abstract away model code (and complexity) and expose a pure input-output interface: clients send us the input, we return a prediction.



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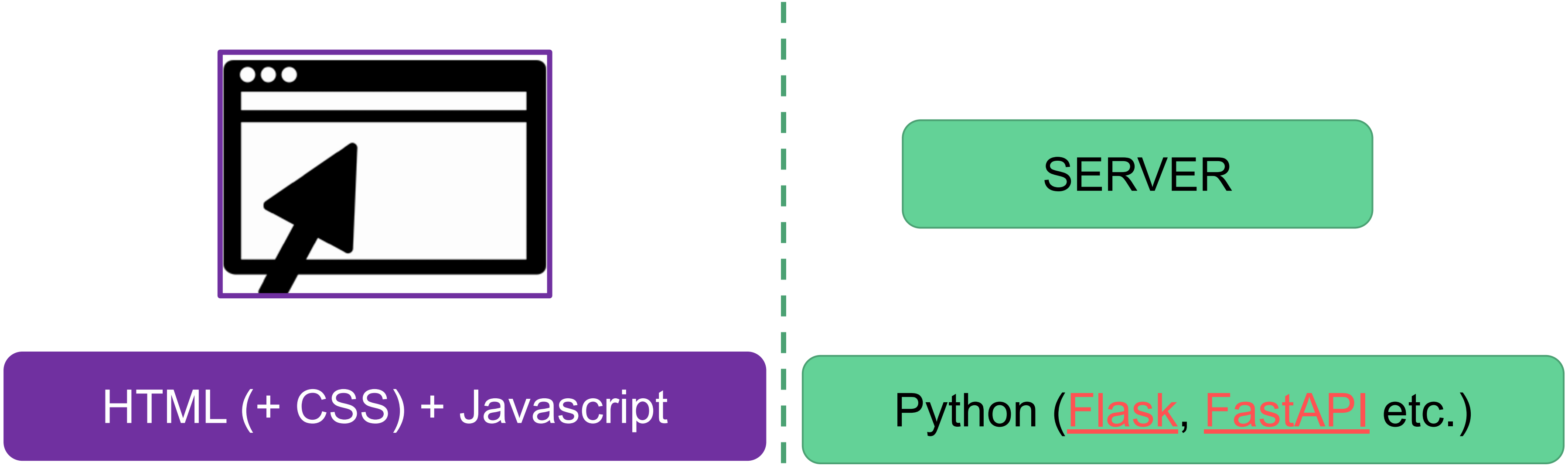


Show me first!

Intro to Flask applications

- We will be using Flask as a simple framework to serve model predictions after training
- Flask has several attractive features:
  - Helps with structuring both the front-end (the web page) and back-end (the endpoint)
  - Pure Python back-end
  - Minimal syntax for routing, GET / POST etc.

Step 1: prepare a web page

```html
<!DOCTYPE html>
<html>
<head>
        <title>{{ project }} app</title>
        <script src="https://ajax.googleapis.com/ajax/libs/jquery/3.5.1/jquery.min.js"></script>
</head>
<script type="text/javascript">

    $(function() {
        $('#predict').click(function() {
            event.preventDefault();
            var form_data = new FormData($('#myform')[0]);
            console.log(form_data);
            $.ajax({
                type: 'POST',
                url: '/',
                data: form_data,
                contentType: false,
                processData: false,
            }).done(function(data, textStatus, jqXHR){
                $('#result').text(data);
            }).fail(function(data){
                alert('error!');
            });
        });
    });

</script>
<body>
        <h1>{{ project }}</h1>
```

- Prepare a simple HTML page for users to interact with our endpoint.
    - It is not much different than the streamlit app we built before!
- Note that we use a simple Javascript function with jQuery to perform a POST request.

Step 2: prepare the Flask back-end application

```python
# We need to initialise the Flask object to run the flask app
# By assigning parameters as static folder name,templates folder name
app = Flask(__name__, static_folder='static', template_folder='templates')
```

- Initialize a Flask app in [app.py]()
  - Note the *templates* folder contains the HTML we created before!
- Make sure the app is started when we run “flask run”: the script will spin up a web server that will be ready to listen for incoming requests (from our HTML page, of course)

```python
if __name__=='__main__':
    # Run the Flask app to run the server
    app.run(debug=True)
```

Step 3: load the ML model in memory

```python
#### THIS IS GLOBAL, SO OBJECTS LIKE THE MODEL CAN BE RE-USED ACROSS REQUESTS ####

FLOW_NAME = 'MyRegressionFlow' # name of the target class that generated the model
# Set the metadata provider as the src folder in the project,
# which should contains /.metaflow
metadata('../src')
# Fetch currently configured metadata provider to check it's local!
print(get_metadata())

def get_latest_successful_run(flow_name: str):
    "Gets the latest successfull run."
    for r in Flow(flow_name).runs():
        if r.successful:
            return r

# get artifacts from latest run, using Metaflow Client API
latest_run = get_latest_successful_run(FLOW_NAME)
latest_model = latest_run.data.model
```

- As in all Python scripts, what is declared outside the functions is “global”.
  - In this context, this means that objects can live *across requests*: if the client ask for prediction 1 and then prediction 2, we do not need to reload the model, as it is already **in memory**!
- We want the model to be “global” as retrieving the model from Metaflow storage may be slow and expensive.

Step 4: defining our endpoint

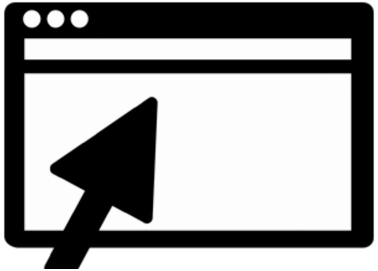
```python
@app.route('/',methods=['POST','GET'])
def main():

  # on GET we display the page
  if request.method=='GET':
    return render_template('index.html', project=FLOW_NAME)
  # on POST we make a prediction over the input text supplied by the user
  if request.method=='POST':
    # debug
    # print(request.form.keys())
    _x = request.form['_x']
    val = latest_model.predict([[float(_x)]])
    #  debug
    print(_x, val)
    # Returning the response to the client
    return "Predicted Y is {}".format(val)
```

- We use a decorator to define our route (empty in this case, but could be, say, “predict”).
  - If it was “predict”, our server would be listening for calls at **URL/predict**
- We distinguish between page load (GET) and request from a prediction (POST).

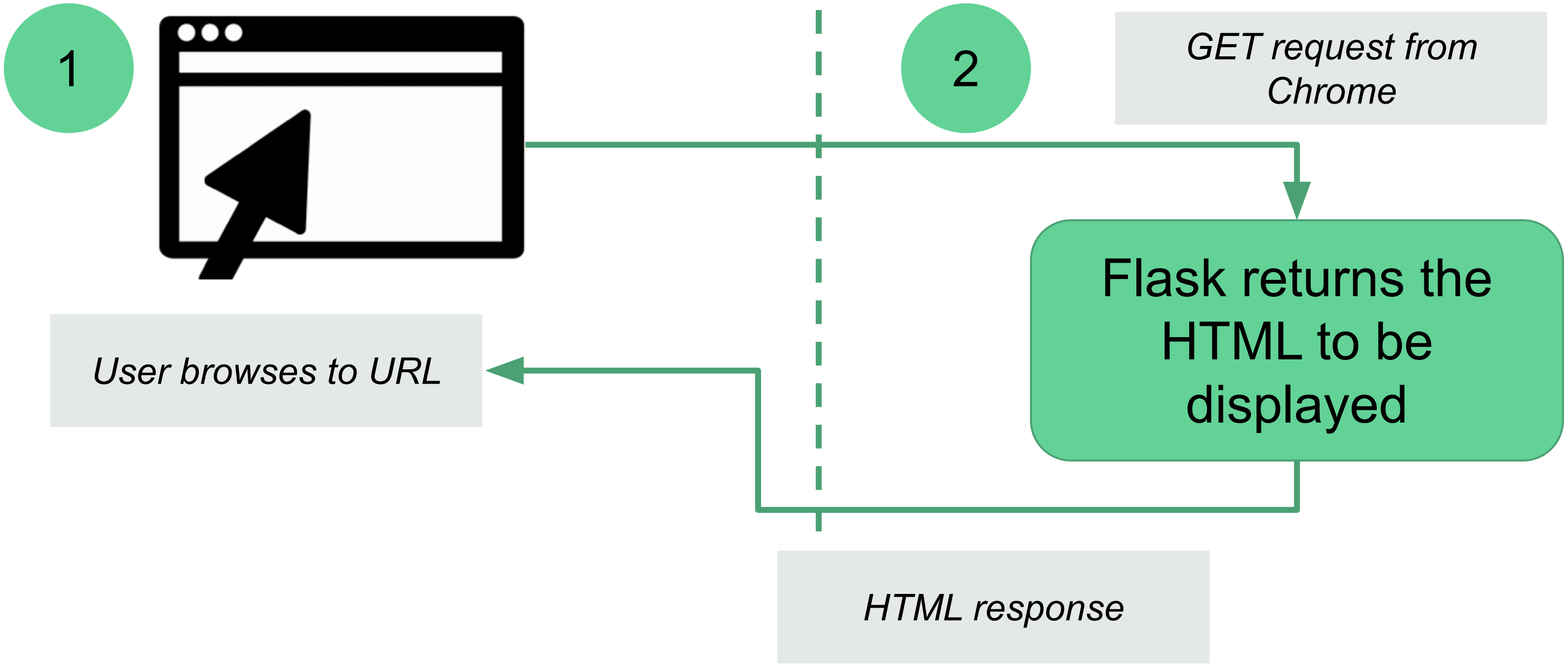
The full workflow

1



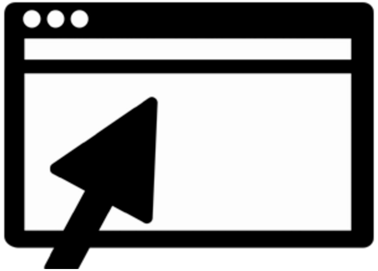
User browses to URL

The full workflow



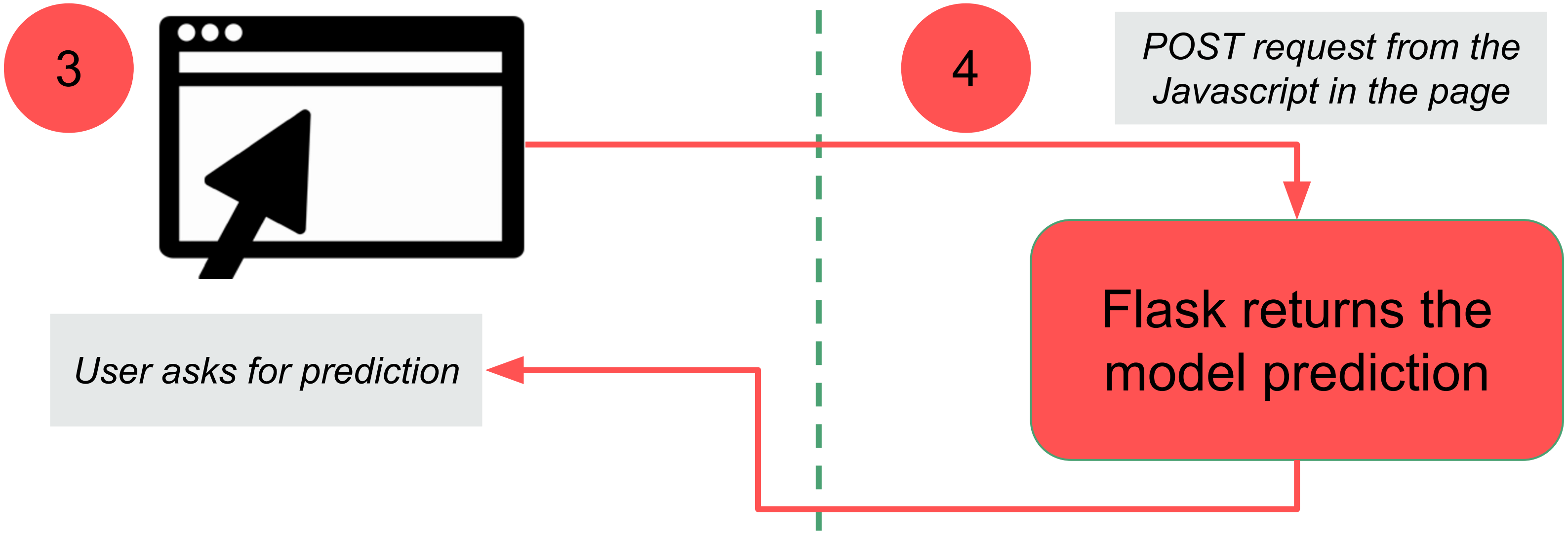
The full workflow

3



User asks for prediction

The full workflow



BONUS: Structuring the response

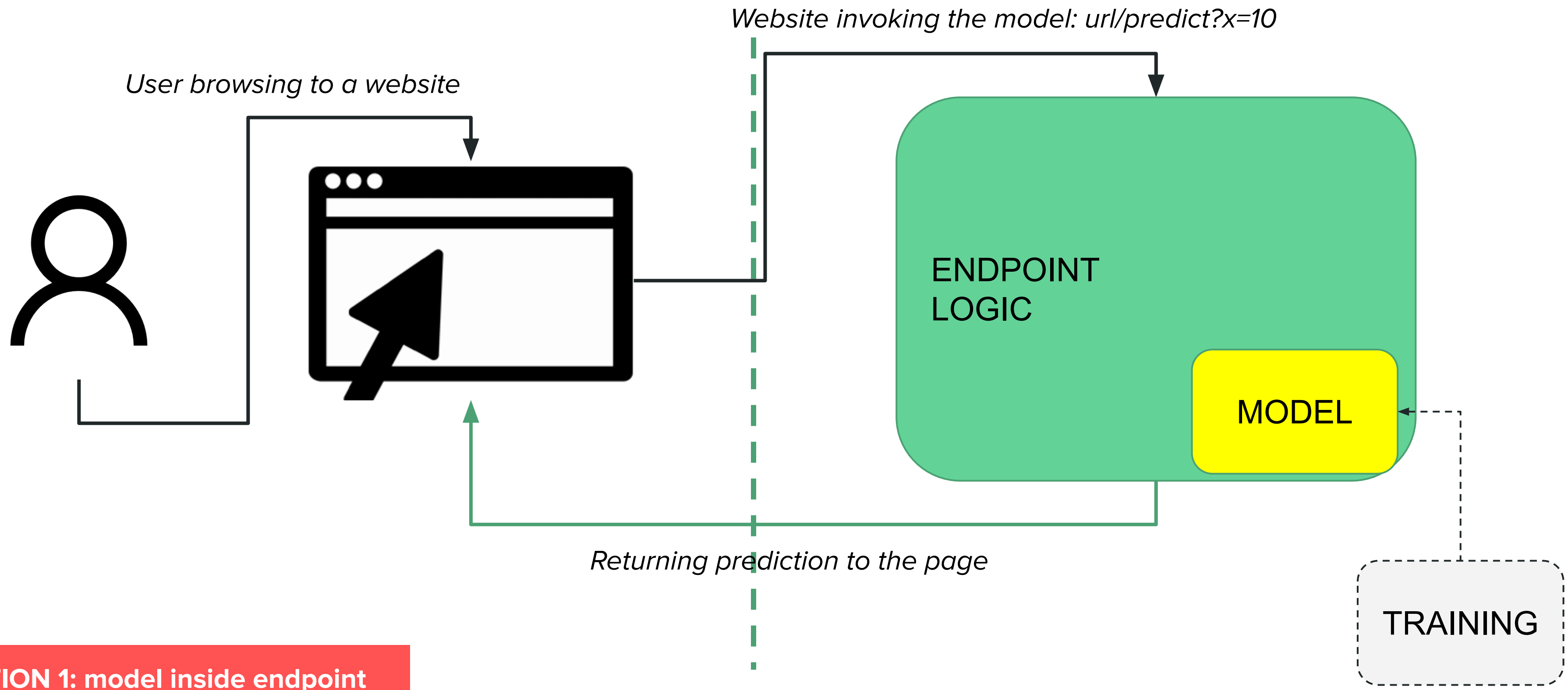
- Now **everybody** with the URL can use your awesome model!
- Can we make the response a bit clearer?

```
{
    "data": {
        "predictions": [167.068]
    },
    "metadata": {
        "eventId": "167b7129-cea1-4156-932f-f8d89c4b4066",
        "serverTimestamp": 163353256012,
        "time": 0.00022029876708984375
    }
}
```

This is the actual prediction from the model (why is it a list?)

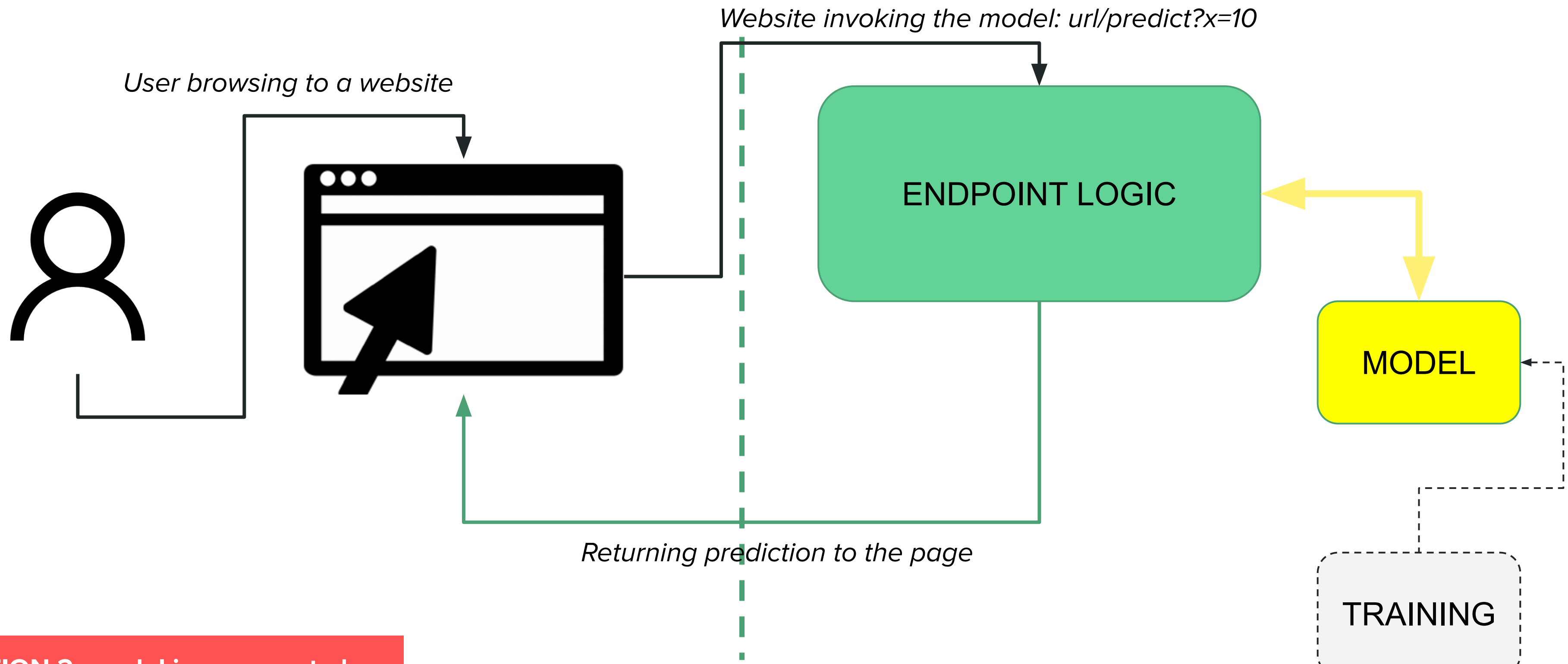
This is useful information about the call itself (debugging, monitoring, etc.)

Scenario 1: Endpoint with Model (ours)



OPTION 1: model inside endpoint

Scenario 2: Endpoint + Model



OPTION 2: model in a separate box

Flask... in the cloud

- There's 1M and one tutorials on how to use the very same tools (a Flask web app, a simple HTML + Javascript page) to port your app into the cloud.
- **BONUS points for your final demo if you can show your endpoint in the cloud**, either through an EC2 or Streamlit Cloud (**make sure to use the free resources / plan to avoid incurring in costs!**)

Alternative deployment scenarios

There is a ton of alternatives when it comes to *serving predictions* from the cloud, ranging from pure infrastructure to fully managed services. For example:

- You can deploy your model manually on a virtual machine, by installing Flask and run through screen (like they do here)
- You can deploy your model through a web app hosted by Elasticbeanstalk (like they do here)
- You can deploy your model through a web app hosted by Fargate (like they do here)
- You can deploy your model through Sagemaker, and expose it through a lambda (like we did in the 2021 repository)

After deployment: monitoring

We are not going to discuss monitoring, as we are not launching new apps in this course (for now!). However, after our model is live we need to:

- monitor how the pipeline is doing:
  - How is the new data coming in?
  - Does the model need re-training?
  - Is my new model better than the old one?
- check what users are doing with it!

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  - Is my new model better than the old one?
- check what users are doing with it!
  - You never know how people would use stuff!

The adventure never stops!

There is a ton of recent developments in the "MLOps" space (we do our small part as well in the community). If you want to know more, reach out!