# Searching for an *(un)stable equilibrium*

## experiments in training generative models without data

Terence Broad* & Mick Grierson†
t.broad@gold.ac.uk, m.grierson@arts.ac.uk
*Department of Computing, Goldsmiths, University of London
†Creative Computing Institute, University of the Arts London

## Overview

*(un)stable equilibrium* is an ongoing series of works training generative neural networks without data.

We treat modern machine learning toolkits and generative architectures as new *aesthetic structures* to be explored through intuition and aesthetic exploration.

We liken this practice to traditional generative art, where dynamical systems are explored intuitively for their latent generative possibilities.

## Case Study: *Series 1*

For the works in *Series 1*, two generators try to compete to have their output passed off as the other network's in an adversarial fashion. They also compete to produce more colours than the other generator.

Each work is the product of a unique configuration of training regimes and loss functions. Varying in their use of metrics for measuring difference and distance, and their sequences of training and methods for (dis)optimisation.

After training, the work is presented as a synchronised interpolation of their respective latent spaces with the output of each generator presented side-by-side.

## Guiding Principles

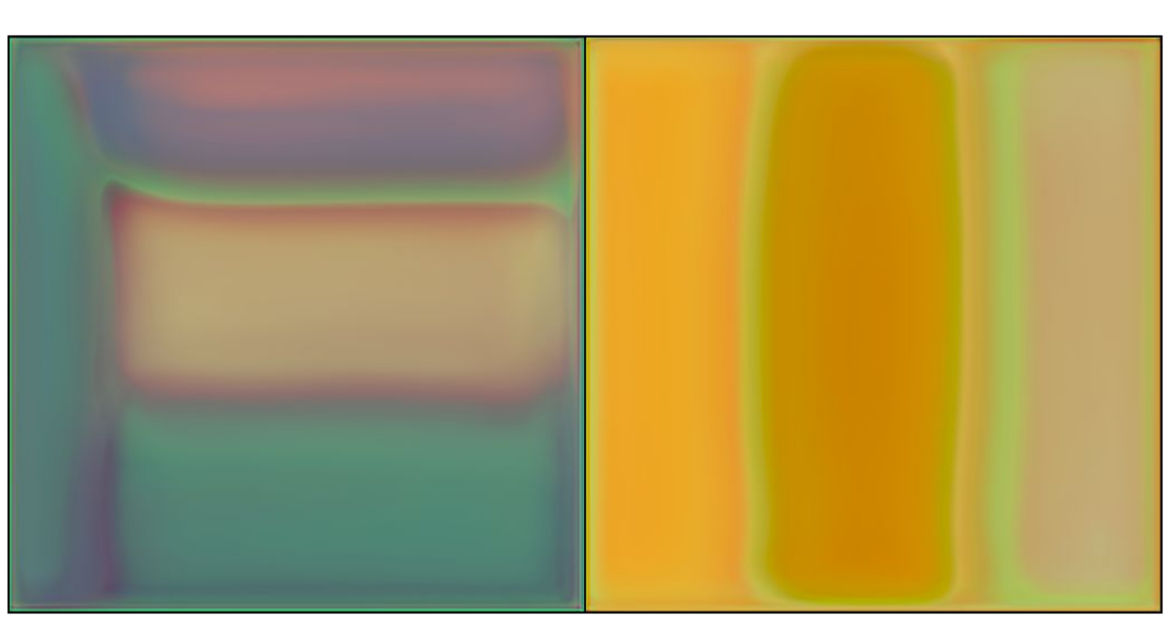
**Complexity | Stochasticity**
It is important to find the right balance of complexity and stochasticity. The batch size is key: too low and gradients quickly explode, too high and the error signal averages out into stasis.

**Relational Constraints**
We utilise constraints that are relative to the output of a given batch. Such as distances in embedding spaces or measuring diversity in the pixel space of a generated batch.

**Exploiting Boundaries**
We exploit the small differences in the way different functions measure distance and difference, to create internal system dynamics that continually inject a level of randomness into the training dynamics.

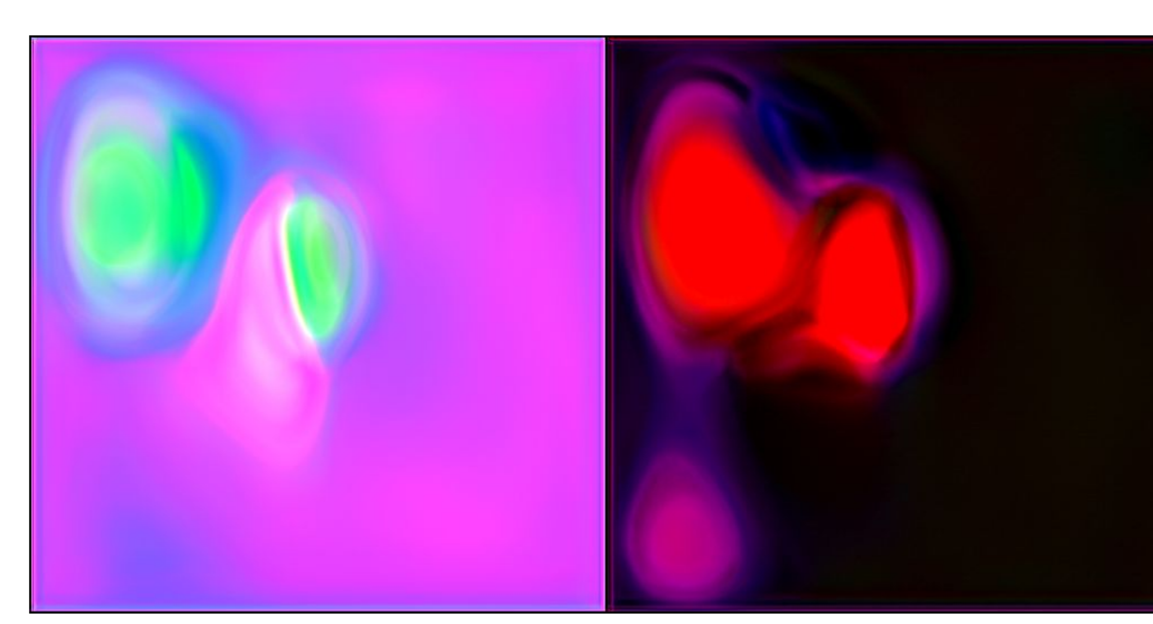
**Diametric Optimisation**
In some cases, we train the discriminator network with two diametrically opposed loss functions, providing an anchor of stability in the network ensemble.

**Discovering (Un)stable Equlibria**
These principles serve to the goal of finding a balance of randomness and stability: to find an equilibrium in the space of potential system dynamics which is stable enough to train, but unstable enough to produce unexpected results.

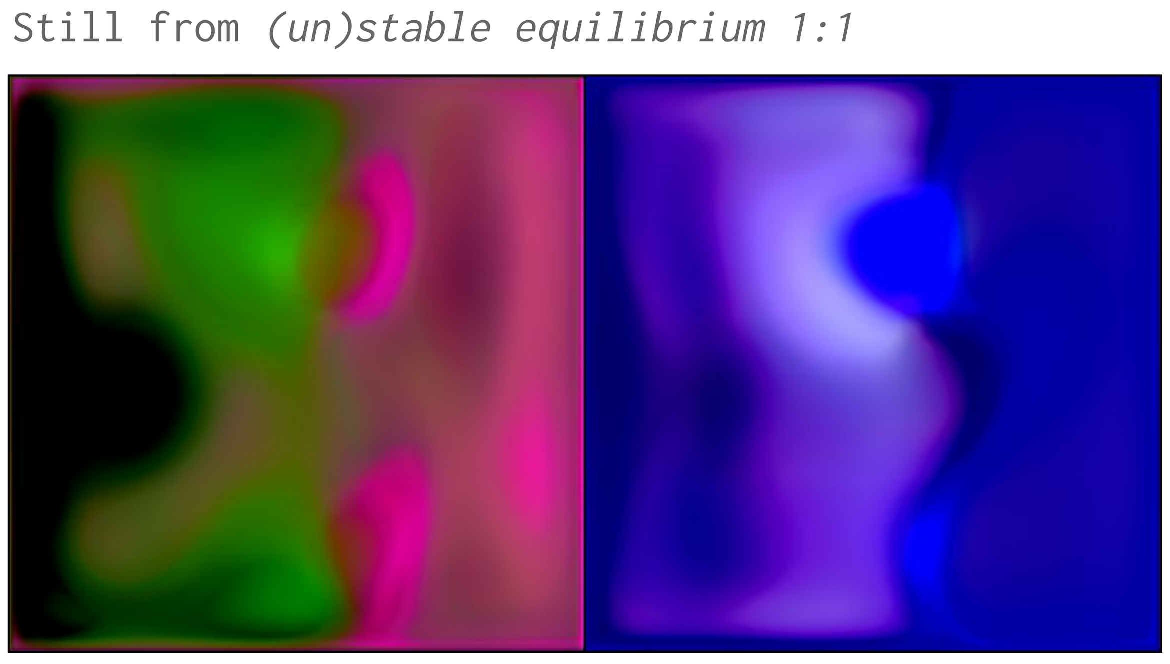


Still from *(un)stable equilibrium 1:1*

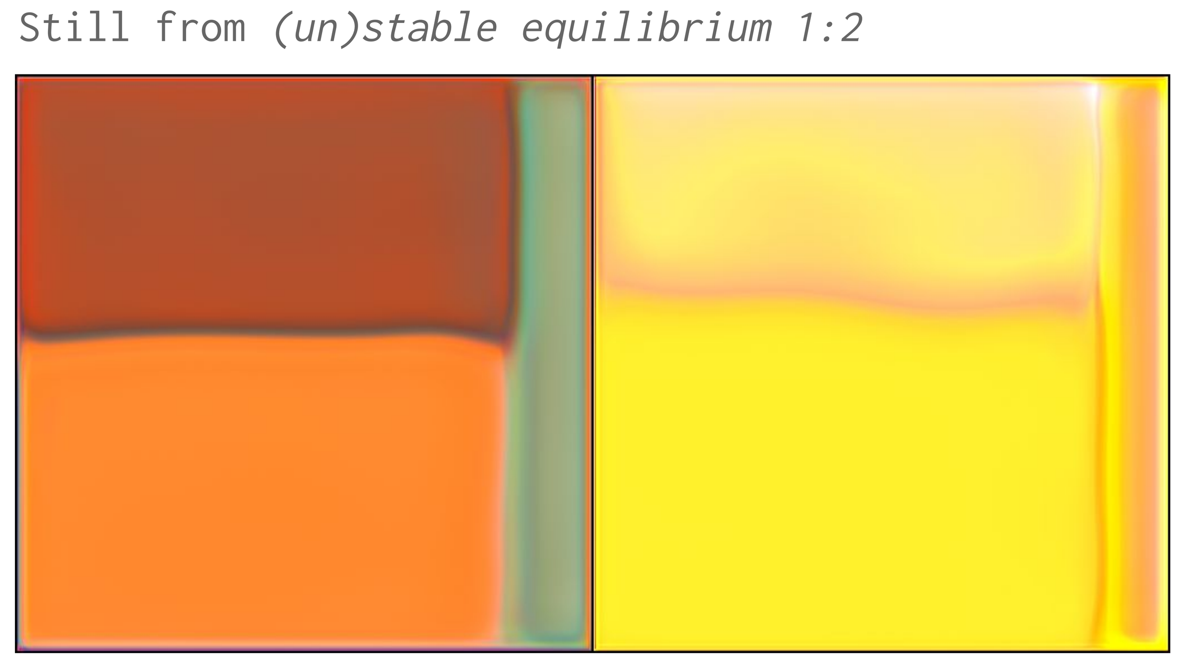
Still from *(un)stable equilibrium 1:2*



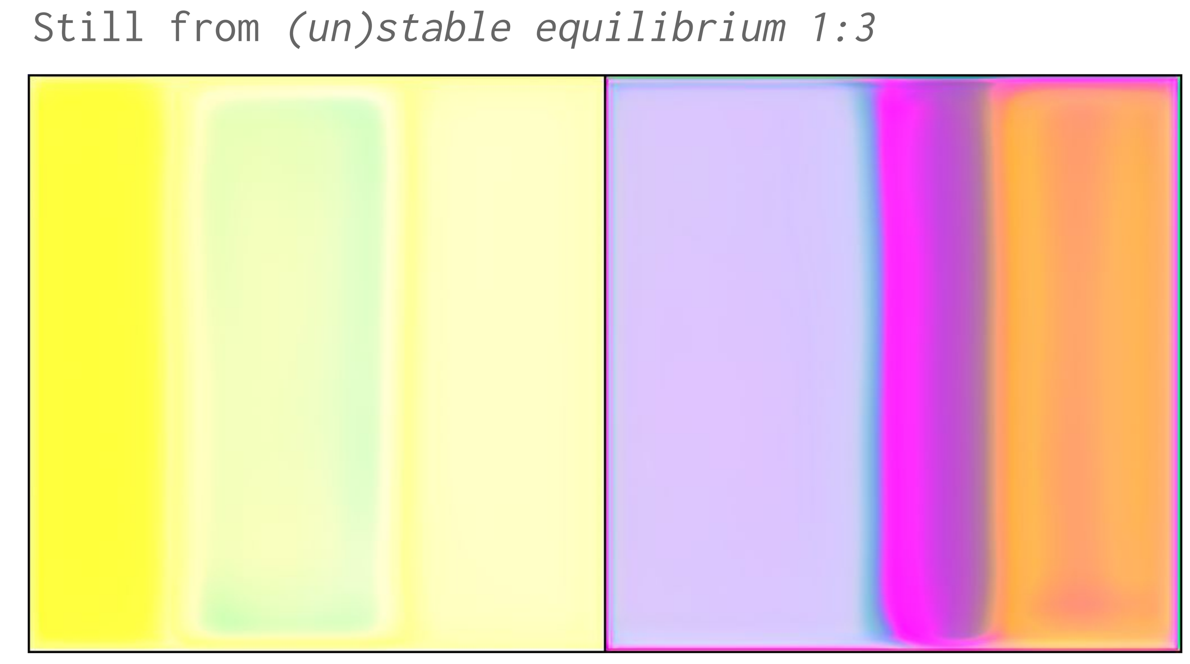
Still from *(un)stable equilibrium 1:3*



Still from *(un)stable equilibrium 1:4*



Still from *(un)stable equilibrium 1:5*



Still from *(un)stable equilibrium 1:6*

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Goldsmiths UNIVERSITY OF LONDON

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ual: creative computing institute

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