VRIJE
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COMPUTER GENERATED CAR DESIGN

Assignment 2 - Computational Creativity

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Abstract

As per requirement of the Computational Creativity course, a small computational creative system will be designed and constructed. This will be done by completing multiple smaller milestones. This report focuses on the second of those milestones. Relevant literature to the creative domain, car design, is analysed and discussed in this report.

In part I the studied literature is discussed. Section 1.1 explores the domain of generative AI for visual documents. In section 1.2 the black-box problem is discussed and relative literature to combat this problem is analyzed. The last section of this part compares the evaluation criteria used in the creative domain.

The second and last part summarizes the findings by giving a proposed vision on how to create the system in section 2.1 with section 2.2 discussing some hurdles that might be encountered.

All source files for this project are available on GitHub (Bontinck, 2021). It is noted that this report is written by modifying the VUB based LaTeX template from De Smet (2020).

Contents

Part I

Relevant literature

1.1 Generating visuals

Since the goal of the creative system is to generate car designs, a technology that is capable of generating visuals has to be studied. Generative adversarial networks (GANs), first introduced by Goodfellow et al. (2014), seem most appropriate for this task as such networks have also been used for similar, non-scientific, projects by Soomar et al. (2020), Amitesh (2020), ODSC (2019) and more.

Whilst GANs are great, they require a lot of training data. This data directly influences the learning of the generating agent and can be used as a way of controlling the behaviour of the AI. Several datasets are publicly available containing labelled images of cars, with the LSUN-Stanford Car Dataset by Kramberger and Potočnik (2020) being one of many. These datasets could be used to train GANs bypassing the time-consuming task of initial data collecting.

Successful attempts at making convincing GANs using this dataset have been achieved by Singh et al. (2018) and Karras et al. (2019). The latter of which makes use of and improves upon StyleGAN by Karras et al. (2018). There exist multiple official implementations of StyleGAN that are free to use and modify, making it a popular start for many GAN related projects.

A particularly interesting research paper worth mentioning is the one by Radhakrishnan et al. (2018). In this paper, a creative system is developed which takes a pen-and-paper sketch of a car and returns a graphical representation of what that car could look like in real life. The authors of this paper deem this system to be creative since it is capable of generating images from angles of the car that are not visible in the input sketch.

1.2 Black-box problem

From the previous section, it's clear that powerful GANs such as StyleGAN are capable of producing the desired results for this project. However, these results are not guaranteed and a big issue with GANs is the fact that they are black-box models as they often rely on deep convolutional neural networks (CNNs). This means that the actual working of these models is hard to humanly reason about and have influential power over besides from the training data. This also makes it hard to troubleshoot and steer a model if it doesn't achieve the desired results. Manipulations to StyleGAN that allow for more control such as that from Tewari et al. (2020) prove this isn't impossible but remains a hard task.

This black-box problem is also present with CNNs and other AI models which means there's also a lot of active research in this field. Research by Bau et al. (2020) shows it is possible to disable specific hidden units from a CNN by nullifying their output. By disabling these hidden units their role and impact on a model can be studied.

If all of the above would fail to give a desired result an existing pre-trained model can be used as starting point. The official documentation of StyleGAN provides such models for a car optimized GAN.

1.3 Evaluating creativity

Perhaps the most challenging part of this project is evaluating the creativity of the system. One important step that should be tackled by the next milestone is describing the system in terms of the creative systems framework. The creativity can be evaluated by using Ritchie's and Jourdanous's criteria as seen during the computation creativity course.

Even just determining whether a system is creative or not is a difficult task that often includes subjectivity. The already discussed research by Radhakrishnan et al. (2018) claims their system is creative without giving clear objective reasoning. Some of their incentives to claim it as a creative system are:

- The car design domain is deemed a creative domain.
- The output of the system would be deemed creative if it were developed by a human.
- Their system generates car designs in multiple hitherto unseen perspectives.
- Their model, only trained on cars, shows pleasing results for sketches of bikes and non-automobile entities such as trees.

Some of these points hold for the proposed system of this project and others can be validated once the system is implemented. A survey can be held to check if:

- People would deem the output creative if it were from a human.
- Design elements from existing cars are recognized.
  - This is also the case in human-generated car designs.
  - It would have to be checked if the output differs enough from the given input to validate the system is P-creative.

Part II

Conclusions

2.1 Proposed vision

The performed literature study has given a deeper insight into the viability and creativity of the proposed system from the previous milestone. Taking into account this extra knowledge the following is proposed to be implemented by the next milestone:

- A StyleGAN based system.
  - Preferably based on a faster StyleGAN2 variant due to limited computational power.
- Making use of existing labelled datasets as a time-saving measure.
- Having a fallback to existing pre-trained systems if the computational overhead would be too big or results non-satisfactory.

2.2 Hurdles

The expected hurdles remain unchanged from the previous milestone being mainly:

- A lack of insight on the working of the system.
- The need for more computational power then is available.
- Failing to objectively deem the system creative.

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