End to End Machine Learning: From Data Collection to Deployment 🚀

Learn how to build and deploy a machine learning application from scratch. An end-to-end tutorial on data scraping, modeling, and deployment.

Ahmed Besbes Follow
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Disclaimer: code and demo at the end of the article.

This started out as a challenge. I wanted with a friend of mine to see if it was possible to build something from scratch and push it to production. In 3 weeks. This is our story. Here for more posts like this.

In this post, we'll go through the necessary steps to build and deploy a machine learning application. This starts from data collection to deployment and the journey, as you'll see it, is exciting and fun 😀 .

Before we begin, let's have a look at the app we'll be building:

As you see, this web app allows a user to evaluate random brands by writing reviews. While writing, the user will see the sentiment score of his input updating in real-time along with a proposed rating from 1 to 5.

The user can then change the rating in case the suggested one does not reflect his views, and submit.

You can think of this as a crowdsourcing app of brand reviews with a sentiment analysis model that suggests ratings that the user can tweak and adapt afterward.

To build this application we'll follow these steps:

- Collecting and scraping 🧹 customer reviews data using Selenium and Scrapy
- Training a deep learning sentiment classifier 🤖 on this data using PyTorch
- Building an interactive web app using Dash 📲
- Setting a REST API and a Postgres database 💻
- Dockerizing the app using Docker Compose 🐋
- Deploying to AWS 🚀

All the code is available in our Github repository and organized in independent directories, so you can check it, run it and improve it.

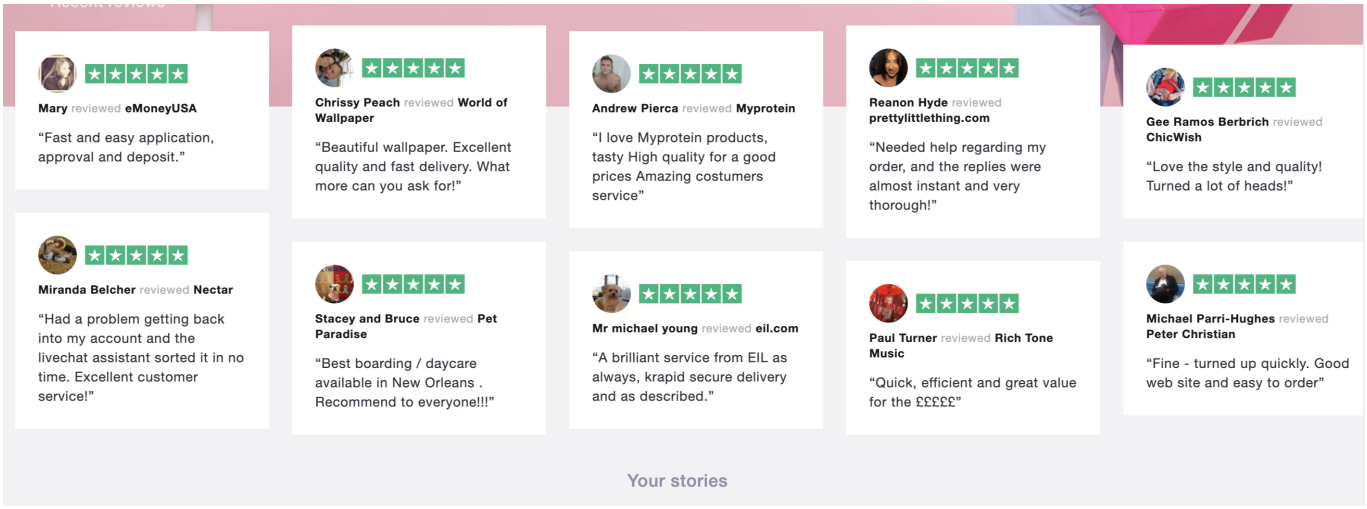
Let's get started! 💻

1 — Scraping the data from Trustpilot with Selenium and Scrapy 🧹

⚠️ **Disclaimer: The scripts below are meant for educational purposes only: scrape responsibly.**

In order to train a sentiment classifier, we need data. We can sure download open-source datasets for sentiment analysis tasks such as Amazon Polarity or IMDB movie reviews but for the purpose of this tutorial, **we'll build our own dataset**. We'll scrape customer reviews from Trustpilot.

Trustpilot.com is a consumer review website founded in Denmark in 2007. It hosts reviews of businesses worldwide and nearly 1 million new reviews are posted each month.



Trustpilot is an interesting source because each customer review is associated with a number of stars.

By leveraging this data, we are able to map each review to a sentiment class.

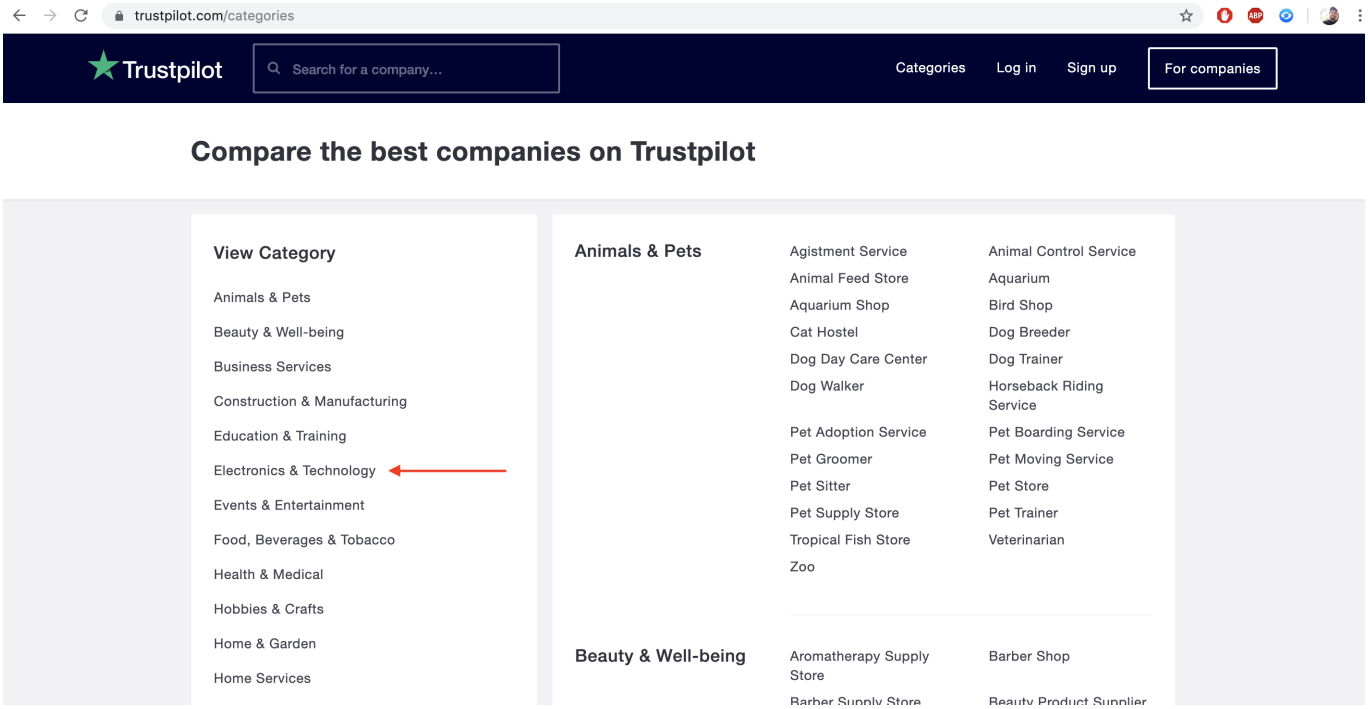
In fact, we defined reviews with:

- 1 and 2 stars as **bad reviews** ❌
- 3 stars as **average reviews** ⚠️

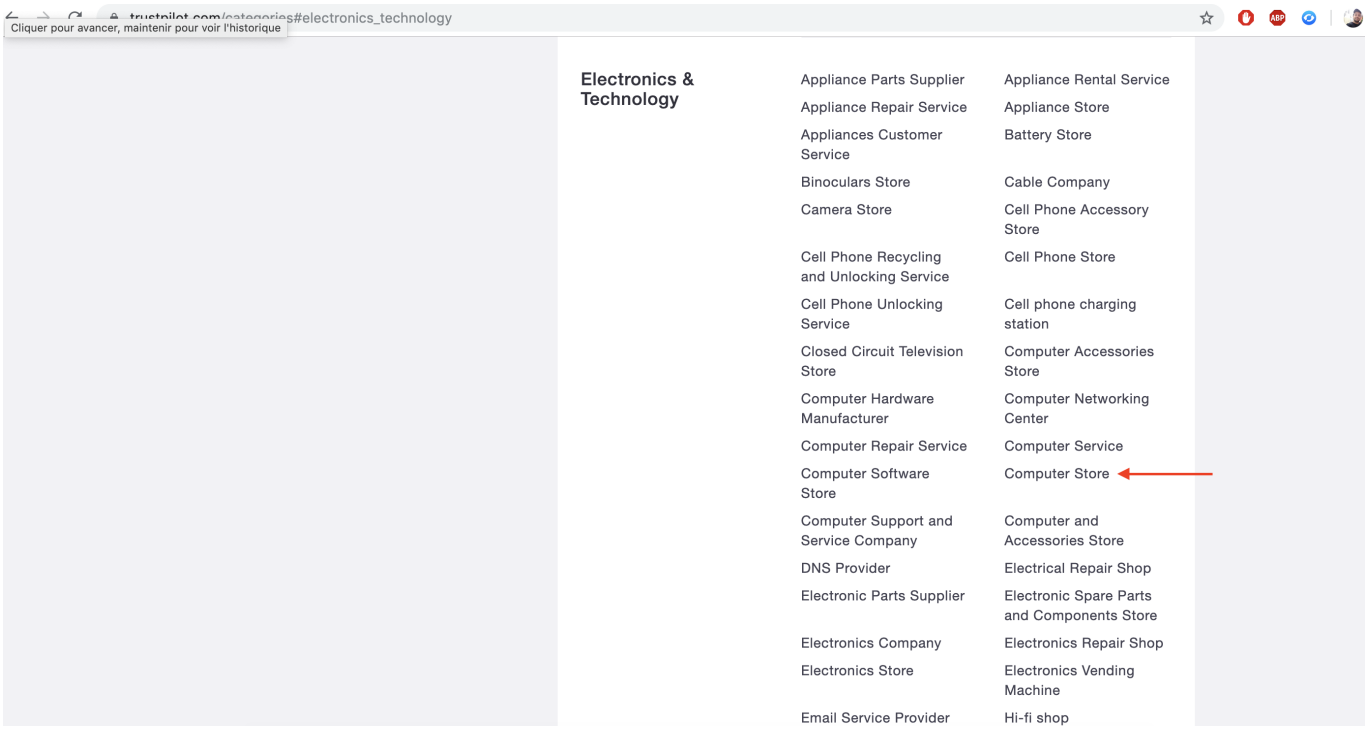
- 4 and 5 stars as **good reviews** ✅

In order to scrape customer reviews from Trustpilot, we first have to understand the structure of the website.

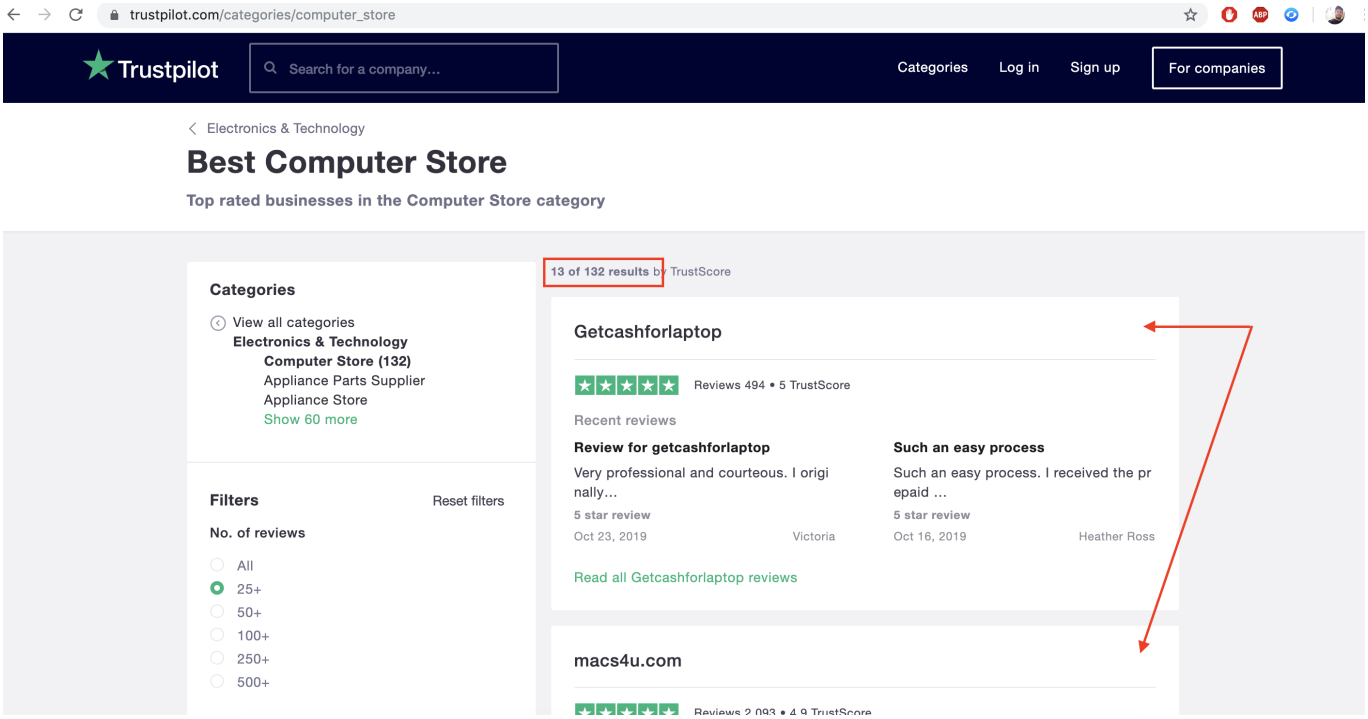
Trustpilot is organized by categories of businesses.



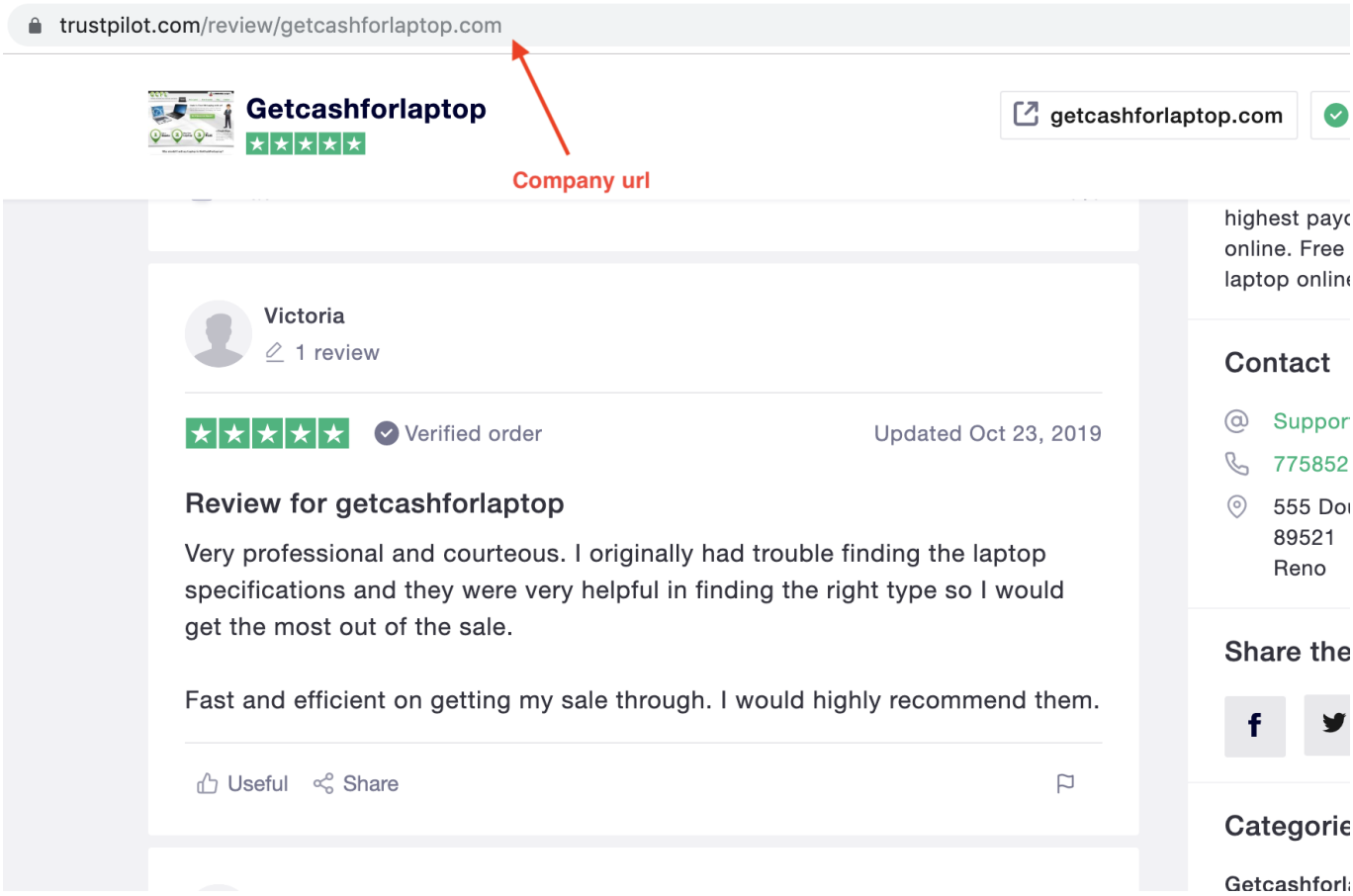
Each category is divided into sub-categories.

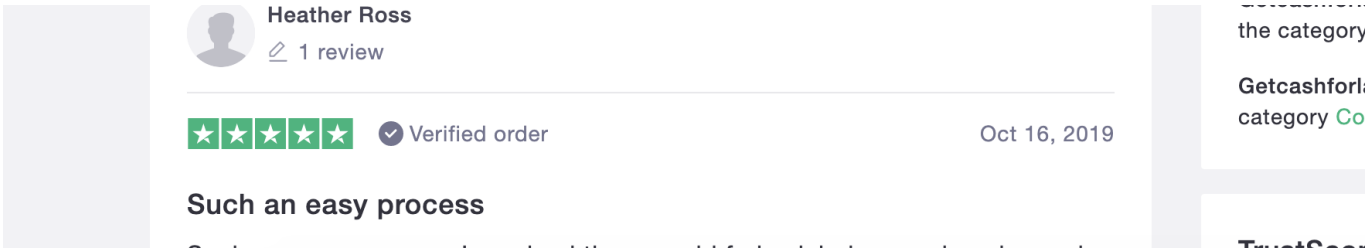


Each sub-category is divided into companies.



And then each company has its own set of reviews, usually spread over many pages.





As you see, this is a top-down tree structure. In order to scrape the reviews out of it, we'll proceed in two steps.

- Step 1️⃣ : use Selenium to fetch each company page URL
- Step 2️⃣ : use Scrapy to extract reviews from each company page

Scrape company URLs with Selenium: step 1

All the Selenium code is available and runnable from this notebook 📓

We first use Selenium because the content of the website that renders the URLs of each company is dynamic which means that it cannot be directly accessed from the page source. It's rather rendered on the front end of the website through Ajax calls.

Selenium does a good job extracting this type of data: it simulates a browser that interprets javascript rendered content. When launched, it clicks on each category, narrows down to each sub-category and goes through all the companies one by one and extracts their URLs. When it's done, the script saves these URLs to a CSV file.

Let's see how this is done:

We'll first import Selenium dependencies along with other utility packages.

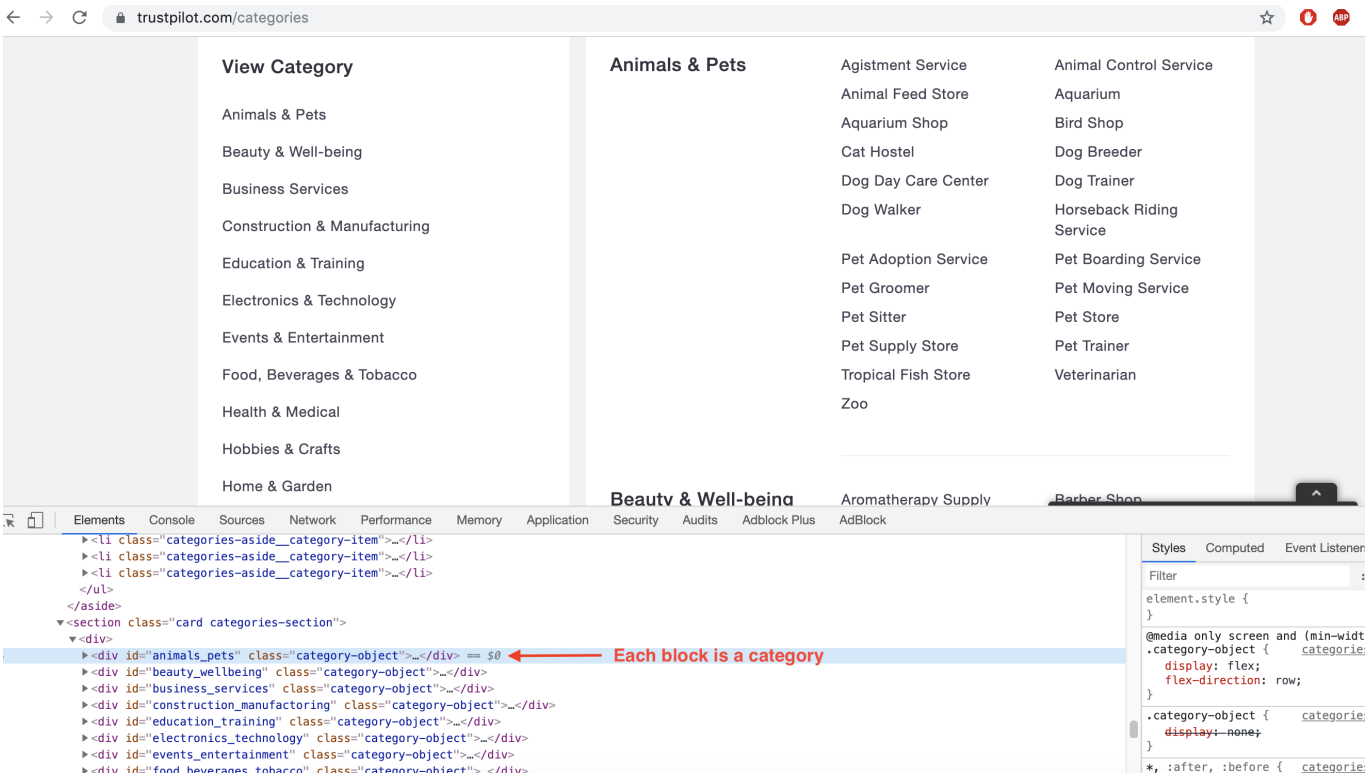
```
import json
import time

from bs4 import BeautifulSoup
import requests
import pandas as pd

from selenium import webdriver
from selenium.common.exceptions import NoSuchElementException
from selenium.common.exceptions import TimeoutException
from selenium.webdriver.support.ui import WebDriverWait
```

```python
from selenium.webdriver.support import expected_conditions as EC
from selenium.webdriver.common.by import By
from selenium.webdriver.chrome.options import Options

from tqdm import tqdm_notebook

base_url = "https://trustpilot.com"


def get_soup(url):
    return BeautifulSoup(requests.get(url).content, 'lxml')
```

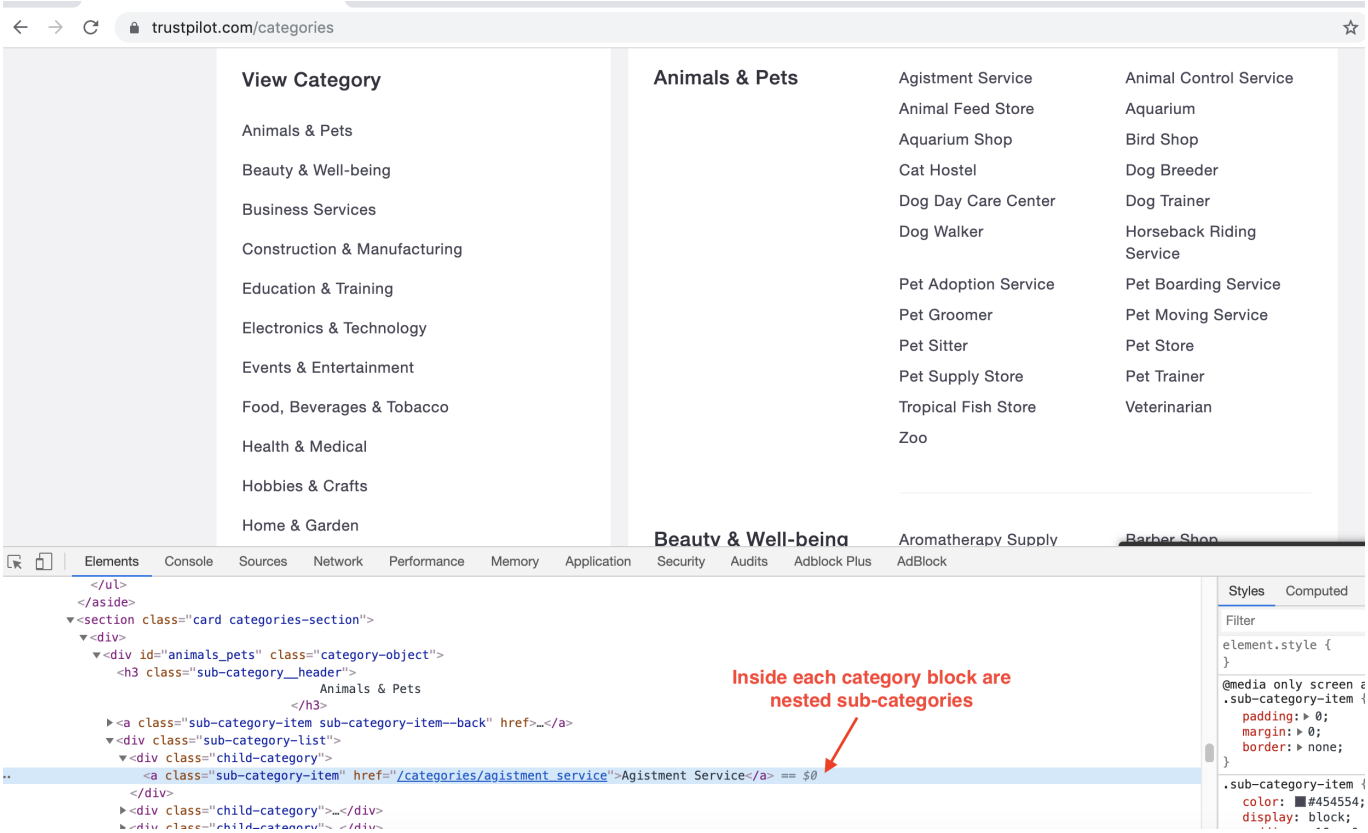
e2e_1.py hosted with ❤️ by GitHub view raw

We start by fetching the sub-category URLs nested inside each category.

If you open up your browser and inspect the source code, you'll find out 22 category blocks (on the right) located in `div` objects that have a `class` attribute equal to `category-object`



Each category has its own set of sub-categories. Those are located in `div` objects that have `class` attributes equal to `child-category`. We are interested in finding the URLs of these subcategories.



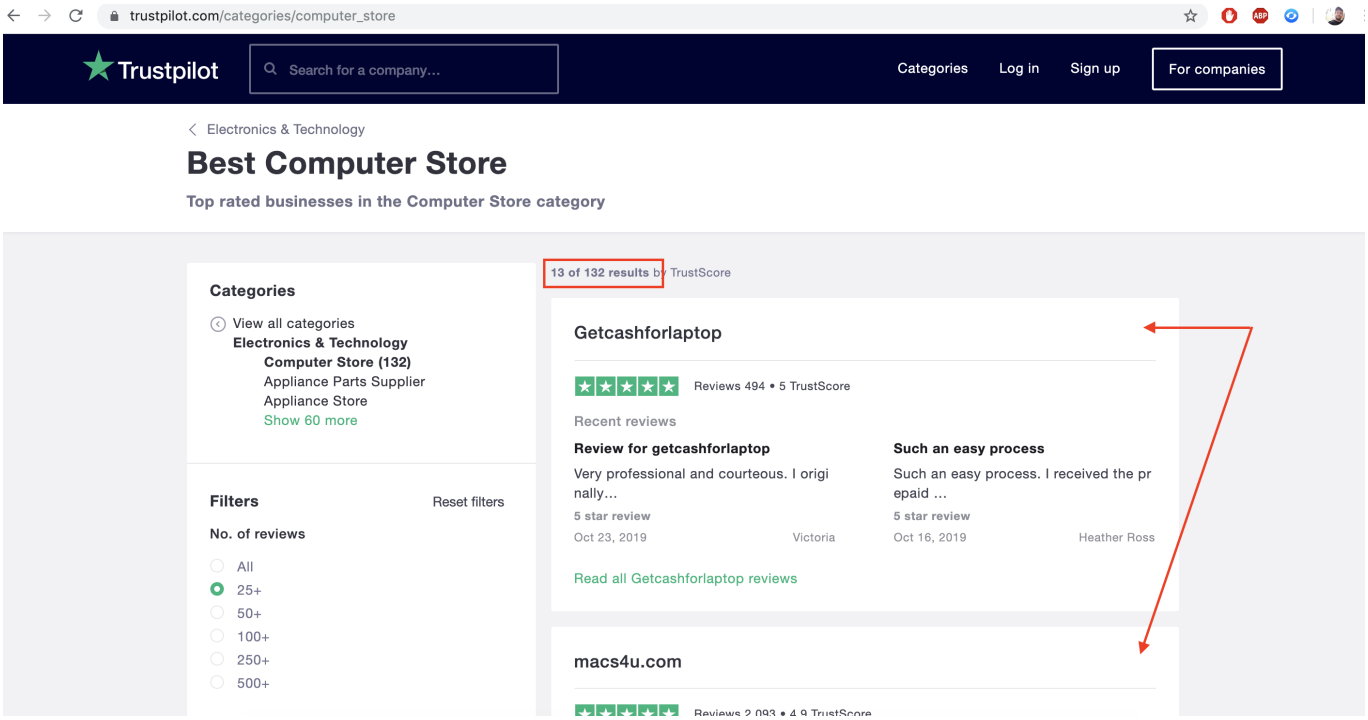
Let's first loop over categories and for each one of them collect the URLs of the sub-categories. This can be achieved using Beautifulsoup and requests.

```
data = {}

soup = get_soup(base_url + '/categories')
for category in soup.findAll('div', {'class': 'category-object'}):
    name = category.find('h3', {'class': 'sub-category__header'}).text
    name = name.strip()
    data[name] = {}
    sub_categories = category.find('div', {'class': 'sub-category-list'})
    for sub_category in sub_categories.findAll('div', {'class': 'child-category'}):
        sub_category_name = sub_category.find('a', {'class': 'sub-category-item'}).text
        sub_category_uri = sub_category.find('a', {'class': 'sub-category-item'})['href'
        data[name][sub_category_name] = sub_category_uri
```

e2e_2.py hosted with ❤ by GitHub view raw

Now comes the selenium part: we'll need to loop over the companies of each sub-category and fetch their URLs.

Remember, companies are presented inside each sub-category like this:



We first define a function to fetch company URLs of a given subcategory:

```
def extract_company_urls_form_page():
    a_list = driver.find_elements_by_xpath('//a[@class="category-business-card card"]')
    urls = [a.get_attribute('href') for a in a_list]
    dedup_urls = list(set(urls))
    return dedup_urls
```

e2e_3.py hosted with ❤ by GitHub view raw

and another function to check if a next page button exists:

```
def go_next_page():
    try:
        button = driver.find_element_by_xpath('//a[@class="button button--primary next-pa
        return True, button
    except NoSuchElementException:
        return False, None
```

e2e_4.py hosted with ❤ by GitHub view raw

Now we initialize Selenium with a headless Chromedriver. This prevents Selenium from opening up a Chrome window thus accelerating the scraping.

PS: You'll have to download Chromedriver from this link and choose the one that matches your operating system. It's basically a binary of a Chrome browser that Selenium uses to start.

```
options = Options()
options.add_argument('--headless')
options.add_argument('--no-sandbox')
options.add_argument('start-maximized')
options.add_argument('disable-infobars')
options.add_argument("--disable-extensions")

prefs = {"profile.managed_default_content_settings.images": 2}
options.add_experimental_option("prefs", prefs)

driver = webdriver.Chrome('./driver/chromedriver', options=options)

timeout = 3
```

e2e_5.py hosted with ❤ by GitHub view raw

The timeout variable is the time (in seconds) Selenium waits for a page to completely load.

Now we launch the scraping. This approximatively takes 50 minutes with a good internet connexion.

```
company_urls = {}
for category in tqdm_notebook(data):
    for sub_category in tqdm_notebook(data[category], leave=False):
        company_urls[sub_category] = []

        url = base_url + data[category][sub_category] + "?numberofreviews=0&timeperiod=0
        driver.get(url)
        try:
            element_present = EC.presence_of_element_located(
                (By.CLASS_NAME, 'category-business-card card'))

            WebDriverWait(driver, timeout).until(element_present)
```

```
        except:
            pass

        next_page = True
        c = 1
        while next_page:
            extracted_company_urls = extract_company_urls_form_page()
            company_urls[sub_category] += extracted_company_urls
            next_page, button = go_next_page()

            if next_page:
                c += 1
                next_url = base_url + data[category][sub_category] + "?numberofreviews=0
                driver.get(next_url)
                try:
                    element_present = EC.presence_of_element_located(
                        (By.CLASS_NAME, 'category-business-card card'))

                    WebDriverWait(driver, timeout).until(element_present)
                except:
                    pass
```

e2e_6.py hosted with ❤️ by GitHub view raw

Once the scraping is over, we save the company URLs to a CSV file.

```
consolidated_data = []

for category in data:
    for sub_category in data[category]:
        for url in company_urls[sub_category]:
            consolidated_data.append((category, sub_category, url))

df_consolidated_data = pd.DataFrame(consolidated_data, columns=['category', 'sub_categor

df_consolidated_data.to_csv('./exports/consolidate_company_urls.csv', index=False)
```

e2e_7.py hosted with ❤️ by GitHub view raw

And here's what the data looks like:

	category	sub_category	company_url
0	Animals & Pets	Agistment Service	https://www.trustpilot.com/review/nomuggle.com
1	Animals & Pets	Animal Control Service	https://www.trustpilot.com/review/zooeasy.com
2	Animals & Pets	Animal Control Service	https://www.trustpilot.com/review/rentokil.com
3	Animals & Pets	Animal Feed Store	https://www.trustpilot.com/review/www.topdogra...
4	Animals & Pets	Animal Feed Store	https://www.trustpilot.com/review/agrizoo-shop...

Pretty neat right? Now we'll have to go through the reviews listed in each one of those URLs.

Scrape customer reviews with Scrapy: step 2

All the Scrapy code can be found in this folder 🗂️

Ok, now we're ready to use Scrapy.

First, you need to install it either using:

- Conda: `conda install -c conda-forge scrapy`

or

- pip: `pip install scrapy`

Then, you'll need to start a project:

```
cd src/scraping/scrapy
scrapy startproject trustpilot
```

This command creates the structure of a Scrapy project. Here's what it looks like:

```
scrapy/
    scrapy.cfg            # deploy configuration file

    trustpilot/             # project's Python module, you'll import your code from here
        __init__.py

        items.py          # project items definition file
```

```
8
9           middlewares.py    # project middlewares file
10
11          pipelines.py      # project pipelines file
12
13          settings.py       # project settings file
14
15          spiders/          # a directory where you'll later put your spiders
16              __init__.py
```

e2e_8.sh hosted with ❤️ by GitHub view raw

Using Scrapy for the first time can be overwhelming, so to learn more about it, you can visit the official tutorials.

To build our scraper, we'll have to create a spider inside the `spiders` folder. We'll call it `scraper.py` and change some parameters in `settings.py`. We won't change the other files.

What the scraper will do is the following:

- It starts with a company URL
- It goes through each customer review and yields a dictionary of data containing the following items
- comment: the text review
- rating: the number of stars (1 to 5)
- url_website: the company URL on Trustpilot
- company_name: the company name being reviewed
- company_website: the website of the company being reviewed
- company_logo: the URL of the logo of the company being reviewed
- It moves to the next page if any

Here's the full script.

To fully understand it, you should inspect the source code. It's really easy to get.

In any case, if you have a question don't hesitate to post it in the comment section ⬇

```python
import re
import pandas as pd
import scrapy

class Pages(scrapy.Spider):
    name = "trustpilot"

    company_data = pd.read_csv('../selenium/exports/consolidate_company_urls.csv')
    start_urls = company_data['company_url'].unique().tolist()

    def parse(self, response):
        company_logo = response.xpath('//img[@class="business-unit-profile-summary__imag
        company_website = response.xpath("//a[@class='badge-card__section badge-card__se
        company_name = response.xpath("//span[@class='multi-size-header__big']/text()").
        comments = response.xpath("//p[@class='review-content__text']")
        comments = [comment.xpath('.//text()').extract() for comment in comments]
        comments = [[c.strip() for c in comment_list] for comment_list in comments]
        comments = [' '.join(comment_list) for comment_list in comments]

        ratings = response.xpath("//div[@class='star-rating star-rating--medium']//img/@
        ratings = [int(re.match('\d+', rating).group(0)) for rating in ratings]

        for comment, rating in zip(comments, ratings):
            yield {
                'comment': comment,
                'rating': rating,
                'url_website': response.url,
                'company_name': company_name,
                'company_website': company_website,
                'company_logo': company_logo
            }

        next_page = response.css('a[data-page-number=next-page] ::attr(href)').extract_f
        if next_page is not None:
            request = response.follow(next_page, callback=self.parse)
            yield request
```

e2e_9.py hosted with ❤️ by GitHub view raw

Before launching the scraper, you have to change a couple of things in the **settings.py**:

Here are the changes we made:

```
# Obey robots.txt rules
ROBOTSTXT_OBEY = False

# Configure maximum concurrent requests performed by Scrapy (default: 16)
CONCURRENT_REQUESTS = 32

#Export to csv
FEED_FORMAT = "csv"
FEED_URI = "comments_trustpilot_en.csv"
```

e2e_10.py hosted with ❤️ by GitHub view raw

This indicates to the scraper to ignore robots.txt, to use 32 concurrent requests and to export the data into a: format under the filename: `comments_trustpilot_en.csv`.

Now time to launch the scraper:

```
cd src/scraping/scrapy
scrapy crawl trustpilot
```

We'll let it run for a little bit of time.

Note that we can interrupt it at any moment since it saves the data on the fly on this output folder is `src/scraping/scrapy`.

2 — Training a sentiment classifier using PyTorch 🤖

The code and the model we'll be using here are inspired by this Github repo so go check it for additional information. If you want to stick to this project's repo you can look at this link.

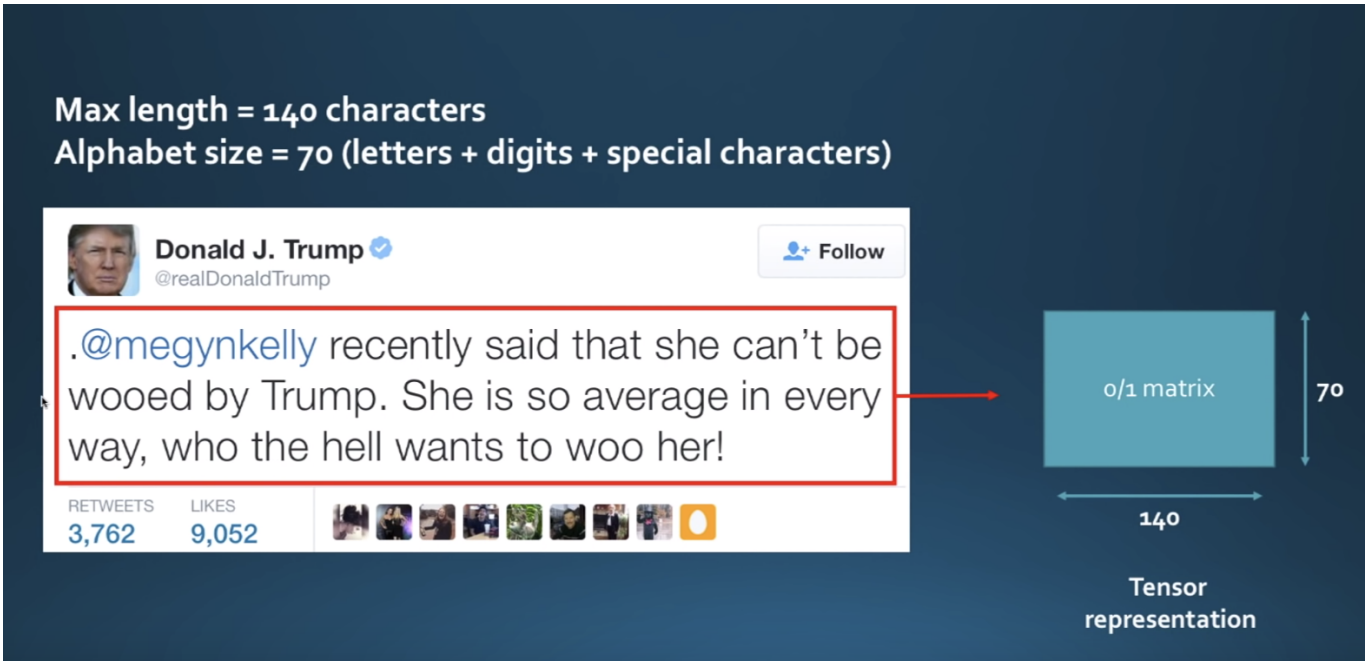
Now that the data is collected, we're ready to train a sentiment classifier to predict the labels we defined earlier.

There is a wide range of possible models to use. The one we'll be training is a character-based convolutional neural network. It's based on this paper and it proved to be really good on text classification tasks such as binary classification of Amazon Reviews datasets.

The question you'd be asking up-front though is the following: how would you use CNNs for text classification? Aren't these architectures specifically designed for image data?

Well, the truth is, CNNs are way more versatile and their application can extend the scope of image classification. In fact, they are also able to capture sequential information that is inherent to text data. The only trick here is to efficiently represent the input text.

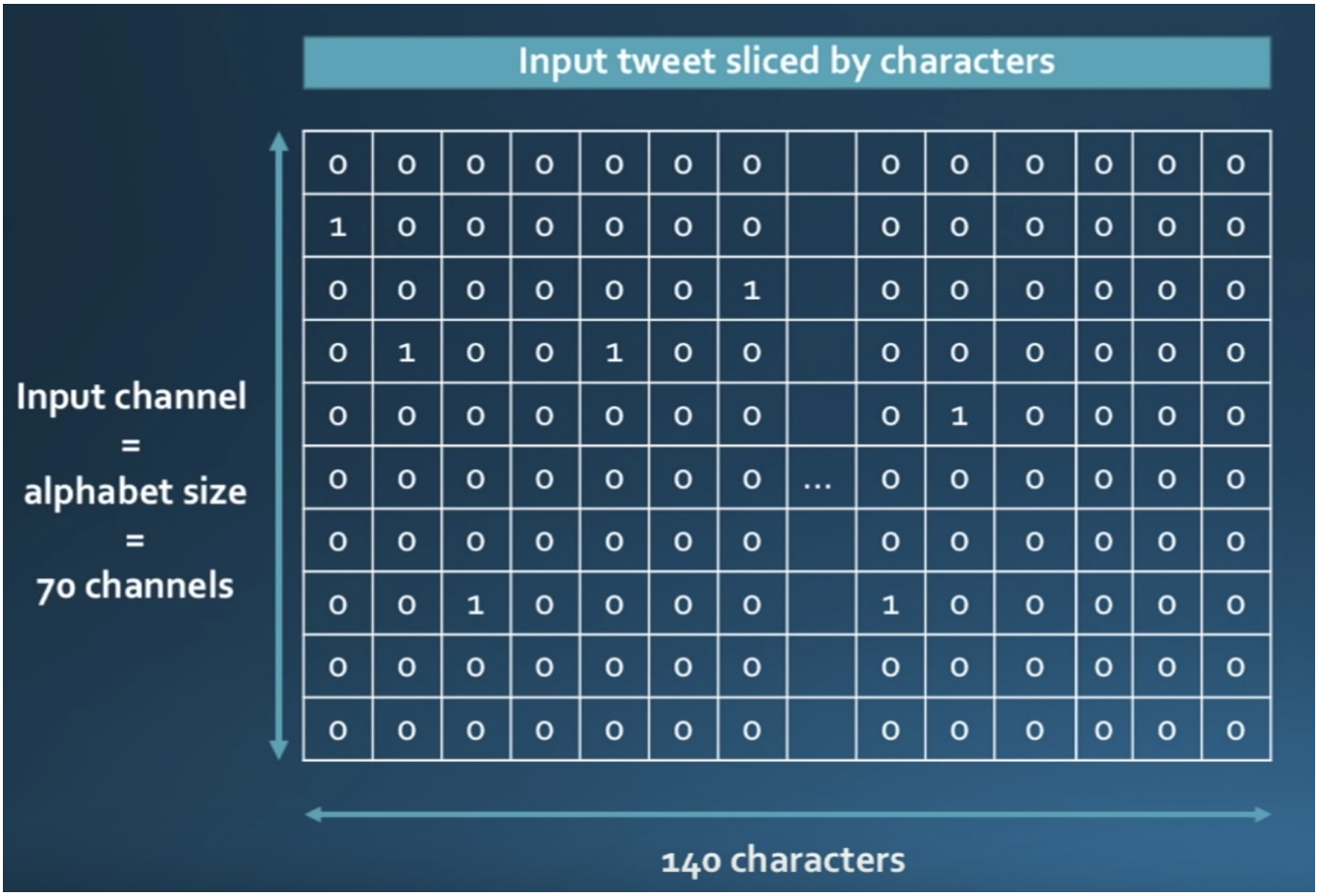
To see how this is done, imagine the following tweet:



Assuming an alphabet of size 70 containing the English letters and the special characters and an arbitrary maximum length of 140, one possible representation of this sentence is a (70, 140) matrix where each column is a one-hot vector indicating the position of a given character in the alphabet and 140 being the maximum length of tweets. This process is called **quantization**.

Note that if a sentence is too long, the representation truncates up to the first 140 characters. On the other hand, if the sentence is too short 0 column vectors are padded until the (70, 140) shape is reached.

So what to do now with this representation?



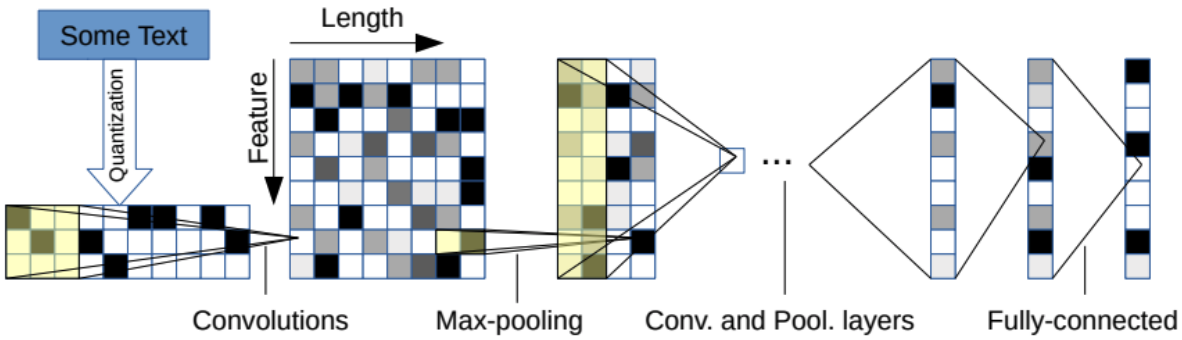
Feed it to a CNN for classification, obviously 😄

But there's a small trick though. Convolutions are usually performed using 2D-shaped kernels because these structures capture the 2D spatial information lying in the pixels. Text is however not suited to this type of convolutions because letters follow each other sequentially, in one dimension only, to form a meaning. To capture this 1-dimensional dependency, we'll use **1D convolutions**.

So how does a 1-D convolution work?

Unlike 2D-convolutions that make a 2D kernel slide horizontally and vertically over the pixels, 1D-convolutions use 1D kernels that slide horizontally only over the columns (i.e. the characters) to capture the dependency between characters and their compositions. You could think for example about a 1D kernel of size 3 as a character 3-gram detector that fires when it detects a composition of three successive letters that is relevant to the prediction.

The diagram below shows the architecture we'll be using:



It has 6 convolutional layers:

Layer	Number of Kernels	Kernel size	Pool
1	256	7	3
2	256	7	3
3	256	3	N/A
4	256	3	N/A
5	256	3	N/A
6	256	3	3

and 2 fully connected layers:

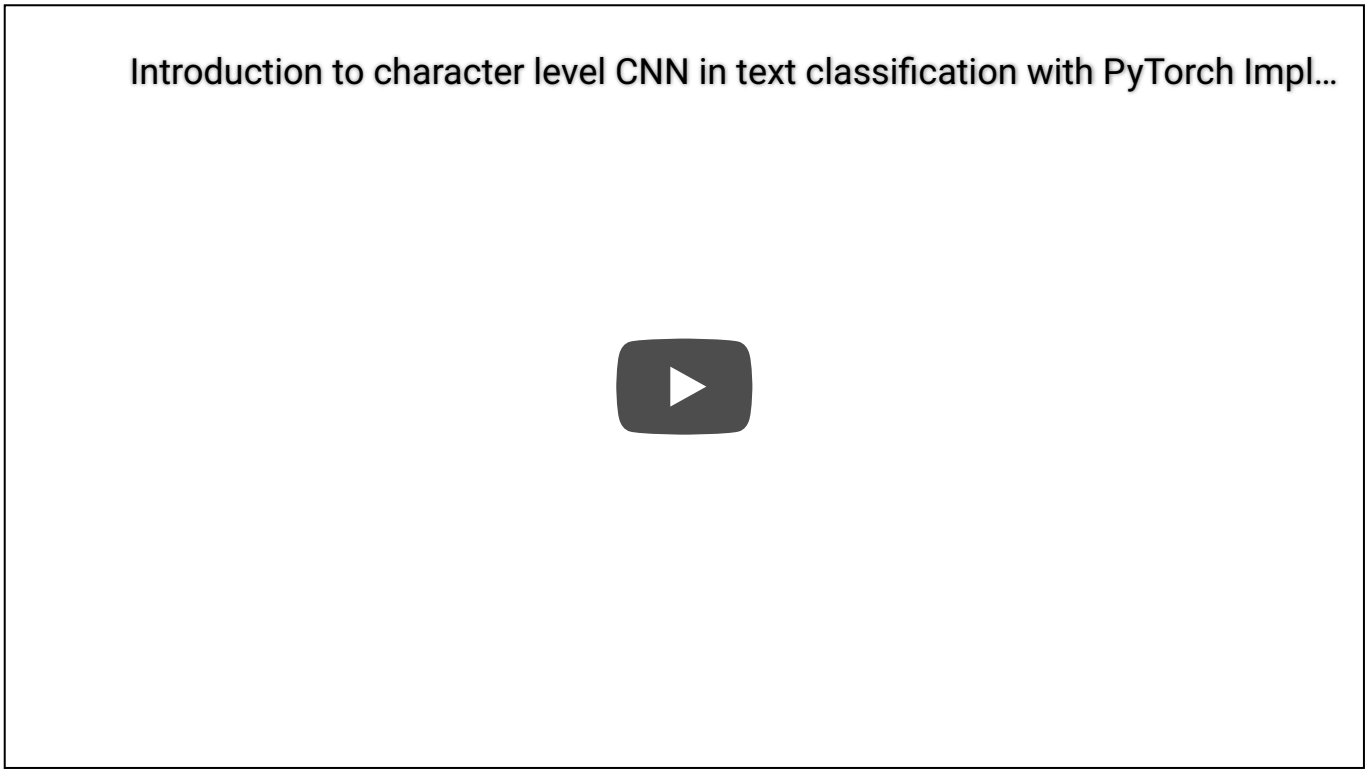
Layer	Number of neurons
7	1024
8	1024

```
9       3
```

On the raw data, i.e. the matrix representation of a sentence, convolutions with a kernel of size 7 are applied. Then the output of this layer is fed to a second convolution layer with a kernel of size 7 as well, etc, until the last Conv layer that has a kernel of size 3.

After the last convolution layer, the output is flattened and passed through two successive fully connected layers that act as a classifier.

To learn more about character level CNN and how they work, you can watch this video



Character CNNs are interesting for various reasons since they have nice properties 💡

- They are quite powerful in text classification (see paper's benchmark) even though they don't have any notion of semantics
- You don't need to apply any text preprocessing (tokenization, lemmatization, stemming …) while using them
- They handle misspelled words and OOV (out-of-vocabulary) tokens

- They are faster to train compared to recurrent neural networks
- They are lightweight since they don't require storing a large word embedding matrix. Hence, you can deploy them in production easily

That's all about the theory now!

How to train the model using PyTorch 🔥

In order to train a character level CNN, you'll find all the files you need under the `src/training/` folder.

Here's the structure of the code inside this folder:

`train.py` : used for training a model
`predict.py` : used for the testing and inference

src: a folder that contains:

- `model.py` : the actual CNN model (model initialization and forward method
- `dataloader.py` : the script responsible for passing the data to the training after processing
- `utils.py` : a set of utility functions for text preprocessing (URL/hashtag/user_mention removal)

To train our classifier, run the following commands:

```
cd src/training/

python train.py --data_path ./data/tp_amazon.csv \
                --validation_split 0.1 \
                --label_column rating \
                --text_column comment \
                --max_length 1014 \
                --dropout_input 0 \
                --group_labels 1  \
                --balance 1 \
                --ignore_center 0 \
                --model_name en_trustpilot \
                --log_every 250
```

e2e_11.sh hosted with ❤️ by GitHub view raw

When it's done, you can find the trained models in `src/training/models` directory.

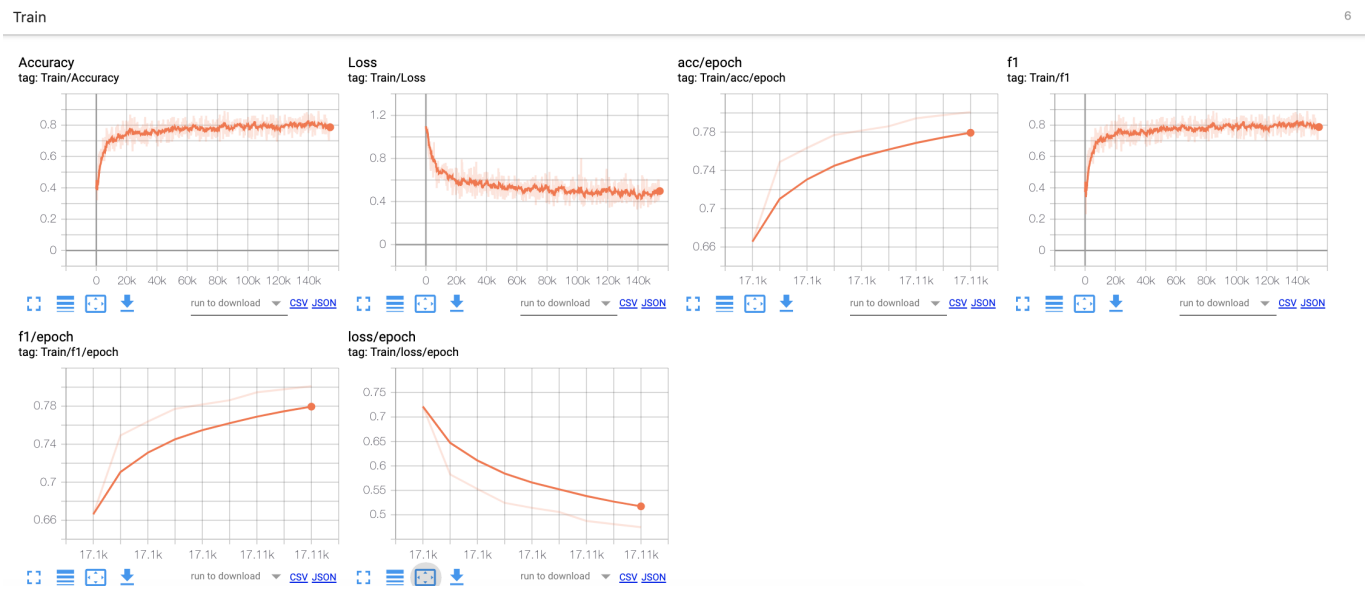
Model performance 🎯

On training set

On the training set we report the following metrics for the best model (epoch 5):

```
Training on Epoch 4
Average loss: 0.5142003893852234
Average accuracy: 0.7816822002923977
F1 score: 0.7817934777867804

              precision    recall  f1-score   support

           0       0.79      0.78      0.78    729594
           1       0.69      0.70      0.70    729605
           2       0.87      0.87      0.87    729601

    accuracy                           0.78   2188800
   macro avg       0.78      0.78      0.78   2188800
weighted avg       0.78      0.78      0.78   2188800
```

Here are the corresponding Tensorboard training logs:

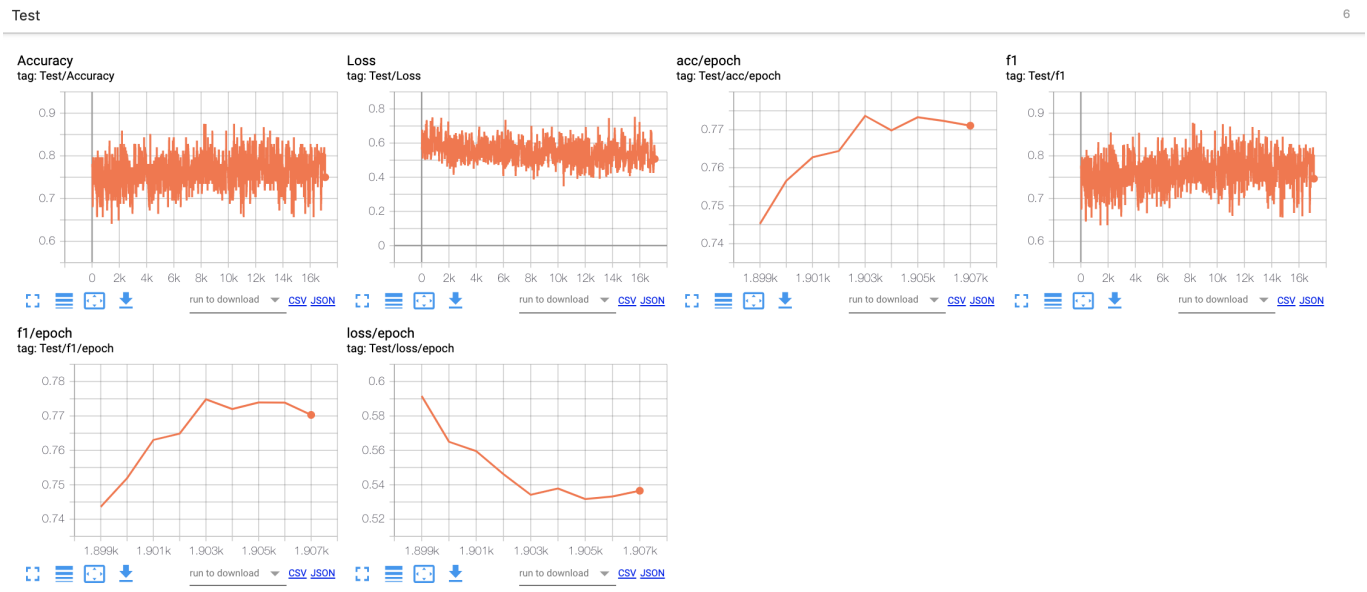


On validation set

On the validation set we report the following metrics for the best model (epoch 5):

```
Validation on Epoch 4
Average loss: 0.534199059009552
Average accuracy: 0.7736636513157895
F1 score 0.7748438459906258

              precision    recall  f1-score   support

           0       0.81      0.73      0.77     81066
           1       0.67      0.74      0.70     81066
           2       0.86      0.86      0.86     81068

    accuracy                           0.77    243200
   macro avg       0.78      0.77      0.77    243200
weighted avg       0.78      0.77      0.77    243200
```

Here are the corresponding validation Tensorboard logs:



• • •

Few remarks according to these figures:

- The model is learning and correctly converging as we see it in the decreasing losses
- The model is very good at identifying good and bad reviews. It has a slightly lower performance on average reviews though. This can be explained by the core nature of these reviews. They are more nuanced in general and easily, even for a human, misinterpreted as bad or good reviews.
- A three-class classification problem is more difficult than a binary one. In fact, if you focus on a binary classification problem, you can reach 95% accuracy. Nevertheless, training a 3 class classifier has the advantage of identifying mitigated reviews which can be interesting.

To learn more about the training arguments and options, please check out the original repo.

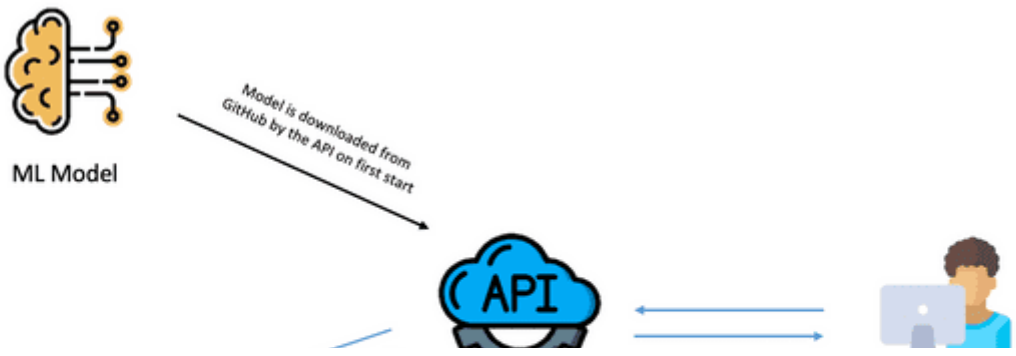
From now on, we'll use the trained model that is saved as a release here. When running the app for the first time, it'll get downloaded from that link and locally saved (in the container) for the inference.

3 — Building an interactive web app 📲 with Dash, Flask, and PostgreSQL

The dash code can be found here and the API code here

Now that we have trained the sentiment classifier, let's build our application so that end-users can interact with the model and evaluate new brands.

Here is a schema of our app architecture:



As you can see, there are four building blocks in our app:

- A visualization application built using Dash.
- A Flask REST API.
- A PostgreSQL database
- Our trained Machine Learning model.

The Dash app will make HTTP requests to the Flask API, which will, in turn, interact with either the PostgreSQL database by writing or reading records to it or the ML model by serving it for real-time inference.

If you are already familiar with Dash, you know that it is built on top of Flask. So we could basically get rid of the API and put everything within the dash code.

We chose not to for a very simple reason: **it makes the logic and the visualization parts independent**. Indeed, because we have a separated API, we can with very little effort to replace the Dash app with any other frontend technology or add a mobile or desktop app.

Now, let's have a closer look at how those blocks are built.

PostgreSQL Database

Nothing fancy or original regarding the database part. We chose to use one of the most widely used relational databases: PostgreSQL.

To run a PostgreSQL database for local development, you can either download PostgreSQL from the official website or, more simply, launch a Postgres container using Docker:

```
docker pull postgres
docker run --name postgres -e POSTGRES_USER=postgres -e
POSTGRES_PASSWORD=password -e POSTGRES_DB=postgres -p 5432:5432 -d
postgres
```

If you are not familiar with docker yet, don't worry, we'll talk about it very soon.

The two following commands allow to:

- pull a Postgres Docker image from Docker Hub
- run this image in a container

Flask API

The RESTful API is the most important part of our app. It is responsible for the interactions with both the machine learning model and the database.

Let's have a look at the routes needed for our API:

- Sentiment Classification: `POST /api/predict`
- Create a review: `POST /api/review`
- Get reviews: `GET /api/predicts`

Sentiment Classification Route

`POST /api/predict`

This route used to predict the sentiment based on the review's text.

Body:

```
{
    "review": "I hate this brand..."
}
```

Response:

```
0.123
```

As you can see, this route gets a text field called `review` and returns a sentiment score based on that text.

It starts by downloading the trained model from Github and saving it to disk. Then it loads it and passes it to GPU or CPU.

When the API receives an input review it passes it to the `predict_sentiment` function. This function is responsible for representing the raw text in a matrix format and feeding it to the model.

```
from ml.model import CharacterLevelCNN
from ml.utils import predict_sentiment

model_name = 'model_en.pth'
model_path = f'./ml/models/{model_name}'
model = CharacterLevelCNN()

# download the trained PyTorch model from Github
# and save it at src/api/ml/models/
# this is done at the first run of the API

if model_name not in os.listdir('./ml/models/'):
    print(f'downloading the trained model {model_name}')
    wget.download(
        "https://github.com/ahmedbesbes/character-based-cnn/releases/download/english/mo
        out=model_path
    )
else:
    print('model already saved to api/ml/models')

#####

# load the model
# pass it to GPU / CPU

if torch.cuda.is_available():
    trained_weights = torch.load(model_path)
else:
    trained_weights = torch.load(model_path, map_location='cpu')
```

```
    trained_weights = torch.load(model_path, map_location='cpu')
model.load_state_dict(trained_weights)
model.eval()
print('PyTorch model loaded !')

#####

@api.route('/predict', methods=['POST'])
def predict_rating():
    '''
    Endpoint to predict the rating using the
    review's text data.
    '''
    if request.method == 'POST':
        if 'review' not in request.form:
            return jsonify({'error': 'no review in body'}), 400
        else:
            parameters = model.get_model_parameters()
            review = request.form['review']
            output = predict_sentiment(model, review, **parameters)
            return jsonify(float(output))
```

e2e_12.py hosted with ❤️ by GitHub view raw

Create Review

`POST /api/review`

This route is used to save a review of the database (with associated ratings and user information).

Body:

```
{
    "review": "I hate this brand...",
    "rating": 2,
    "suggested_rating": 1,
    "sentiment_score": 0.123,
    "brand": "Apple",
    "user_agent": "Mozilla/...",
    "ip_address": "127.0.0.1"
}
```

Response:

```
{
  "id": 123,
  "review": "I hate this brand...",
  "rating": 2,
  "suggested_rating": 1,
  "sentiment_score": 0.123,
  "brand": "Apple",
  "user_agent": "Mozilla/...",
  "ip_address": "127.0.0.1"
}
```

In order to interact with the database, we will use the Object Relational Mapping (ORM) peewee. It lets us define the database tables using python objects, and takes care of connecting to the database and querying it.

This is done in the `src/api/db.py` file:

```
import peewee as pw
import config

db = pw.PostgresqlDatabase(
    config.POSTGRES_DB,
    user=config.POSTGRES_USER,
    password=config.POSTGRES_PASSWORD,
    host=config.POSTGRES_HOST,
    port=config.POSTGRES_PORT
)

class BaseModel(pw.Model):
    class Meta:
        database = db

# Table Description
class Review(BaseModel):

    review = pw.TextField()
    rating = pw.IntegerField()
    suggested_rating = pw.IntegerField()
    sentiment_score = pw.FloatField()
    brand = pw.TextField()
```

```
    user_agent = pw.TextField()
    ip_address = pw.TextField()

    def serialize(self):
        data = {
            'id': self.id,
            'review': self.review,
            'rating': int(self.rating),
            'suggested_rating': int(self.suggested_rating),
            'sentiment_score': float(self.sentiment_score),
            'brand': self.brand,
            'user_agent': self.user_agent,
            'ip_address': self.ip_address
        }

        return data

# Connection and table creation
db.connect()
db.create_tables([Review])
```

e2e_13.py hosted with ❤️ by GitHub view raw

Having done all this using peewee makes it super easy to define the API routes to save and get reviews:

```
import db

@api.route('/review', methods=['POST'])
def post_review():
    '''
    Save review to database.
    '''
    if request.method == 'POST':
        expected_fields = [
            'review',
            'rating',
            'suggested_rating',
            'sentiment_score',
            'brand',
            'user_agent',
            'ip_address'
        ]
        if any(field not in request.form for field in expected_fields):
```

```
            return jsonify({'error': 'Missing field in body'}), 400

        query = db.Review.create(**request.form)
        return jsonify(query.serialize())
```

e2e_14.py hosted with ❤️ by GitHub view raw

Get Reviews

`GET /api/reviews`

This route is used to get reviews from the database.

Response:

```
[
    {
    "id": 123,
    "review": "I hate this brand...",
    "rating": 2,
    "suggested_rating": 1,
    "sentiment_score": 0.123,
    "brand": "Apple",
    "user_agent": "Mozilla/...",
    "ip_address": "127.0.0.1"
    }
]
```

Similar to what we have done for the route `POST /api/review`, we use peewee to query the database. This makes the route's code quite simple:

```
@api.route('/reviews', methods=['GET'])
def get_reviews():
    '''
    Get all reviews.
    '''
    if request.method == 'GET':
        query = db.Review.select()
        return jsonify([r.serialize() for r in query])
```

e2e_15.py hosted with ❤️ by GitHub view raw

Dash front-end

Dash is a visualization library that allows you to write HTML elements such as divs, paragraphs, and headers in a python syntax that gets later rendered into React components. This allows great freedom to those who want to quickly craft a little web app but don't have front-end expertise.

Dash is easy to grasp. Here's a small hello world example:

```python
# -*- coding: utf-8 -*-
import dash
import dash_core_components as dcc
import dash_html_components as html

external_stylesheets = ['https://codepen.io/chriddyp/pen/bWLwgP.css']

app = dash.Dash(__name__, external_stylesheets=external_stylesheets)

app.layout = html.Div(children=[
    html.H1(children='Hello Dash'),

    html.Div(children='''
        Dash: A web application framework for Python.
    '''),

    dcc.Graph(
        id='example-graph',
        figure={
            'data': [
                {'x': [1, 2, 3], 'y': [4, 1, 2], 'type': 'bar', 'name': 'SF'},
                {'x': [1, 2, 3], 'y': [2, 4, 5], 'type': 'bar', 'name': u'Montréal'},
            ],
            'layout': {
                'title': 'Dash Data Visualization'
            }
        }
    )
])

if __name__ == '__main__':
    app.run_server(debug=True)
```

e2e_16.py hosted with ❤ by GitHub view raw

As you see, components are imported from `dash_core_components` and `dash_html_components` and inserted into lists and dictionaries, then affected to the `layout` attribute of the dash `app`. If you're experienced with Flask, you'll notice some similarities here. In fact, Dash is built on top of Flask.

Here's what the app looks like in the browser when you visit: localhost:8050

Source

Pretty neat right?

Dash allows you to add many other UI components very easily such as buttons, sliders, multi selectors, etc. You can learn more about dash-core-components and dash-html-components from the official documentation.

In our app, we also used dash bootstrap components to make the UI mobile responsive.

Callbacks

To make these components interact with each other, dash introduced the concept of `callback`. Callbacks are functions that get called to affect the appearance of an HTML

element (the **Output**) every time the value of another element (the **Input**) changes. Imagine the following situation: you have an HTML input field of id="A" and you want when every time it gets input to copy it inside a paragraph element of id="B", dynamically, without reloading the page.

Here's how you'd do it with a callback:

```
from dash.dependencies import Input, Output

@app.callback(
    [
        Output('A', 'value'),
    ],
    [
        Input('B', 'value')
    ]
)
def copie_from_A_to_B(A_input):
    B_input = A_input
    return B_input
This
```

e2e_17.py hosted with ❤️ by GitHub view raw

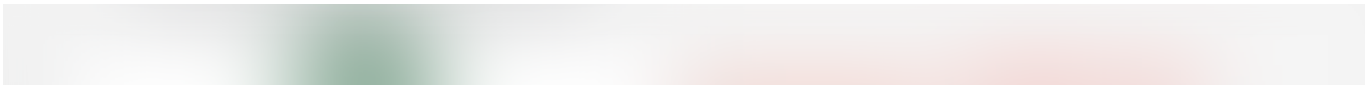
This callback listens to any change of input value inside the element of id A to affect it to the input value of the element of id B. This is done, again, dynamically.

Now I'll let you imagine what you can do with callbacks when you can handle many inputs to outputs and interact with other attributes than `value`. You can learn more about callbacks here or here.

. . .

Now back to our app!

Here's what it looks like. Each red arrow indicates the id of each HTML element.



These elements obviously interact with each other. To materialize this, we defined two callback functions which can be visualized in the following graph.

Callback 1

At every change of the input value of the text area of id `review`, the whole text review is sent through an HTTP post request to the API route `POST /api/predict/` to receive a sentiment score. Then this score is used by the callback to update the value (in percentage) inside the progress bar (proba), the length and the color of the progress bar again, the rating from 1 to 5 on the slider, as well as the state of the submit button (which is disabled by default when no text is present inside the text area.) What you'll have out of all this is a dynamic progress bar that fluctuates (with color code) at every change of input as well as a suggested rating from 1 to 5 that follows the progress bar.

Here's how you'd do it in code:

```
@app.callback(
    [
        Output('proba', 'children'),
        Output('progress', 'value'),
        Output('progress', 'color'),
        Output('rating', 'value'),
        Output('submit_button', 'disabled')
    ],
    [Input('review', 'value')]
)
def update_proba(review):
    if review is not None and review.strip() != '':
        response = requests.post(
            f"{config.API_URL}/predict", data={'review': review})
        proba = response.json()
        proba = round(proba * 100, 2)
```

```
        suggested_rating = min(int((proba / 100) * 5 + 1), 5)
        text_proba = f"{proba}%"

        if proba >= 67:
            return text_proba, proba, 'success', suggested_rating, False
        elif 33 < proba < 67:
            return text_proba, proba, 'warning', suggested_rating, False
        elif proba <= 33:
            return text_proba, proba, 'danger', suggested_rating, False
    else:
        return None, 0, None, 0, True
```

e2e_18.py hosted with ❤️ by GitHub view raw

Callback 2

This callback does two things.

1. When the `submit_button` is clicked, it inserts a row in the database (through the API). The row contains the current data of the brand being reviewed (brand name, review, sentiment, etc) as well as the user agent and the user IP. Then it randomly changes the brand by switching the name, the logo and the URL, and resetting the review textarea.
2. You can also change the brand without submitting the review to the database, by clicking on the `switch_button` instead.

Here's the code:

```
@app.callback(
    [
        Output('company_logo', 'src'),
        Output('company_name', 'children'),
        Output('review', 'value'),
        Output('company_link', 'href')
    ],
    [
        Input('submit_button', 'n_clicks_timestamp'),
        Input('switch_button', 'n_clicks_timestamp')
    ],
    [
        State('review', 'value')
```

```
        State('review', 'value'),
        State('progress', 'value'),
        State('rating', 'value'),
        State('company_name', 'children')
    ]
)
def change_brand(submit_click_ts, another_brand_click_ts, review_text, score, rating, br
    if submit_click_ts > another_brand_click_ts:
        sentiment_score = float(score) / 100
        ip_address = request.remote_addr
        user_agent = request.headers.get('User-Agent')
        response = requests.post(
            f"{config.API_URL}/review",
            data={
                'review': review_text,
                'rating': rating,
                'suggested_rating': min(int(sentiment_score * 5 + 1), 5),
                'sentiment_score': sentiment_score,
                'brand': brand_name,
                'user_agent': user_agent,
                'ip_address': ip_address
            }
        )

        if response.ok:
            print("Review Saved")
        else:
            print("Error Saving Review")

    random_company = companies.sample(1).to_dict(orient="records")[0]

    company_logo_url = random_company['company_logo']
    if not company_logo_url.startswith('http'):
        company_logo_url = 'https://' + company_logo_url

    company_name = random_company['company_name']
    company_website = random_company['company_website']

    return company_logo_url, company_name, '', company_website
```

e2e_19.py hosted with ❤️ by GitHub view raw

We'll skip the definition of the dash app layout. You can check it directly from the source code on the repo.

If you have any question you can ask it, as always, in the comment section below ⬇.

4 — Dockerizing the application with Docker Compose 🐳

Now that we have built our app, we're going to deploy it. But it's actually easier said than done. Why?

Well, installing all our dependencies (Flask, Peewee, PyTorch, and so on…) can be tedious, and this process can differ based on the host's OS (yours or any other cloud instance's). We also need to install a PostgreSQL database, which can be laborious as well. Not to mention the services that you have to manually create to run all the processes.

Wouldn't it be nice to have a tool that takes care of all this? Here is where Docker comes in.

Docker is a popular tool to make it easier to build, deploy and run applications using containers. Containers allow us to package all the things that our application needs like such as libraries and other dependencies and ship it all as a single package. In this way, **our application can be run on any machine and have the same behavior**.

Docker also provides a great tool to manage multi-containers applications: **docker-compose**. With Compose, you use a YAML file to configure your application's services. Then, with a single command, you create and start all the services from your configuration.

Here is an example of a simple Docker Compose that runs two services (`web` and `redis`):

```
version: '3'
services:
  web:
    build: .
    ports:
      - "5000:5000"
  redis:
    image: "redis:alpine"
```

e2e_20.yml hosted with ❤️ by GitHub view raw

To learn more about Docker and Docker Compose, have a look at this great tutorial

. . .

Let's see now how we dockerized our app.

First of all, we separated our project into three containers, each one is responsible for one of the app's services

- **`db`**
- **`api`**
- **`dash`**

To manage these containers we'll use, as you expect, Docker Compose.

Here's our docker-compose.yml file, located at the root of our project:

```
version: '3'
services:
  db:
    image: postgres
    environment:
      - POSTGRES_DB=postgres
      - POSTGRES_USER=postgres
```

```
      - POSTGRES_PASSWORD=password
    volumes:
      - ~/pgdata:/var/lib/postgresql/data
    restart: always
  api:
    build:
      context: src/api
      dockerfile: Dockerfile
    environment:
      - ENVIRONMENT=prod
      - POSTGRES_HOST=db
      - POSTGRES_PORT=5432
      - POSTGRES_DB=postgres
      - POSTGRES_USER=postgres
      - POSTGRES_PASSWORD=password
    depends_on:
      - db
    restart: always
  dash:
    build:
      context: src/dash
      dockerfile: Dockerfile
    ports:
      - "8050:8050"
    environment:
      - ENVIRONMENT=prod
      - API_URL=http://api:5000/api
    depends_on:
      - api
    restart: always
```

e2e_21.yml hosted with ❤️ by GitHub view raw

Let's have a closer look at our services.

- **db**

To manage the database service, docker-compose first pulls an official image from the Postgres dockerhub repository

```
db:
  image: postgres # official postgres image
  environment:
```

```
      - POSTGRES_DB=postgres
      - POSTGRES_USER=postgres
      - POSTGRES_PASSWORD=password
    volumes:
      - ~/pgdata:/var/lib/postgresql/data
    restart: always
```

e2e_22.yml hosted with ❤️ by GitHub view raw

It then passes connection information to the container as environment variables and maps the `/var/lib/postgresql/data` directory of the container to the `~/pgdata` directory of the host. This allows data persistence.

You can also notice the `restart: always` policy, which ensures that our service will restart if it fails or if the host reboots.

- **`api`**

To manage the API service, docker-compose first launches a build of a custom image based on the Dockerfile located at `src/api`. Then it passes environment variables for the database connection.

```
api:
  build:
    context: src/api
    dockerfile: Dockerfile
  environment:
    - ENVIRONMENT=prod
    - POSTGRES_HOST=db
    - POSTGRES_PORT=5432
    - POSTGRES_DB=postgres
    - POSTGRES_USER=postgres
    - POSTGRES_PASSWORD=password
  depends_on:
    - db
  restart: always
```

e2e_23.yml hosted with ❤️ by GitHub view raw

This service depends on the database service, that has to start before the API. This is ensured by the `depends_on` clause:

```
depends_on:
  - db
```

Now here's the Dockerfile to build the API docker image.

```
FROM python:3

ADD requirements.txt /app/
WORKDIR /app

RUN pip install -r requirements.txt

ADD . /app

EXPOSE 5000

CMD ["gunicorn", "-b", "0.0.0.0:5000", "app:app"]
```

e2e_24.dockerfile hosted with ❤️ by GitHub view raw

When running this file, docker will pull an official python image from Dockerhub, copy a requirements.txt to /app/, install the dependencies using pip, expose a port and run a web server.

Notice that we are using gunicorn instead of just launching the flask app using the `python app.py` command.

Indeed, Flask's built-in server is a development only server, and should not be used in production.

From the official deployment documentation:

When running publicly rather than in development, you should not use the built-in development server (flask run). The development server is provided by Werkzeug for convenience but is not designed to be particularly efficient, stable, or secure.

You can use any python production web server (tornado, gunicorn, …) instead.

- `dash`

For the dash service, similar to what has been done for the API, docker-compose launches a build of a custom image based on the Dockerfile located at `src/dash`. Then it passes two environment variables. One of them is `API_URL`. **Notice that the hostname `API_URL` is the name of the `api` service.**

```
dash:
  build:
    context: src/dash
    dockerfile: Dockerfile
  ports:
    - "8050:8050"
  environment:
    - ENVIRONMENT=prod
    - API_URL=http://api:5000/api
  depends_on:
    - api
  restart: always
```

e2e_25.yml hosted with ❤ by GitHub view raw

To build the image, Docker will be running this file, which is basically the same as the previous one, except for the port.

```
FROM python:3

ADD requirements.txt /app/
WORKDIR /app
RUN pip install -r requirements.txt

ADD . /app

EXPOSE 8050

CMD ["gunicorn", "-b", "0.0.0.0:8050", "app:app.server"]
```

e2e_26.dockerfile hosted with ❤ by GitHub view raw

5 — Deploying to AWS: Demo time 💻

Let's first have a look at the global deployment architecture we designed:

Here's the workflow:

When a user goes to reviews.ai2prod.com from his browser, a request is sent to the DNS server which in turn redirects it to a load balancer. The load balancer redirects its request to an EC2 instance inside a target group. Finally, when docker-compose receives the request on port 8050, it redirects it to the Dash container.

So how did we build this workflow? Below are the main steps.

Deploy the app on an EC2 instance

The very first step to our deployment journey is launching an instance to deploy our app on.

To do this, go to the EC2 page of the AWS Console, and click on the "Launch Instance".

You will need to select an AMI. We used Amazon Linux 2, but you can choose any Linux based instance.

You will then need to choose an instance type. We went for a t3a.large but you could probably select a smaller one.

You will also need to configure a security group so that you can ssh into your instance, and access the 8050 port on which our dash app runs. This is done as follows:

You can finally launch the instance. If you need more explanations on how to launch an EC2 instance you can read this tutorial.

Now that we have our instance, let's ssh into it:

```
ssh -i path/to/key.pem ec2-user@public-ip-address
```

We can then install docker. Below are the installation instructions for Amazon Linux 2 instances. Please refer to the official Docker installation instructions for other OS.

```
sudo yum update -y
sudo amazon-linux-extras install docker
sudo service docker start
sudo usermod -a -G docker ec2-user
```

e2e_27.sh hosted with ❤️ by GitHub view raw

⚠️ You will need to log out and log back in. ⚠️

Then install docker-compose:

```
sudo curl -L "https://github.com/docker/compose/releases/download/1.24.1/docker-compose-$
sudo chmod +x /usr/local/bin/docker-compose
```

e2e_28.sh hosted with ❤️ by GitHub view raw

And test the install

Then clone the git repository:

```
sudo yum install git
git clone https://github.com/MarwanDebbiche/post-tuto-deployment.git
```

e2e_30.sh hosted with ❤️ by GitHub view raw

And finally, run the app:

```
cd post-tuto-deployment
docker-compose up --build -d
```

e2e_31.sh hosted with ❤️ by GitHub view raw

Once it's running, you can access the dashboard from the browser by typing the following address:

We could stop here, but we wanted to use a cooler domain name, a subdomain for this app, and an SSL certificate. These are optional configuration steps, but they're recommended if you want a polished product.

- http://your-ec2-public-DNS:8050

Buy your own domain name

First, you will need to buy a cool domain name. You can choose any domain registrar, but using AWS Route53 will make things easier as we are deploying the app on AWS.

Go the Route53 page of the AWS console, and click on "Domain registration".

Then, follow the domain purchase process which is quite straightforward. The hardest step is finding an available domain name that you like.

Request an SSL certificate using ACM

Once you have purchased your own domain name on Route53, you can easily request an SSL certificate using AWS Certificate Manager.

You will need to enter the list of subdomains that you wish to protect with the certificate (for example `mycooldomain.com` and `*.mycooldomain.com`).

Then, if you registered your domain on Route53, the remainder of the process is quite simple:

- Choose DNS Validation
- Confirm
- Then AWS will offer to automatically create a CNAME record in Route53 to validate the certificate.

According to the documentation, it can then take a few hours for the certificate to be issued. Although from our own experience, it usually doesn't take longer than 30 minutes.

Put the app behind an Application Load Balancer

Load balancers are, as their names suggest, usually used to balance the load between several instances. However, in our case, we deployed our app to one instance only, so we didn't need any load balancing. In fact, we used an AWS ALB (Application Load Balancer) as a reverse proxy, to route the traffic from HTTPS and HTTP ports (443 and 80 respectively) to our Dash app port (8050).

To create and configure your Application Load Balancer go to the Load Balancing tab of the EC2 page in the AWS console and click on the "Create Load Balancer" button:

Then you will need to select the type of load balancer you want. We won't go into too many details here, but for most use-cases, you will need an Application Load Balancer.

Then you will have to:

- Give a name the load balancer
- Select the “internet-facing” scheme
- Add listeners for both HTTP and HTTPS
- Select the Availability Zones to enable for your load balancer (if in doubt you can select them all)

As you added an HTTPS listener, you will be asked to select or import a certificate. Select the one you requested using ACM:

Then you will need to configure the security groups for your ALB. Create a new security group for your load balancer, with ports 80 (HTTP) and 443 (HTTPS) opened.

Once this is done, remains the final step: creating your target group for your load balancer.

To do that you will need to specify the port on which the traffic from the load balancer should be routed. In our case this is our Dash app's port, 8050:

Now you can add the EC2 instance on which we deployed the app as a registered target for the group:

And, here it is, you can finally create your load balancer.

You can test it by going to your-load-balancer-dns-name-amazonaws.com. you should see your app!

BUT, despite the fact that we have used the certificate issued by ACM, it still says that the connection is not secure!

Don't worry, that's perfectly fine. If you remember correctly, the certificate we requested protects `mycooldomain.com`, not `your-load-balancer-dns-name-amazonaws.com`.

So we need to create a record set in Route53 to map our domain name to our load balancer. We will see how to do that very soon.

But before that, we will already put in place a redirection from HTTP to HTTPS in our load balancer. This will ensure that all the traffic is secured when we will finally use our domain.

To do that, you need to edit the HTTP rule of your Application Load Balancer:

Click on the pen symbols:

Delete the previous action (`Forward to`) and then add a new `Redirect to` action:

Finally, select the HTTPS protocol with port 443, and update your rule.

You should now be automatically redirected to https://your-load-balancer-dns-name-amazonaws.com when accessing http://your-load-balancer-dns-name-amazonaws.com

Create a record set in Route53

A Route53 record set is basically a mapping between a domain (or subdomain) and either an IP address or an AWS asset. In our case, our Application Load Balancer. This record will then be propagated in the Domain Name System so that a user can access our app by typing the URL.

To create a record set go to your hosted zone's page in Route53 and click on the `Create Record Set` button:

You will have to:

- Type the subdomain name, or leave it empty if you wish to create a record set for the naked domain
- Select "Yes" for the `Alias` option
- You should be able to select your application load balancer in the `Alias Target` list

And you will soon be able to access the app using your custom domain address (DNS propagation might usually take about an hour).

One last thing that you might want to do is to either redirect traffic from `yourcooldomain.com` to `www.yourcooldomain.com`, or the other way around. We chose to redirect `reviews.ai2prod.com` to www.reviews.ai2prod.com

We won't go into many details here but here is how to do that:

- Create a new application load balancer. It will only be in charge of redirecting to your app's main URL so you don't need to register any instance in its target group.
- Modify HTTP and HTTPS listeners to redirect to your app's main URL
- Create a record set in Route53 to map the subdomain you wish to redirect your traffic from, to this new ALB

Here is a schema representing how everything works in the end:

6 — Next steps 🛠️

When building this application, we thought of many improvements that we hadn't the time to successfully add.

In particular, we wanted to:

- Add server-side pagination for Admin Page and `GET /api/reviews` route.
- Protect admin page with authentication.
- Either use Kubernetes or Amazon ECS to deploy the app on a cluster of containers, instead of on one single EC2 instance.
- Use continuous deployment with Travis CI
- Use a managed service such as RDD for the database

7 — Conclusion 👋

Throughout this tutorial, you learned how to build a machine learning application from scratch by going through the data collection and scraping, model training, web app development, docker and deployment.

Every block of this app is independently packaged and easily reusable for other similar use cases.

We're aware that many improvements could be added to this project and this is one of the reasons we're releasing it. So if you think of any feature that could be added don't hesitate to fork the repo and create a pull request. If you're also facing an issue running the app do not hesitate to report it. We'll try to fix the problem as soon as possible.

That's all folks! 🎉

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