The FaCells. An Exploratory Study about LSTM Layers on Face Sketches Classifiers

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Abstract—Lines are human mental abstractions. A bunch of lines may form a drawing. A set of drawings can feed an LSTM network input layer, considering each draw as a list of lines and a line a list of points. This paper proposes the pointless motive to classify the gender of celebrities’ portraits as an excuse for exploration in a broad, more artistic sense. Investigation results drove compelling ideas here discussed. The experiments compared different ways to represent draws to be input in a network and showed that an absolute format of coordinates (x, y) was a better performer than a relative one (Δx, Δy) with respect to prior points, most frequent in the reviewed literature. Experiments also showed that, due to the recurrent nature of LSTMs, the order of lines forming a drawing is a relevant factor for input in an LSTM classifier not studied before. A minimum ‘pencil’ traveled length criteria for line ordering proved suitable, possible by reducing it to a TSP particular instance. The best configuration for gender classification appears with an LSTM layer that returns the hidden state value for each input point step, followed by a global average layer along the sequence, before the output dense layer. That result guided the idea of removing the average in the network pipeline and return a per-point attribute score just by adjusting tensors dimensions. With this trick, the model detects an attribute in a drawing and also recognizes the points linked to it. Moreover, by overlapping filtered lines of portraits, an attribute's visual essence is depicted. Meet the FaCells.

I. INTRODUCTION

“A line is a dot that went for a walk,” a quote by Paul Klee from the early 20th century, introduces an idea this study tries to explore.

The line is arguably one of the oldest forms of human abstractions. Possibly originated by the need for visual communication in the prehistoric ages as marks on a surface, line drawing was an efficient means to convey useful information about the real world, the first visual record of human actions beyond the moment they happened. People nowadays communicate with each other through a written language that was once essentially just a bunch of lines on a surface, writing and reading letters and words. Over the centuries, what we could call more 'realistic' ways of expression, such as painting, then photograph, and then cinema, took over line-drawing the role of a principal visual medium to depict and communicate scenes,
objects, or faces as here. In the digital era, photo and video camera development contributed to disregarding the idea of representing something from the real world as a sketch, e.g., SVG format, preserving lines’ essential nature.

This study centers on lines that form draws. As Paul Klee stated, they are just points moving on a plane—or evolving in time. If so, a sketch may live stored as a series of simple instructions: move over there, move over there, on, and off, the required input for reproducing it. While so efficiently and lightly represented, draws have the power to form in our brains—through our eyes—shapes, objects, symbols, and even words that can express almost everything expressible.

The drawings adorning the following sections were born from learning portraits of celebrities, obtained by ‘drawing’ the images from CelebA [1], a dataset with more than 260K photos labeled by 40 attributes. To ‘draw’ them, to convert from raster to vectorial format, an adaptation of this fantastic tool produced the lines by an iterative reconstruction of a Canny border detection algorithm output. Figure 2 shows some celebrities’ headshots with their portrait sketches.

Evolution trained us strong to detect faces visually. A parent’s face is one of the first things we can identify with our sight. In our culture, faces are the visual reduction of ourselves, what presents us, our ids. Facial expressions enrich the toolset we use to communicate effectively with other humans—and some mammals, like dogs and cats. We see faces everywhere, even where we know there are no, and we have fun with that.

To learn about faces and their characteristics, the main experiment here presented concerns a peculiar objective: to classify the face sketches by gender as a binary target (attribute variable named noMale in [1]). While almost perfectly balanced in labeled data, nearly 50% of each gender, this classification is mostly pointless since the notion of gender has shifted long ago towards a non-binary concept, to mention one drawback among others. Selecting an absurd target for classification frees us from wasting time finding the best possible classifier to focus more on studying the model components and the data representation, the main objects of study.

Here, line-drawing refers essentially to a set of lines, and a line to a set of points, generally on a plane. Line-drawings are not direct input of deep neural networks due to the variable nature of both sets’ cardinality, the variable number of lines in a draw, and points in a line. Typically, the approach concatenates lines into one long array and creates a convention for elements indicating that a line ends and the next line begins. This conversion allows sequential processing of input with one-dimension variable length, as in LSTM networks.

When a line-drawing inputs an LSTM network, the line order usually follows the original order given by a human drawer. However, sometimes that is unavailable, as here where an algorithm constructed the drawings from photos. Any

Figure 2. Artificial sketch-based portraits paired with their original face images.

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1 https://github.com/LingDong/-linedraw
2 https://www.boredpanda.com/objects-with-faces
particular way of sorting should not make any difference when considering a line-drawing a static concept and not performatic (no one is drawing live one line at the time). Still, it should matter for LSTMs due to their architecture’s recursive nature, as the order of words or sentences matters when learning a piece of text.

Furthermore, an order-free line concatenation has a problem frequently observed in other mathematical modeling fields, e.g., genetic algorithms optimization. Many different representations—genotypes—designate the same individual—phenotype. A line-drawing having n lines converts into n! different representations. The many-to-one association makes inefficient search and exploration processes of the vast space generated. The adoption of a particular way of sorting lines resolves this difficulty. The experiment evaluates the convenience of sorting the lines by a minimum total length criterion, i.e., the shortest traveled euclidean distance by a hypothetical pencil measured not only while drawing but also while going from a line end to a new line start.

Besides line sorting, experiments also tested another significant point related to representation, whether it was better for learning to follow an absolute or a relative coordinate system, the later meaning a point defined with respect to the prior point in the sequence, most frequent in the literature.

The exploration later examines LSTM networks and their layers with a generative mindset, following the excuse of gender classification. Training observed results pointed to a network configuration which, with a few tweaks in its tensors’ dimensions, achieves to return a gender score per point in the drawing, besides a global gender score—our pretext. A fun discovery was to use the model to recognize in one portrait male and noMale lines, whatever that means, finding a fascinating, expressive way of synthesizing the attributes: the FaCells.

Following this intro, a section reviews some related work found and credit sources of inspiration. Section III specifies some experiments to provide insights about raised questions about the representation, the sorting of lines, and the configurations when training an LSTM model. Section IV reports the results obtained. Those introduce the FaCells, discussed in Section V, and other imaginative results implications in VI. Portion of the code and data is available at 3.

II. RELATED WORK AND SOURCES OF INSPIRATION

A foundational paper and art piece was Portrait Drawing by the painter Klee [2]. Perhaps named by the painter Klee, Paul is a robotic installation that produces portraits of people by processes that mimic drawing skills and technique. Paul does not have high-level knowledge of the human face’s structures (such as the mouth, nose, eyes). Instead, it processes digitized photographs rather than develop generative models of vector images. One motivation to perform this study comes from playing around with an XY Plotter—or pen plotter—a robotic arm with a writing instrument in its hand, the enriching path of building my own Paul.

Regarding works exploring generative models of lines, there is [3], where an LSTM model is used to synthesize realistic cursive handwriting in various styles. Also, introduced in [4], sketch-RNN is an awe-inspiring framework to construct stroke-based drawings of common objects. Some works that studied obtaining drawings from photos are [5] and [6]. In particular, the authors in [7] studied the style abstraction in portrait sketching. The reverse-path, obtaining a realistic synthetic photo from a drawing input, was resolved in SketchyGAN [8]. The photos dataset and the idea to detect attributes come from [1] via this essential book [9].

III. METHODS AND EXPERIMENTS

A. Representation

A central matter is the proper representation of line draws for training LSTM networks, the suitable data format to input the draws into the model. The experiment compares the training of models in which the input data is differently encoded. The first format to evaluate is an adaptation of the one used in [4], which was adapted from [3]. According to this format, the origin of coordinates locates at the center of the portrait sketch, and each point consists of 3 elements: (Ax, Δy, p). The first two are the offset distance in the x and y directions from the previous point. The last element represents three possible states: (1, 0, -1), indicating the beginning, continuation, and end of a line, respectively. This way of representing draws, here called relative, is suitable for representing drawings of diverse nature, and they must be invariant to scale or position in the canvas. Alternatively, a format with an absolute definition of points may be more suitable for learning, in cases where the sketches are aligned and scaled, as in this case, since each element of the face sketch—e.g., eyes, mouth, hair—approximately locates in the same canvas region. This format defines a draw as a list of points (x, y, p), where x-y are the absolute coordinates, and p represents the position along a line, same as before.

Besides the format to specify a point on a line—absolute or relative—the experiment also compares two data instances addressing the question regarding the ordering of lines in a draw. In the first instance, named unsorted, lines in each draw were sorted randomly. In the second one, named sorted, the given line order was to the one that leads to the minimum total length, optimizing the distance traveled by a hypothetical plotter. This evaluated criterion for data preprocessing seeks that the lines that make up the same visual element in a face draw—i.e., eyebrows, chin—remain close throughout the representation. The experiment compares the gender classification model training with sorted and unsorted data instances.

A special note deserves the task of finding the line order in which the total length is minimum. It is an np-hard problem, in this case, with n from 100 to 1000, the line number approximate range, to be solved more than 200K times, once per line-drawing observation. A reduction to a particular instance of the Traveling Salesman Problem and the use of Google's OR-Tools [10] made it possible to complete the job in an acceptable time.

3 http://www.columbia.edu/~xig2000/FaCells
B. LSTM configurations

Besides representation, the experiment explores different bidirectional LSTM network configurations for classifying face portraits by gender. This family of models—LSTMs—was selected for study based mainly on the architecture of the encoder-half of the network presented in [4]. The exploration goal is not to find the best LSTM classifier. Instead, it is to investigate what trained LSTM networks can give us to understand line-drawings.

The study reports the training of models with different structural complexity levels, as characterized by two factors: the number of LSTM layers in the network and the number of cells in the last dense layer before the output. Trained configurations take the following nomenclature. The prefix 1bi (3bi) names a network composed—following the input layer—by 1 LSTM with 256 cells (a series of 3 LSTM layers with 150 cells each). Configuration ‘names’ ended by 1d (d40), designate networks containing one fully-connected output layer (one fully-connected layer with 40 cells before one fully-connected output layer). Letters fs and ga designate a component of the last LSTM layer, whether it returns final state values of each cell (fs) or the sequence of hidden state values for each input point, and the sequence is globally averaged and passed to the dense layer (ga), i.e., the area under the curve of the same length as the input drawing. This feature turned out the spark that gave life to the FaCells.

IV. RESULTS

Training report divides into stages: I, II, III. Stage I details the training of approximately 30% of the drawings (~60K) randomly selected for training and 15% for testing. Figure 3 shows ten epochs of training performance in terms of binary-cross-entropy. The absolute-sorted input data format outperforms the other three, which accomplish evenly on a minor level. Regarding network configurations, those tuned with the ga feature achieve better than those with fs. Considering the absolute-sorted input data format, the best performer configurations are 3bi-ga-d1, 3bi-ga-d40, and 1bi-ga-d40, with a cross-entropy at tenth epoch of 0.3328, 0.3348, and 0.3484, respectively. They pass to the next stage.

Summarizing stage II, Figure 4 shows ten new epochs of training performance for the three ‘finalist’ configurations. In this stage, the input includes the entire dataset of draws (more than 260K) formatted as absolute-sorted and divided 95-5% for training and testing, respectively. Although all three perform quite similarly, 3bi-ga-d1 is slightly superior, according to the
last epochs’ binary crossentropy loss, where there is a slight difference. The “winning” configuration, 3bi-ga-d1, adjusted for multilabel classification of the 40 binary attributes, is re-trained with all draws in stage III. Figure 5 shows the balanced accuracy achieved after ten new epochs. At 50% of balanced accuracy, a vertical red line marks the minimum performance required for an attribute to deserve a portrait by one FaCell.

V. THE FACELLS

The best performer model to classify face draws by gender gave rise to the idea behind the FaCells. Named 3bi-ga-d1, it has three LSTM layers—150 cells each—that return sequences of the same length as the draws. The last LSTM layer output is averaged among the input length. Then, the 150 averages are linearly combined to calculate the estimation of the probability that the input portrait is either male or noMale. The combination is not exactly linear due to the ReLU activation function, but the idea is still interesting.

Let us pick the cell which weight in the gender probability estimation is maximum from the third LSTM layer. That cell returns a sequence of intermediate values, and the larger the average of those, the greater the probability of no-masculinity, whatever that means. Therefore, each point in the input line-draw can obtain a score closely related to the attribute presence. Then, besides detecting the attribute, this score can also be used to draw it. A modified version of the trained model that has the average operation at the output of the LSTMs removed and adjusted its following dense layer tensors dimensions can return a probability of gender per point of the drawing. It can annotate how masculine a line can be. Interesting.

Figure 6 visualizes what was discussed with four handsome portraits, each annotated with two attributes. The charts that follow trace, in four aligned line-plots, the sketch points coordinates, the intermediate output of an LSTM cell, and two outputs—corresponding to two attributes—from the modified model. A threshold is defined to circumscribe those lines in a drawing associated with each attribute.

Continuing this idea, the FaCells in Figures 1 and in Appendix I are composed by overlapping the points of many portraits which attribute score passed a threshold. The attributes selected for visualization are those performing a binary balanced accuracy > 50%. The labels in Appendix figures follow the form ‘Attribute X-Y’, which means that X draws whose attribute prediction was positive and whose points returned a score greater than threshold Y, sometimes lower than the negative (Y) to represent the contrary attribute. Meet the FaCells.
This study started with the intention to use an XY Plotter as an artistic tool to produce expressive drawings. The plan was—and still is—to generate artificial, physical portraits by a trained GAN similar to [4]. In this exciting journey, some questions were raised and guided some ideas discussed here.

VI. Final Comments

The first idea appears when acknowledging that an absolute-point representation of draws performs in this model better than a relative one. In the former format, a line is described as a sequence of absolute coordinates, in the latter as deltas from previous points. In this study, the portraits came from face photos previously aligned and scaled. Hence, most visual elements in a face, e.g., mouth, hair, nose, chin, has their expected position in the canvas invariant to different portraits.
Therefore, it is anticipated that the model understands better a sequence of points in their absolute position, rather than in their position with respect to previous points. Adopting the relative format used in [4] implies the notion that each drawing has a unique identity independently of its position on the canvas. For example, let us imagine four lines forming a small rectangle and a large canvas. According to the relative format, the rectangle’s representation is the same, no matter where the rectangle locates, top, bottom, more to the left, or right from the canvas center. Obtained results suggest an alternative idea: to think the canvas’s white space and the lines—both—constitute a draw’s essence. The white space also conveys information valuable to be represented. Keeping the coordinates as a reference outside the drawing points is what allows to capture the role of the white space in a drawing.

The second idea that emerged while experimenting relates to the importance of line ordering in draws for modeling by recurrent neural networks. Reported results indicate that the order given to the series of lines made a big difference. Proposed line ordering corresponds to the minimum length required to physically draw it by an X-Y Plotter, naively assuming that it would also be easy to learn if it is easier to draw it. It worked. No prior work found studied the line sorting to representing a particular drawing points in portrait drawings but also for abstracting the total space in the drawing. Proposed results indicate that the order of lines was input by a human and was not an issue. However, whenever a draw representation artificially generated is required as input in a recurrent neural network, line order is something to consider. In this case, the order of lines that achieve the minimum total length—the total distance traveled by an imaginary pen, either tracing or not touching the paper—worked better than a random ordering. This evidence encourages us to continue investigating the impact of a particular line ordering criteria on the classification performance.

A third idea that captures attention came up with the result of the comparison of different LSTM configurations for portrait gender classification. Returning the sequences and averaging was proved to be better than just passing the final step value. A little hack in a trained model with this feature makes it possible to filter those line points associated with an attribute. So, the model not only classifies attributes in portrait drawings but also generates new drawings of those attributes.

The fourth and last idea is the creation of the FaCells, restoring for a moment the genuine artistic intention of the investigation. The FaCells are a method to synthesize and express a visual element in drawings by tweaking a trained LSTM classification model. This technique is worth studying, at least from an artistic mindset. It makes us think that maybe our mental representations of visual concepts are just that, projections of thousands of labeled observations.

Some may say that lines have no existence in the real world, they exist only inside our minds. They may be wrong.

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Arched eyebrows 1000-19

Bangs 1000-28

Attractive 1000-9
High cheekbones 1000-16

Mouth slightly open 1000-27

Male 1000-14
Smiling 1000-33

No beard 1000-12

Wavy hair 1000-4
Wearing hat 1000-35

Wearing lipstick 1000-25

Young 1000-18
Not No beard 1000-(24)

Not Attractive 1000-(9)

Not Male 1000-(14)