Introduction

Seeing Paris nowadays is within reach after a quick Google Maps search. Imagine, however, that you could travel back in time and immerse yourself in this city when major socio economic changes inspired a massive effort to capture its essence in photographs. With the goal of providing such experience to the public, we have created a platform where the user can move around the city as it looked like in the 1970s.

Our project was made possible thanks to the amateur photo contest: "C'est etait Paris en 1970". The city was divided in 250m by 250m squares, each assigned to one of the more than fourteen thousand participants tasked with documenting that area through photographs. It took place in May of 1970, and it ultimately produced seventy thousand black and white prints, as well as thirty thousand color slides. We worked with a subset of the contest submissions for this recreation of the aesthetics of the city at that time, as it was the object of this vast photoshoot.

Although we have an extensive dataset, black and white images as well as no sense of location will tamper the realistic experience we are striving for. The use of the available metadata, therefore, becomes crucial for our work. We use the square of Paris where the picture was taken to place them spatially in a map of the city, and we use Machine Learning models to colorize them.

Specifically for the colorization, we used a previously developed model of a convolutional neural network that was trained on the Luminosity channel of the images in Lab color space to predict the color channels a and b.This technique is described by

However, the results of this first colorization did not yield colors that typically represent Paris or the 1970s, which prompt us to work toward personalizing the colorization technique. We extracted the most recurring colors in photos of the city nowadays into what we defined as a color dialect, an array of pixels in the ab color space. Coupled with the starting prediction of the colors, the color dialect can produce results more realistic to what we find in Paris.

Our efforts have resulted in a platform where we can interact with a map of Paris where the squares are clearly delimited. Selecting one of these squares will lead to a gallery with its photographs colorized, as well as any information that is available, such as the name of the photographer or the description they left of the photograph.

Methods

1. Clean images and separate them by squares.

2. Colorize them.

3. Place the resulting images in the map based on their location.

Methods (personalized colorization)

Our objective is to personalize the colorization based on the metadata of the image. Specifically, we wish to colorize given the specific colors of a place. Our approach is described below:

- Create a dataset of photos from the place where the picture was taken (or the place we want it to look like)

- Merge all photos of these dataset into one that highlights the most frequent colors (Not solved yet)

- Extract the color dialect from these photos. We define color dialect as the 224x224 array that contains the most significant colors in the ab color space.

- Train a neural net that will aim to minimize the differences between the color dialect of a place and the color dialect of the image obtained after colorization from the generic model.

Issues so far:

- How to merge all photos while maintaining the information.

How do we extract the color dialect from an image in Lab color space:

- First, we classify the points of the image in the ab space by their distance from the origin. For instance, all values with distance under 1 and over 0.5 will be mapped together.

- We calculate the distance between each point in the same range and save it in a dictionary (currently not efficient enough)

- Now we want to form clusters of points (224x224 for it to be compatible with the dimensions of the ab values predicted by the generic model).

- ab usually ranges from -127 to 128 in both the a and the b channels. Thus, we have a space of 256x256.

- The maximum diameter the clusters can have is 256^2/224^2. Therefore, the radius of the clusters can range from 0 to 0.65.

- We perform binary search to find which radius of the clusters gets us closer to our number of clusters.

- We then calculate the average value of each cluster to culminate with 224x224 values in the ab space as desired.