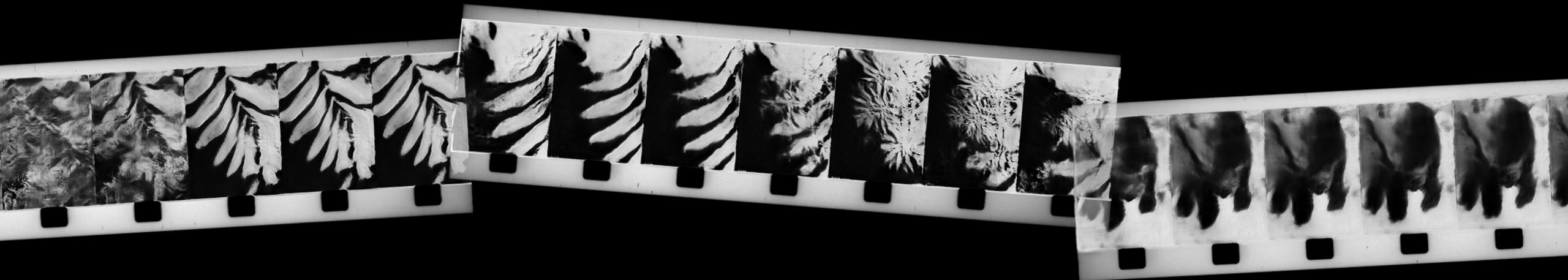


Exploring Machine Intelligence

Week 1, Introduction



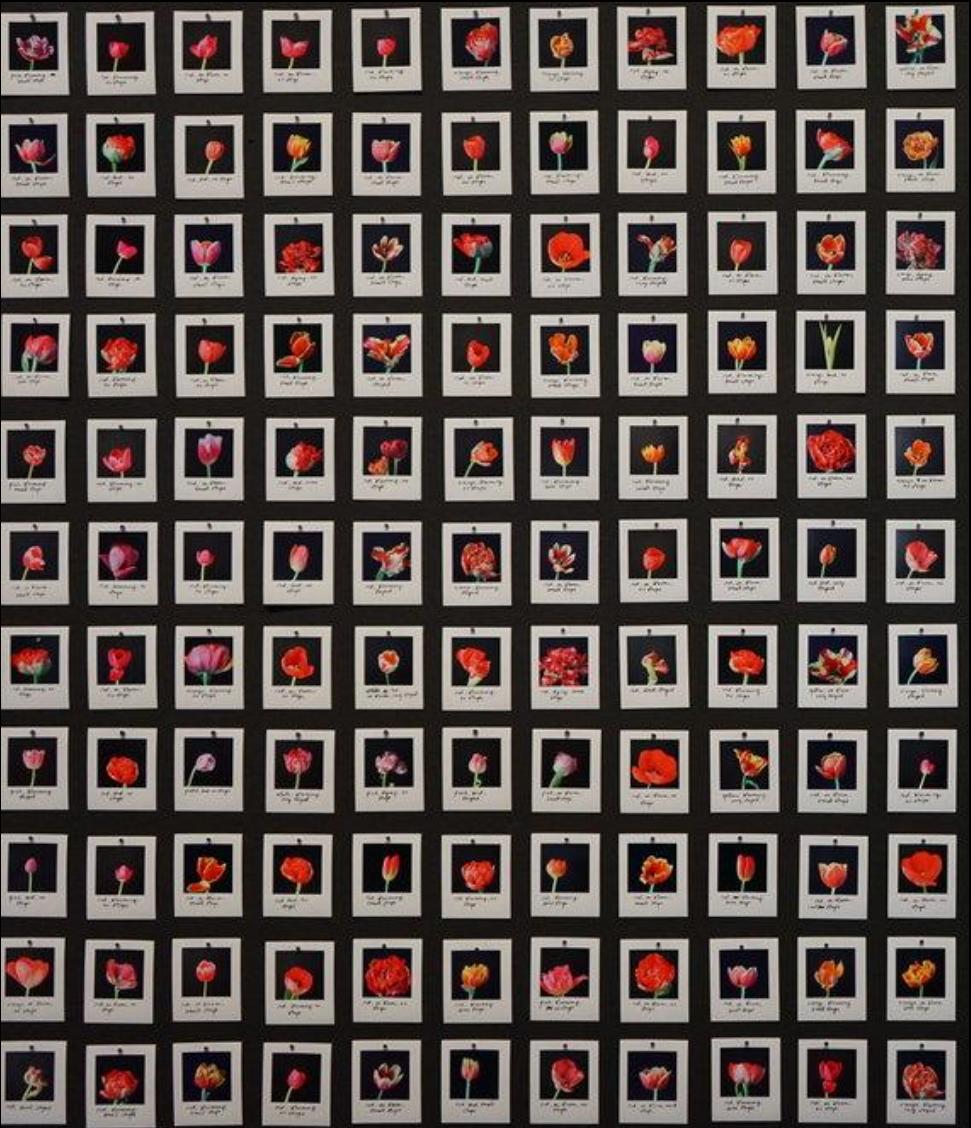
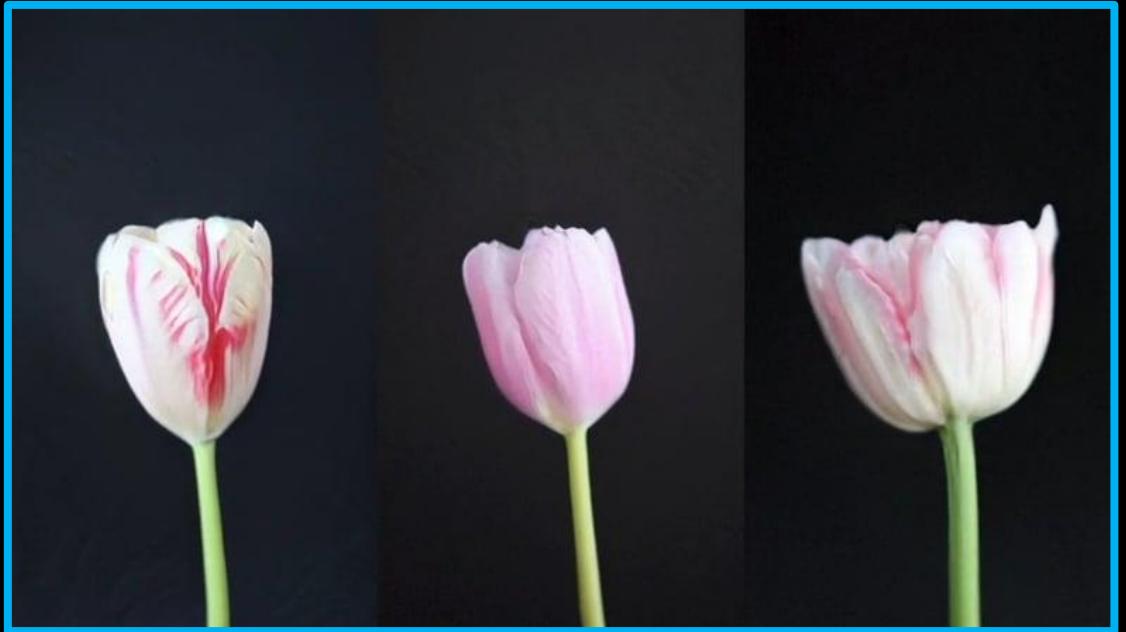
~ Vítek Růžička

Exploring Machine Intelligence

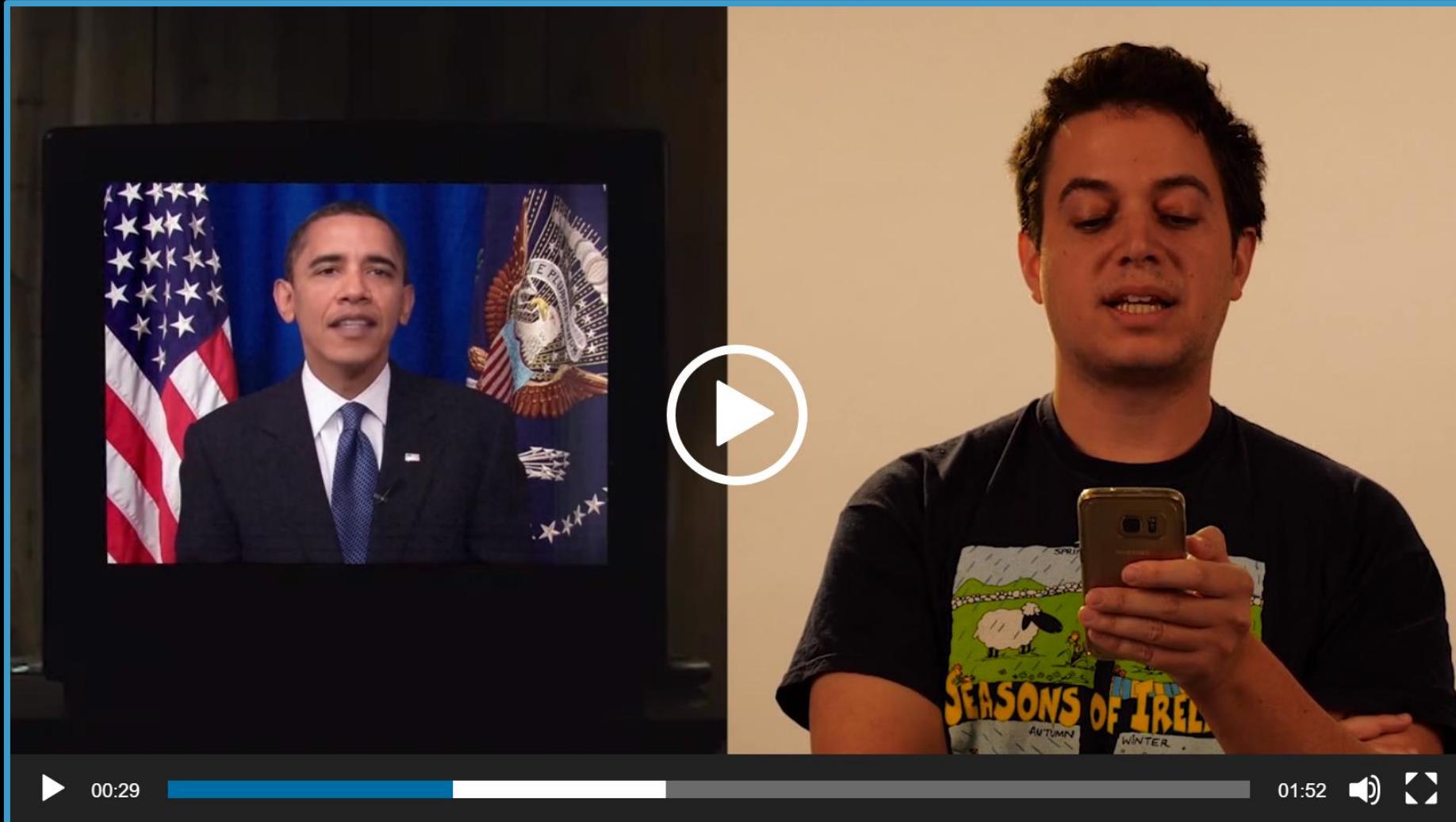
- Machine Learning has become part of our everyday life ... but also part of the current Art scene.
- This class will teach you **how to understand** an artwork created by ML ... and help you **make your own** ML art

Few rapid-fire examples ...

GANs – Anna Ridder – Mosaic Virus (2019)



pix2pix / deep fakes – Canny AI, Imagine (2020)



Watch: youtube.com/watch?v=KHMNPjkd5-0

Embeddings – **Mario Klingemann** - X Degrees of Separation (2018)



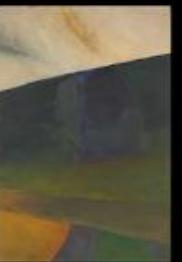
Pieter Bruegel the Elder,
ca. 1568
The Tower of Babel
Museum Boijmans Van Beuningen



William
Mulready,
1810
Lock gate
Yale Center for British



Unknown, 1828 to 1829
Landscape with Lake
Yale Center for British Art



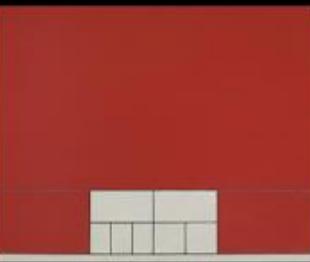
Orest Dubay
At Sunset
Galéria umelcov
Spiša



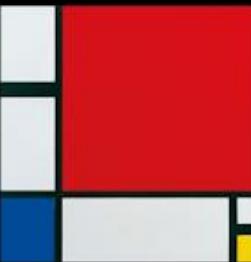
Yoo, Hyun-mi
Still Life
Gyeonggi Museum of
Modern Art



Ralph Balson, 1950
Abstraction
Art Gallery of New South Wales



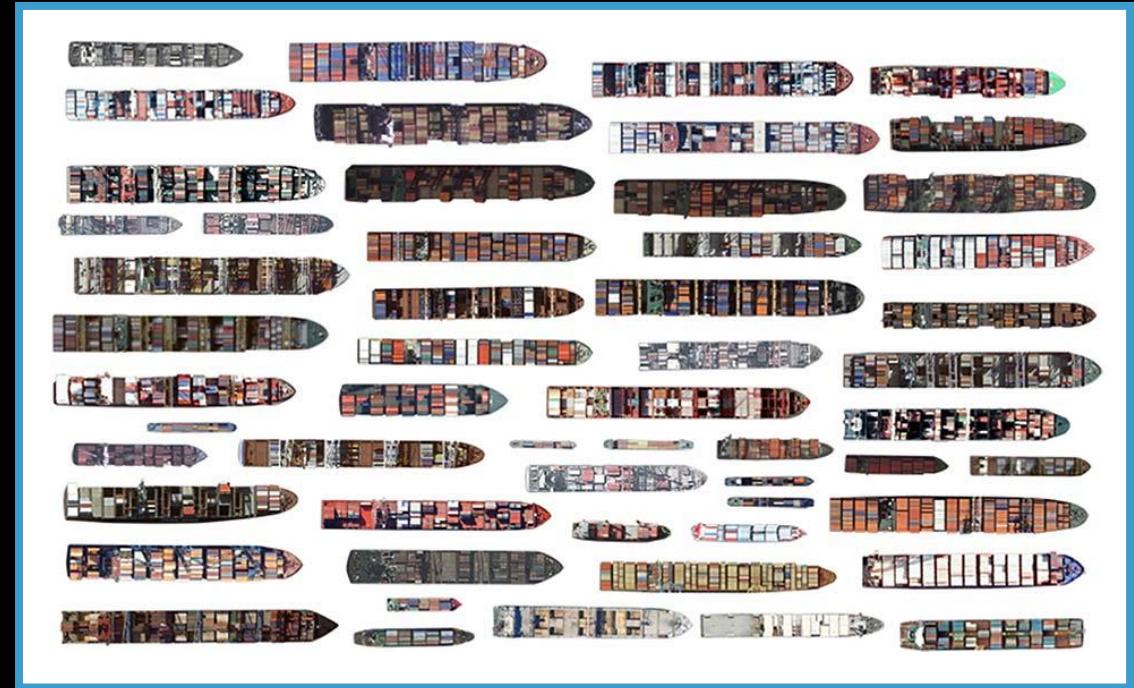
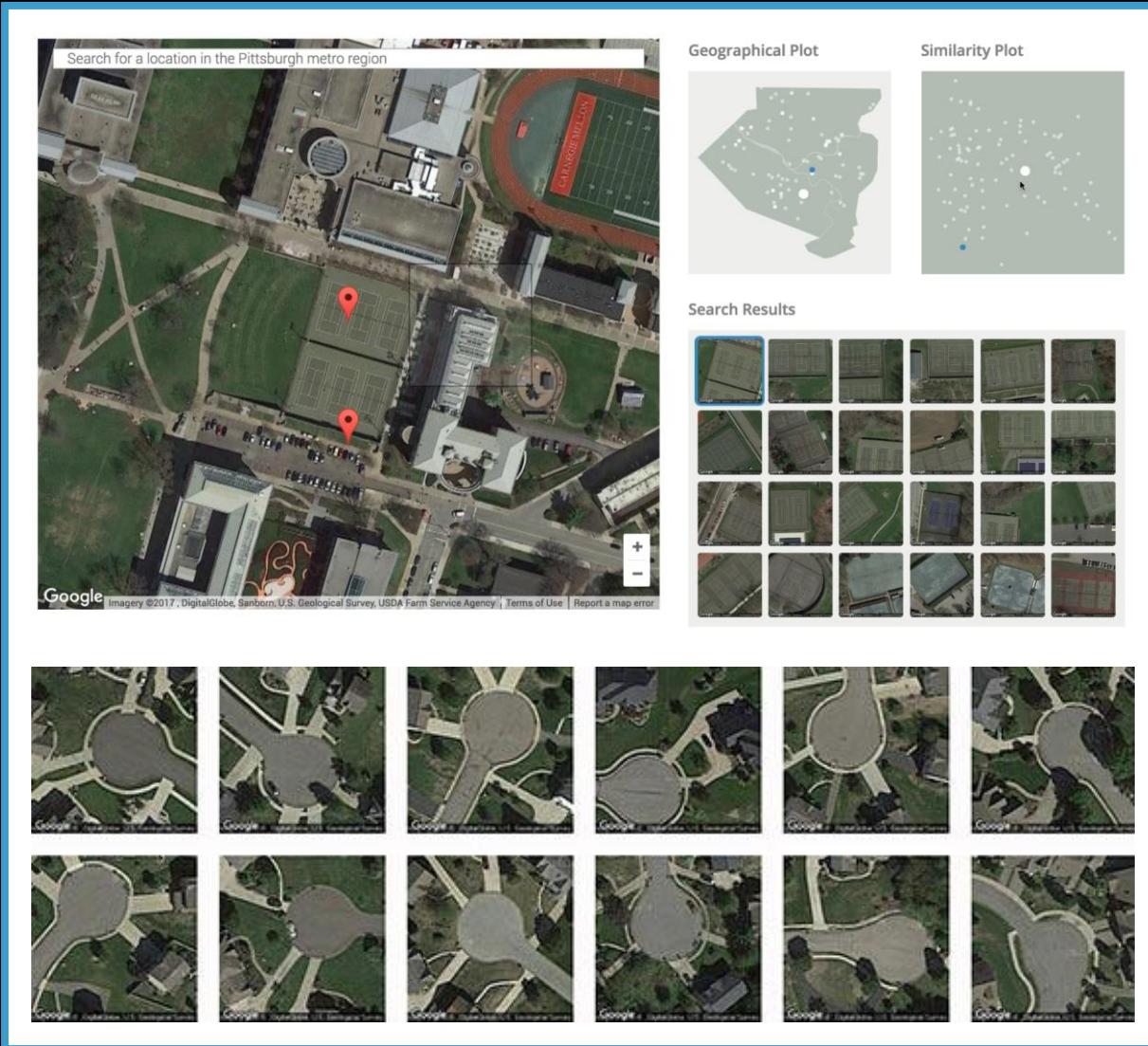
Unknown
Em vermelho
The Adolpho Leirner Collection of
Brazilian Constructive Art at The
Museum of Fine Arts, Houston



Piet Mondrian
*Composition with Red, Blue
and Yellow*
Kunsthaus Zürich

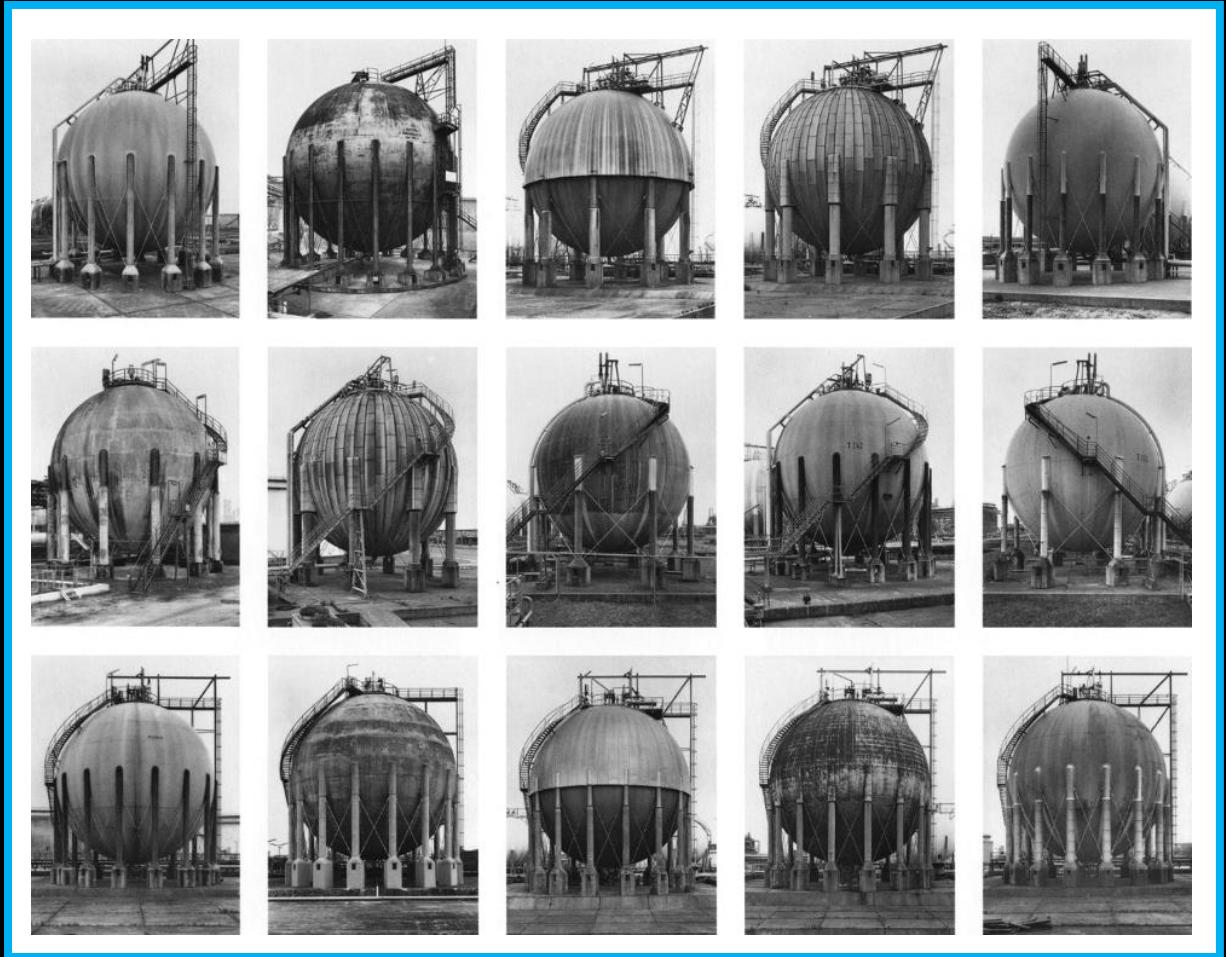
Try: artsexperiments.withgoogle.com/xdegrees/

Patterns – CMU – Terrapattern (2016) / Jenny Odell, Satellite Collections (2009)



Watch: [youtu.be/AErDoe-5OI4 &t=179](https://youtu.be/AErDoe-5OI4?t=179)

Shapes – Jenny Odell, 206 Circular Farms (2009)



New Topography – **Hilla and Bernd Becher** (1983)

Exploring Machine Intelligence

- Plan for the 8 weeks:
 - Start with **the basics**, write simple stuff in Python and Keras
 - **Learn about models** such as AlexNet, YOLO, U-Net, pix2pix, AutoEncoders, GANs, LSTMs, GPT-2 ... and more :)
 - Know when and **how to use them** with our own data and agenda
 - Learn how to miss-use them, **hack them**, use them in different contexts than intended in academia, chain them together
 - Have lessons by the amazing **Rebecca Fiebrink**, expert in ML and Interaction

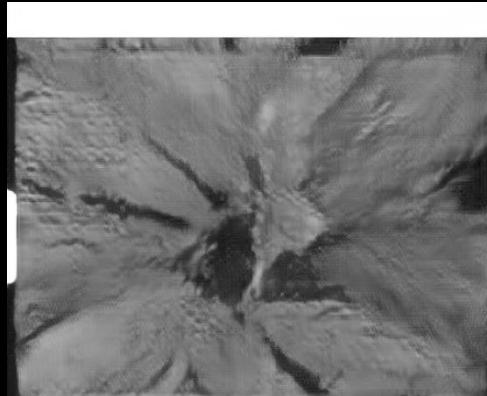
Exploring Machine Intelligence

- What can we do with this class:
 - Strive to **create your own artworks** which could make it into several online galleries focused on works using AI and machine learning?
 - For example: *NeurIPS ML for Creativity Workshop*

Introduction

- Who am I to teach you about this topic?
- What courses are especially influential for this domain?
 - Art and Machine Learning (2018) – CMU Eunsu Kang + Barnabas Poczos, some code available which we will also look at
 - The Neural Aesthetic (2018) – NYU Gene Kogan, online lectures available

GANs – Vít Růžička – Selected generated dataset (+-2020)



Introduction

- Lectures by Rebecca Fiebrink
 - Expertise in interactivity and machine learning
 - Creator of a well-regarded tool Wekinator



Dr Rebecca Fiebrink

Reader in Creative Computing.

Today

Lecture:

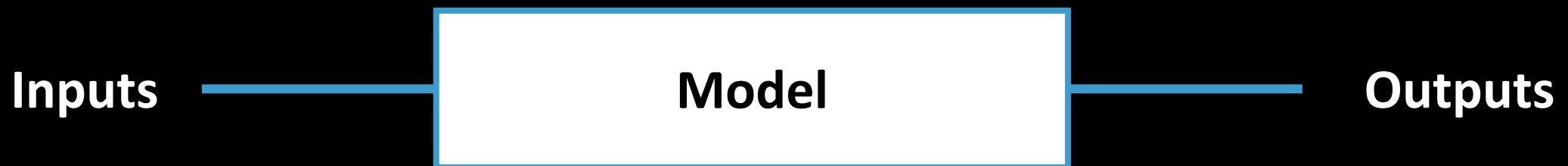
- Very basic concepts
- Further examples of what is Machine Learning capable of
- Examples from Art

Practicum:

- Simple coding in python, modelling data with linear regression

Concepts: Model

- We can understand a **model as a black box** to which we have some **inputs** and **outputs**.
- From this black box, we want it to learn what is the relation between the paired input and output we are showing it = **training**
- Then we usually want to mimic that same relation on some new input, on some new data = **inference / using the model**



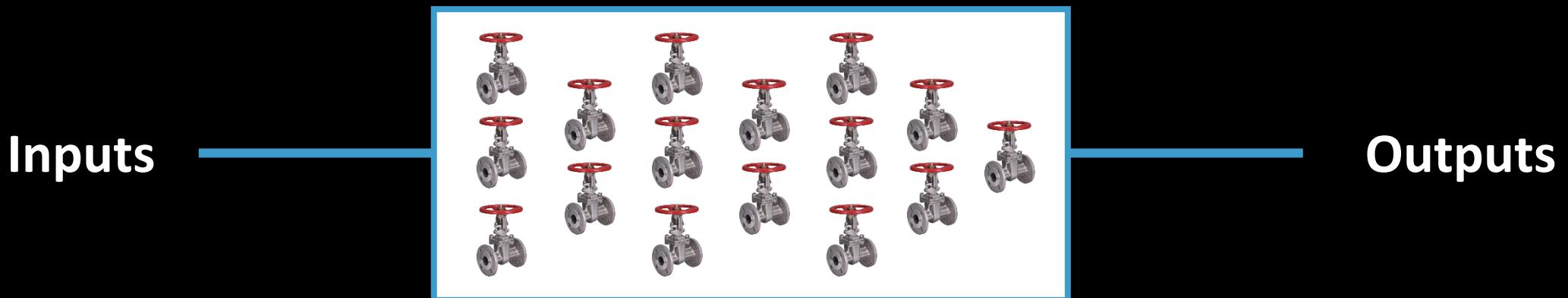
Concepts: Model

- Models tend to have some **parameters**, changeable knobs, inside them that we can turn
- When training we usually change these parameters around until what goes in (inputs) is successfully transformed to something close to what we expect to go out (outputs)



Concepts: Model

- Models tend to have some **parameters**, changeable knobs, inside them that we can turn
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Concepts: Data

- **Data** can be anything we are showing the model – numbers, images, encoded sounds ...
- Usually they have corresponding **labels** assigned to them



“Cat”

“Car”

Concepts: Training vs Testing

- We show the model only some images, the **training set**, we can try measure how well it does on previously not seen images if we set apart some **testing set**
- However we will never know, how well will it fare **in the wild** (with unexpected samples, quality, diversity)



?

Concepts: Creativity?

- “How in the world does this relate to creativity?”



Concepts: Creativity?

- “How in the world does this relate to creativity?”



When one of the domains becomes something we use for creative expression...

Concepts: Creativity?

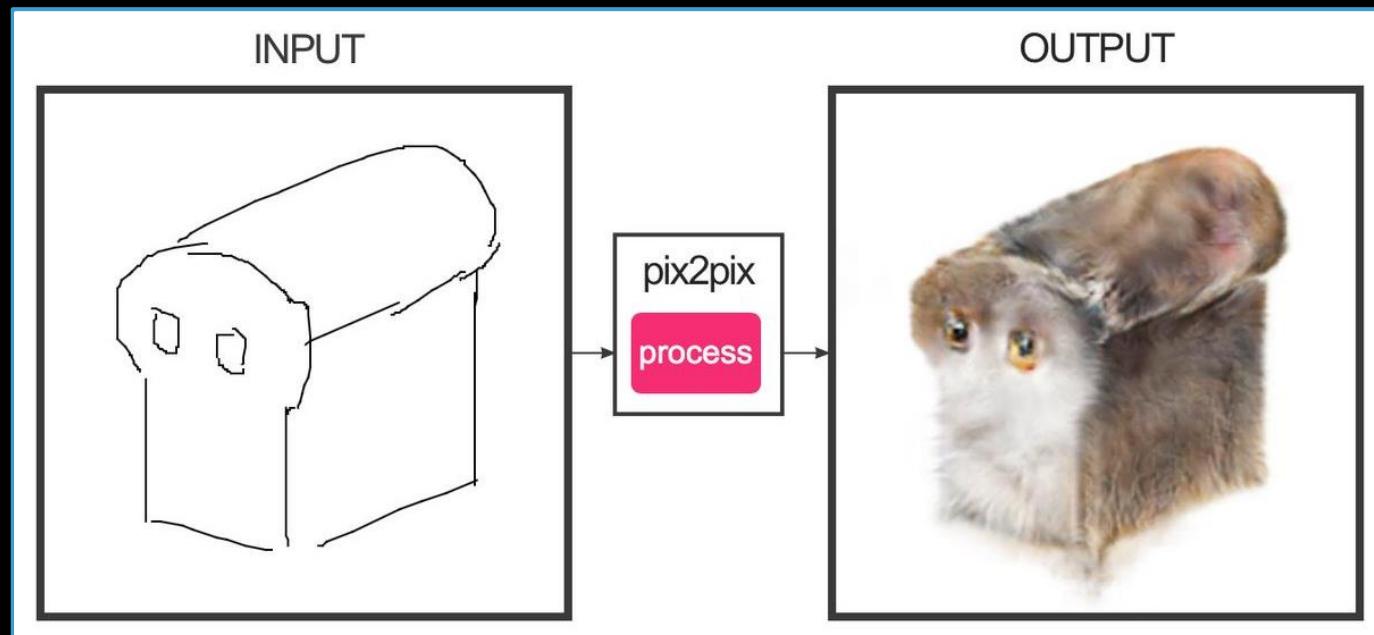
- “How in the world does this relate to creativity?”



Trained
on cats

Concepts: Creativity?

- “How in the world does this relate to creativity?”



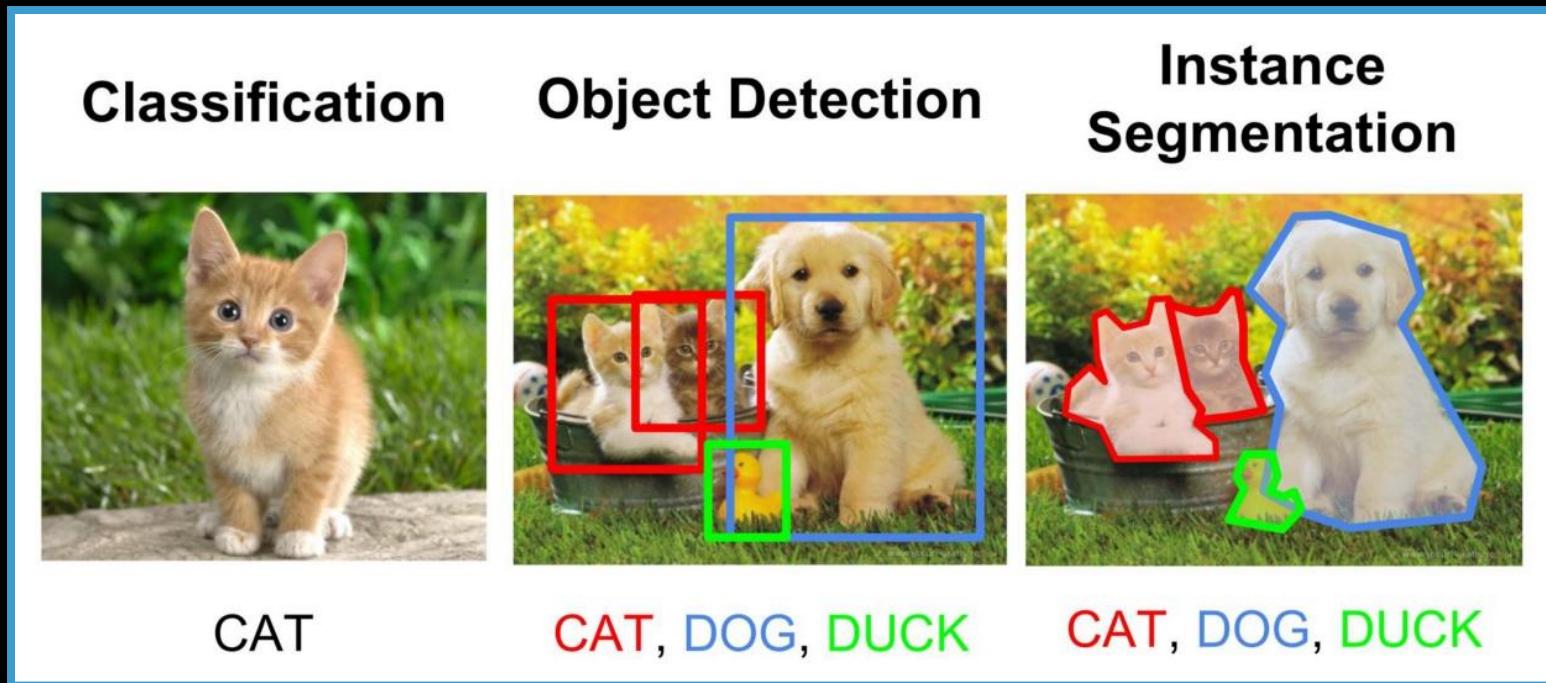
Used for
...
...

“breadcat” - twitter.com/ivymyt/status/834174687282241537

Machine Learning Examples

- Examples of **tasks** – classification, regression, object detection, semantic segmentation
- Types of **generative models** – domain to domain transfers, deepfakes, GANs, autoencoders
- Neural Network **deep dreaming** (*Do androids dream?*)
- Neural Network **hacking**

Types of tasks



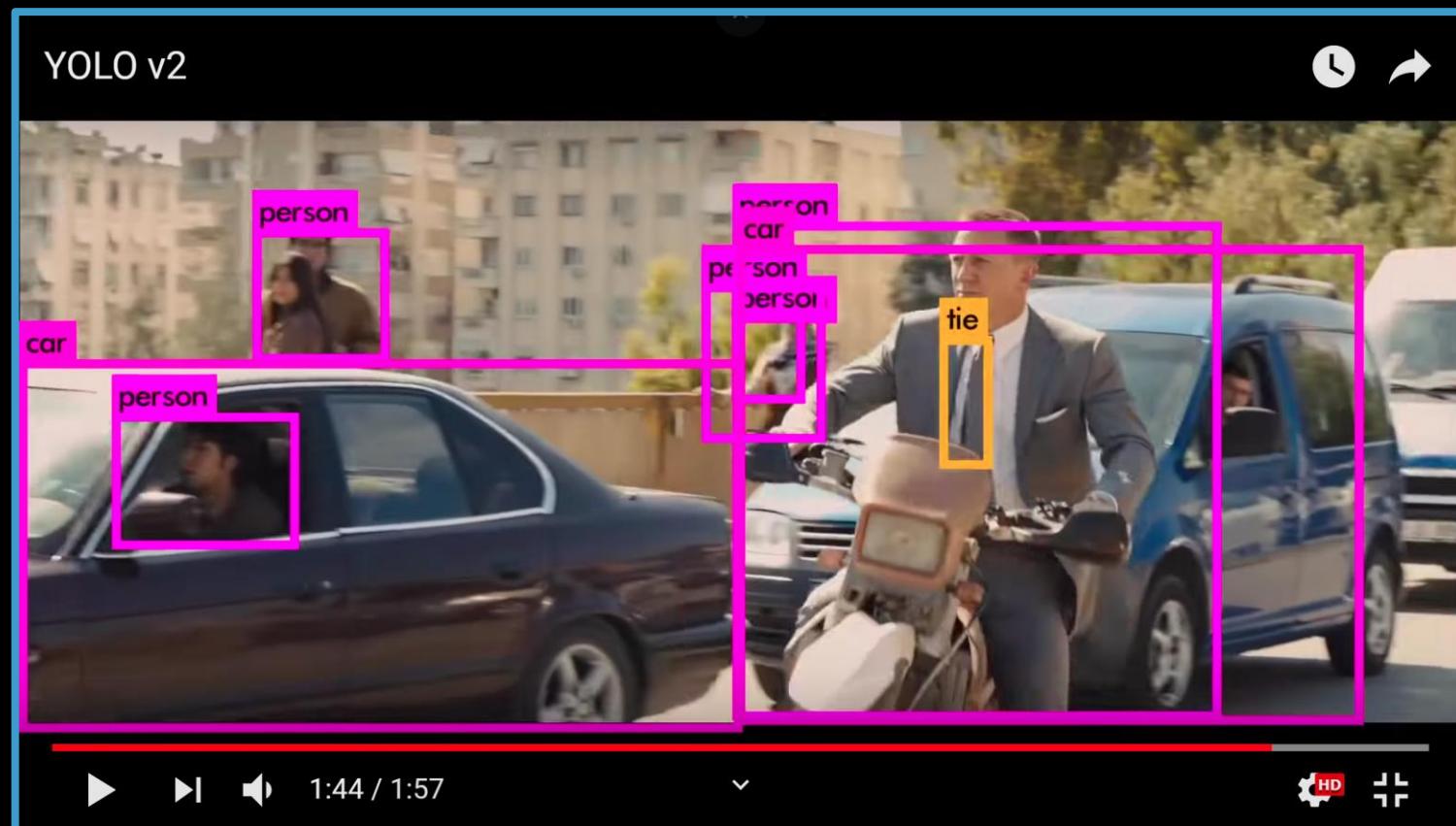
- These vaguely follow the development of models – and availability of labels for each of these tasks.

Classification



- 2012: model AlexNet reaches unprecedented performance in classification on the ImageNet dataset (error 26% > 16% jump)
- *PS: Today it's at 2.3% while human performance is around 5%*

Object Detection



Watch: youtube.com/watch?v=VOC3huqHrss

Yolo v2, **J. Redmon**, 2016



+ in 4K [video](#)

Image Captioning



Watch: youtube.com/watch?v=8BFzu9m52sc

NeuralTalk, **A. Karpathy**, 2015

Generative Adversarial Nets



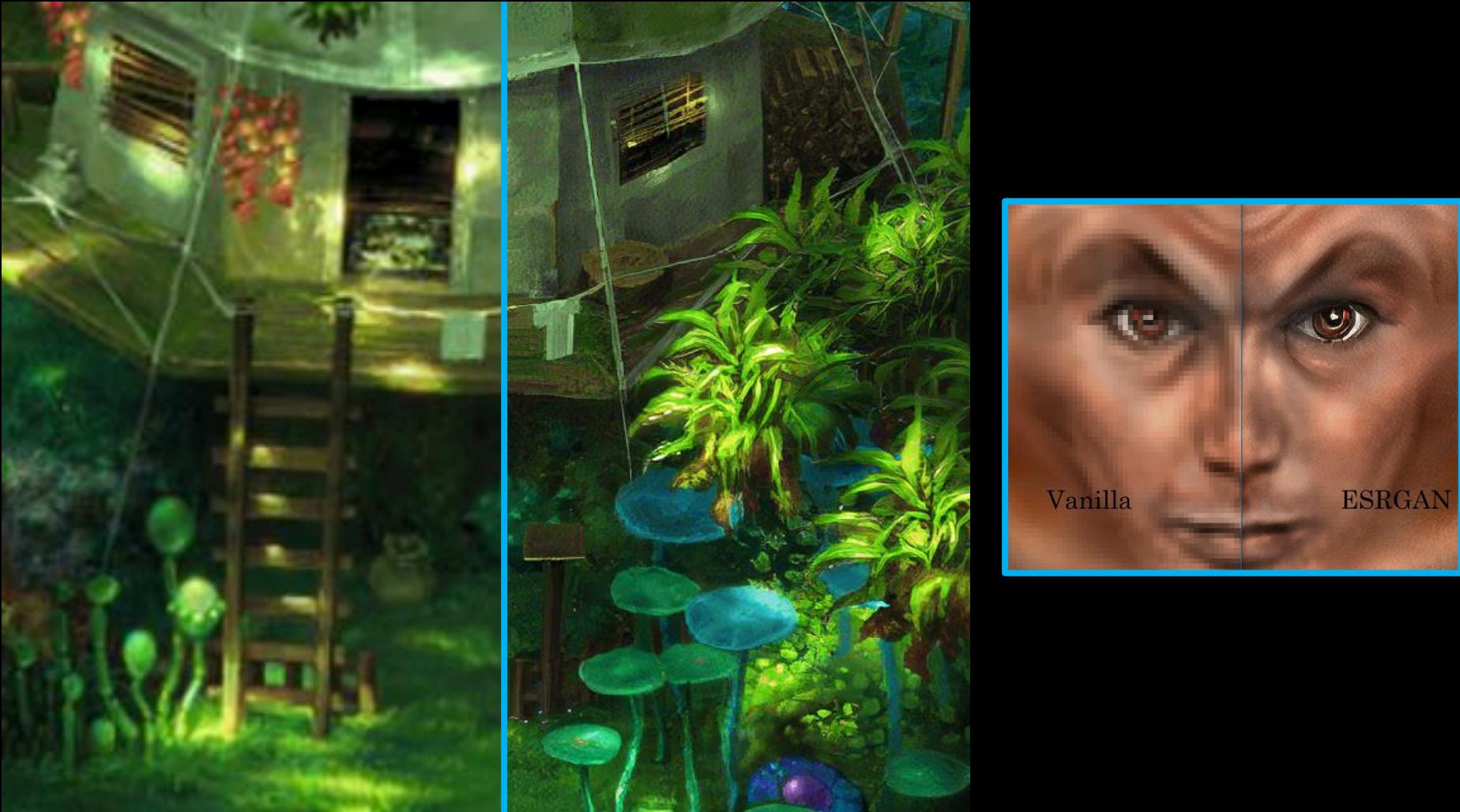
Memo's exploration

Watch: youtube.com/watch?v=6E1_dgYlfc

StyleGAN2, **T. Karras**, 2019 + BigGAN, **A. Brock**, 2018

Super Resolution GANs

Caveat – hallucinating details: [video](#)



AI Dungeon

Text generation using LSTM models

You are Zorro, a wizard living in the kingdom of Larion. You have a staff and a spellbook. You finish your long journey and finally arrive at the ruin you've been looking for. You look around and see that it's just as you remember. The ruins are all that remain of the once great city of Larion. The only thing that looks different is the fact that there are no more buildings to be seen
» invent the internet

You think about how you can use this opportunity to make the world a better place.
You decide to go back to the ruins and try to figure out what happened to the people who lived here before you arrived.

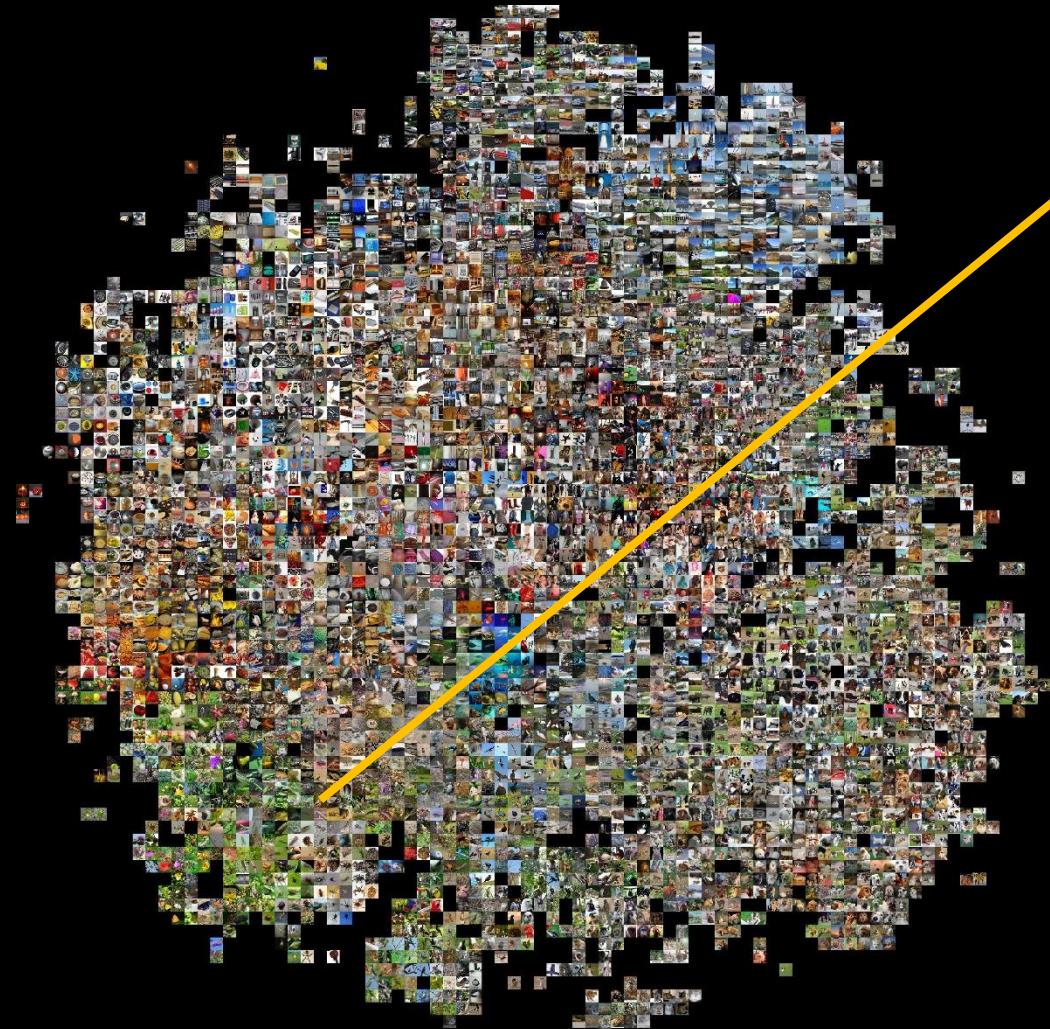
The next day you return to the ruins with your new found knowledge
» invent the internet

You begin by creating a computer program which will allow you to communicate with anyone on the net. It takes some time but eventually you get it working.
You then start sending messages to other wizards who live in the area
» ask them what happened to the city of Larion



Gaming article: [RPS link](#)

Embeddings



Using features of existing neural network models. (*Similarity* based)

Archives / Collections / Curation



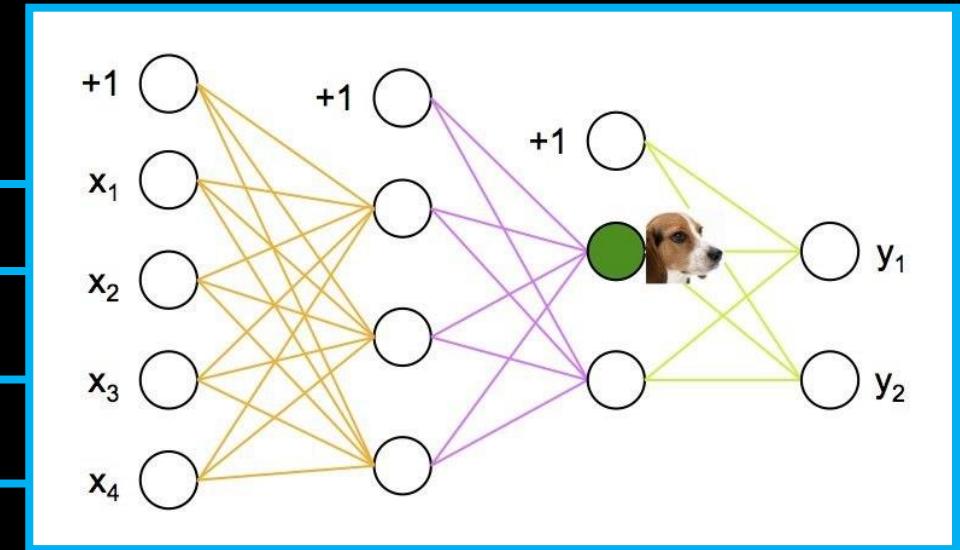
The Barnes Foundation, collection of artworks (paintings, artefacts, ...) collaged across rooms outside of the usual clustering/segmentation by era or art style.



Using features of existing neural network models. (*Similarity* based)

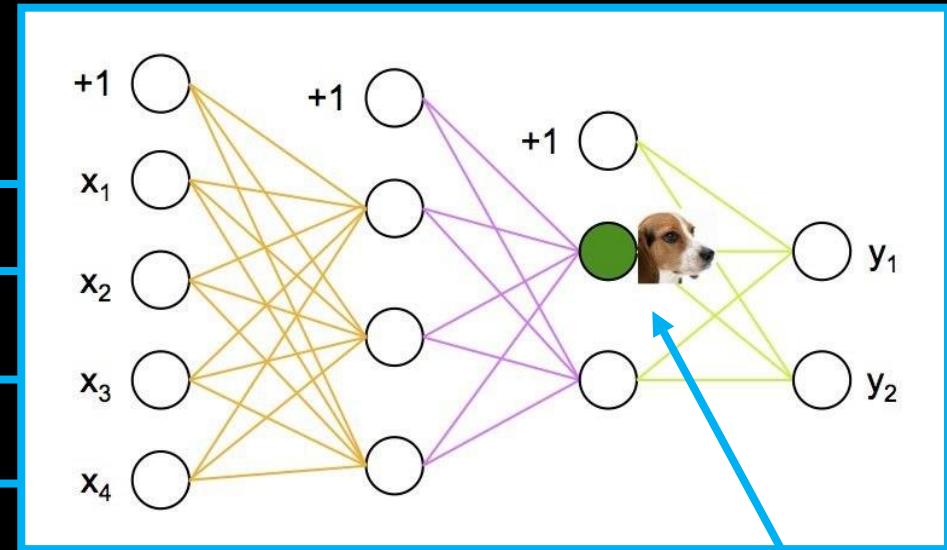
t-SNE visualization, [A. Karpathy](#)

Deep Dream



Inceptionism, [A. Mordvintsev](#), 2015

Deep Dream



← Change/Optimize the input
image so that it maximizes the
activation of selected neuron.

Deep Dream

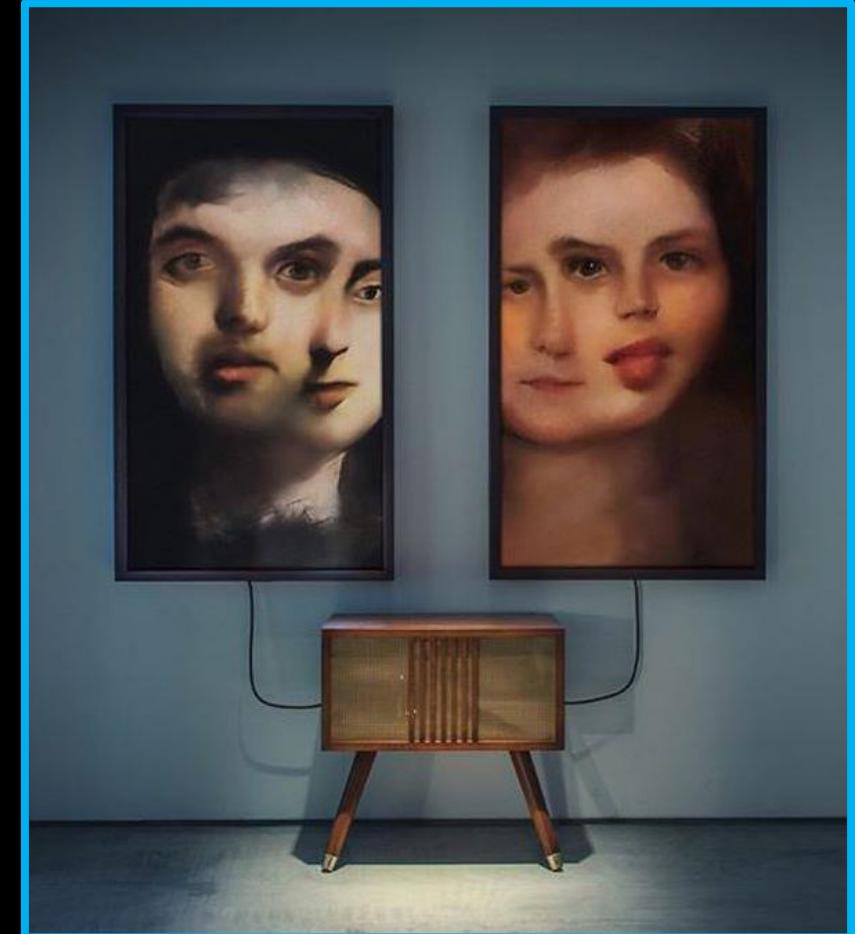


Fear and Loathing:
[youtube.com/watch?v=oyxSerkkP4o](https://www.youtube.com/watch?v=oyxSerkkP4o)

Neural Network Hacking



"I often chain together multiple GANs that have been trained for different purposes: some models generate faces from biometric face markers, others generate face markers from images, others are "transhancement" GANs that hallucinate new details and textures from incomplete information"



Neural Glitch, **Mario Klingemann**, 2018

Pause 1

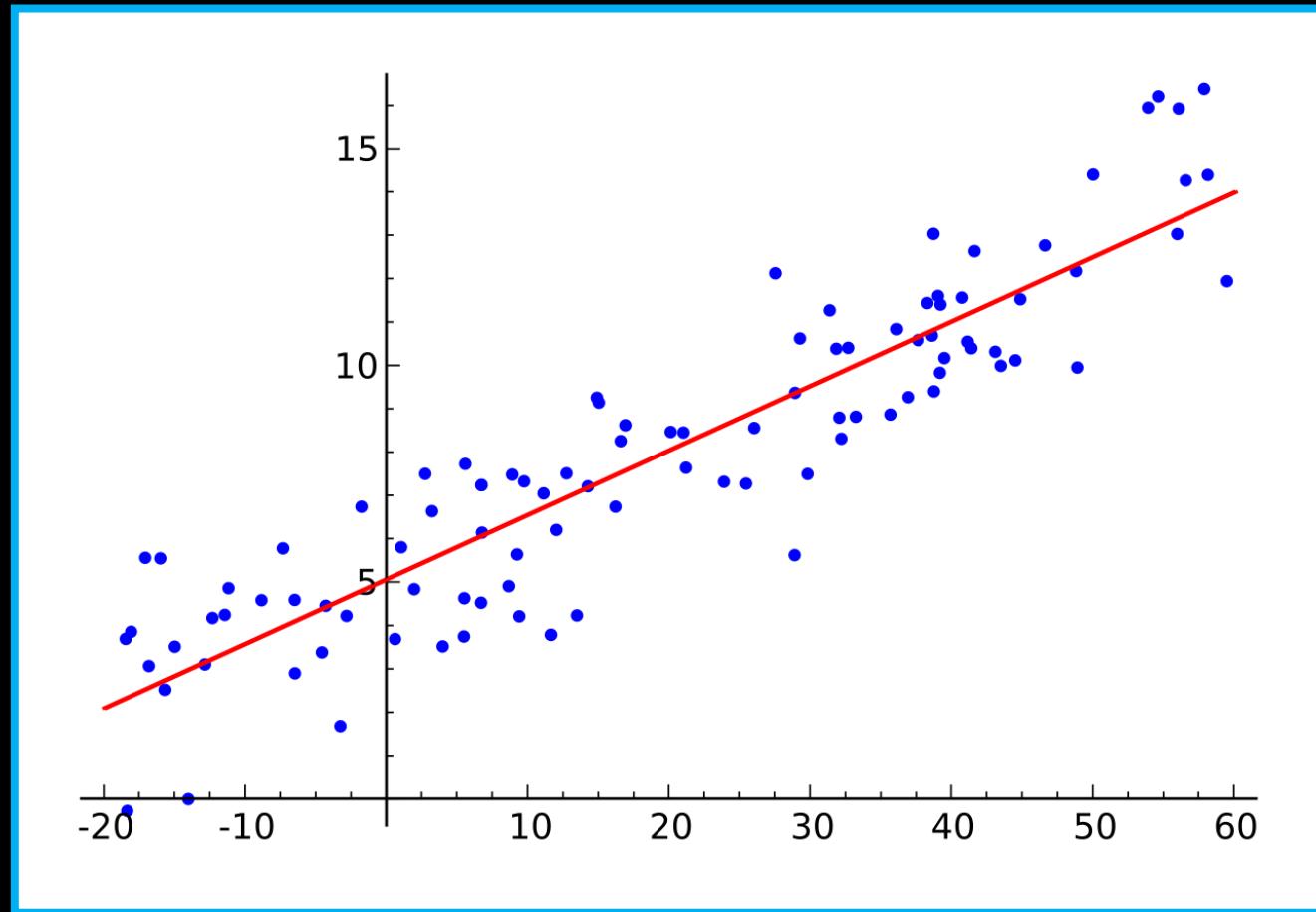
Practicum

Linear regression

Motivation:

- One of the simplest model we can very easily use to show some concepts

Linear regression:



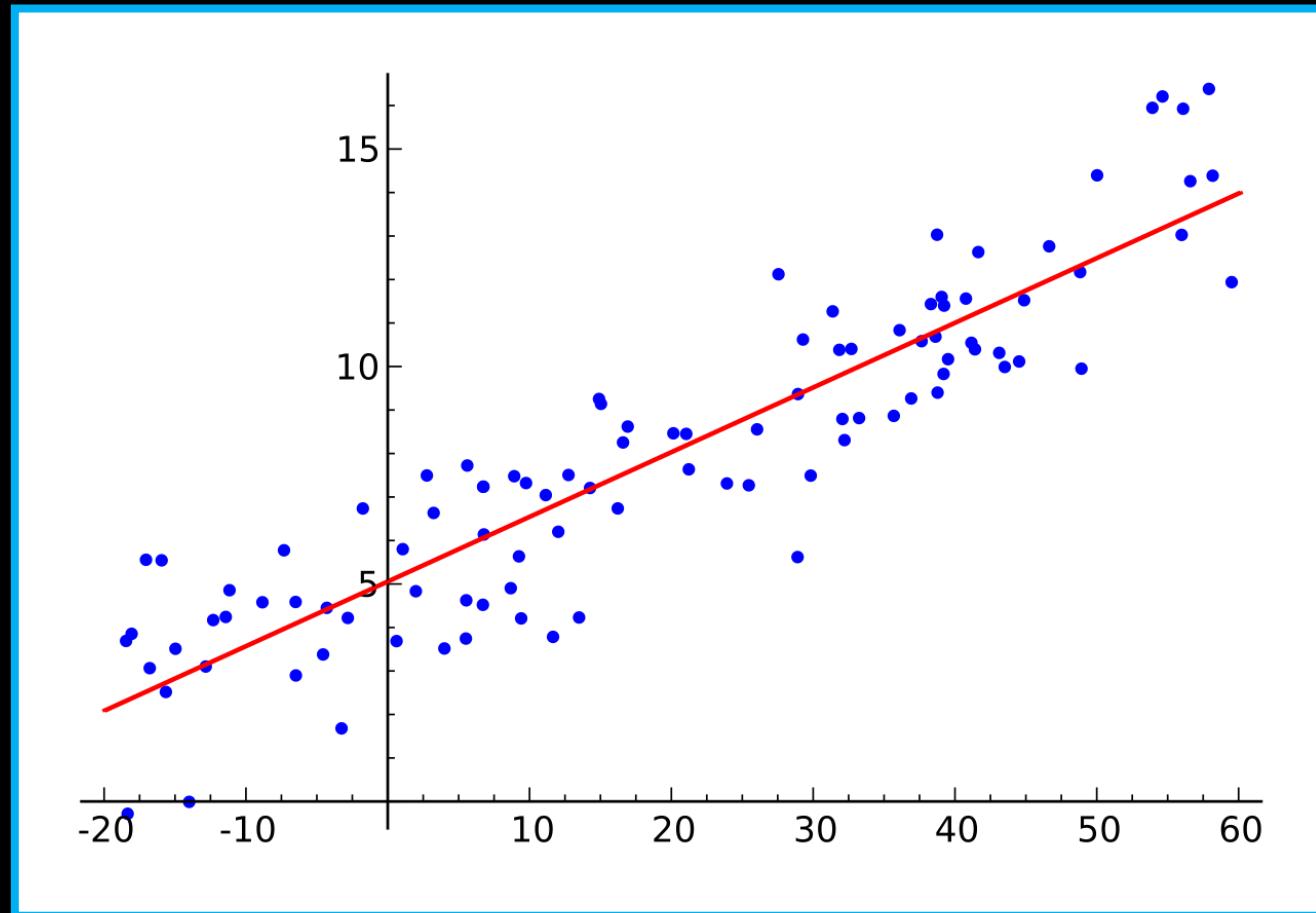
Finding the **best** possible placement for a line to correspond with a set of points.

points: [x,y]

line:

$$y = a^*x + b$$

Linear regression:



What do we mean by **best**?

Best possible placement of the line translates to having a line which one average is not too far from any of the points.

And we can measure the distances between line and points.

Linear regression:

Line function:

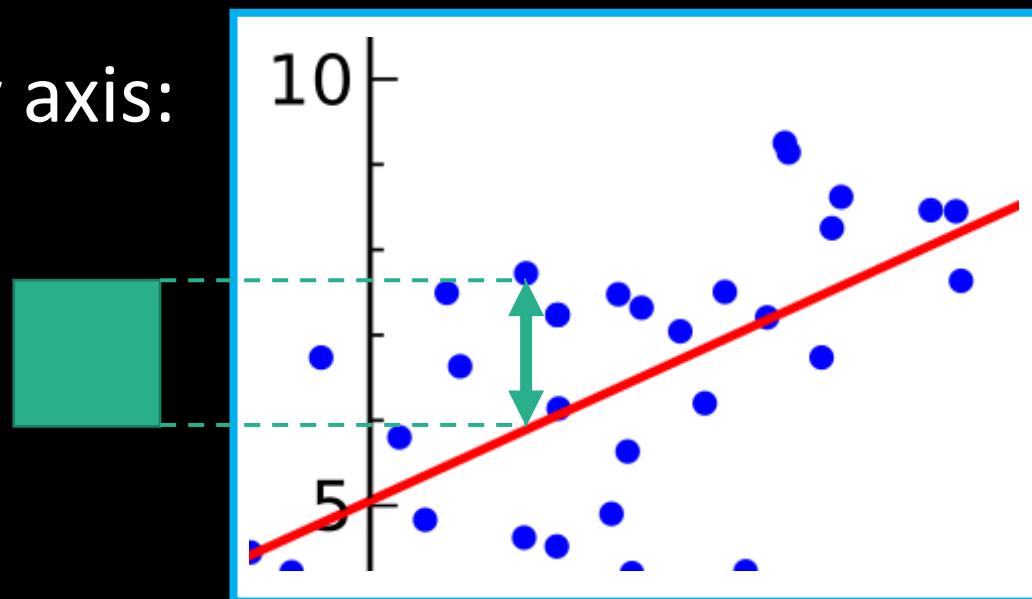
Point $[x, y]$ is on a line if: $y = a*x + b$

- Controlled by it's parameters a (slope) and b (intersect).

Distance between line and point on y axis:

$$\text{dist} = y_{\text{point}} - y_{\text{line}}$$

$$\text{squared_dist} = \text{dist} * \text{dist}$$

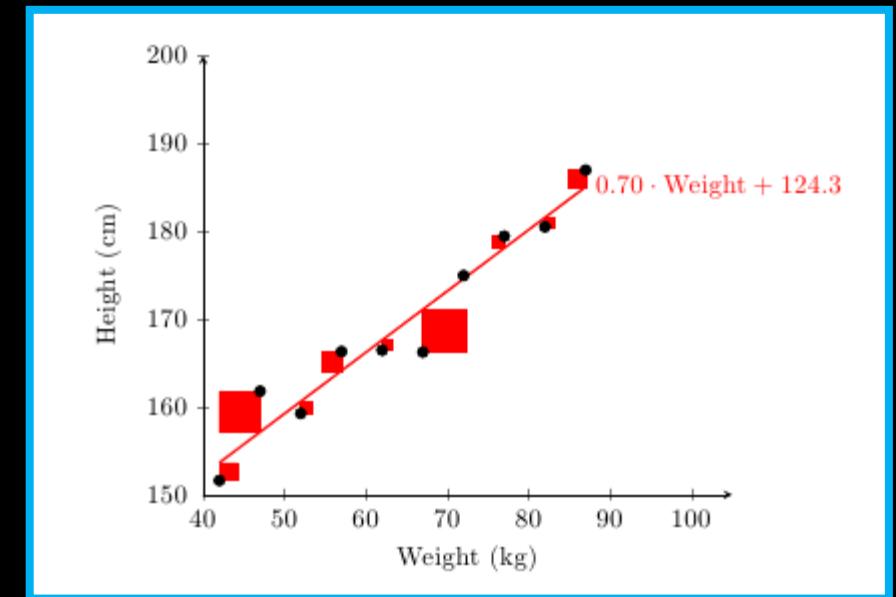


Linear regression:

Measure for all the points – sum of these squared distances

Mean square error:

$$MSE = \frac{1}{n} * \sum (y_{point} - y_{line})^2$$



This tells us how to choose the parameters for the best line.

Linear regression:

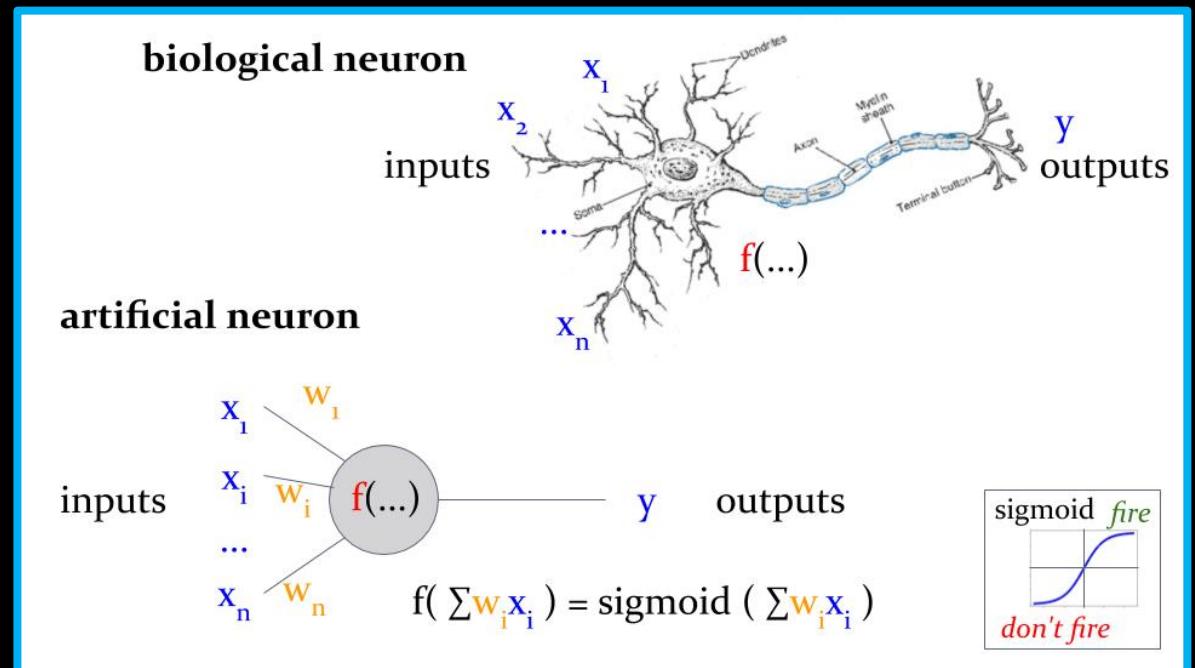
Continue with code on our Github:

- github repo: github.com/previtus/cci_exploring_machine_intelligence
- notebook: [week01_intro-motivation/ml01_linear_regression.ipynb](https://github.com/previtus/cci_exploring_machine_intelligence/blob/main/week01_intro-motivation/ml01_linear_regression.ipynb)

Next class

Building blocks of neural networks

- Neurons!
- Networks
- Datasets
- Practicum: working with Keras



Homework:

Read a paper:

- CAN: Creative Adversarial Networks, Generating "Art" by Learning About Styles and Deviating from Style Norms

Weekly quiz - write about yourself:

- Your background
- Possible interests in machine learning

Homework:

Please read:

1 Introduction
2 Methodology

Then skim through:

4 Results and Validation
5 Discussion and Conclusion

We gratefully acknowledge support from the Simons Foundation and member institutions.

Cornell University

arXiv.org > cs > arXiv:1706.07068

Search... All fields Search

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Computer Science > Artificial Intelligence

[Submitted on 21 Jun 2017]

CAN: Creative Adversarial Networks, Generating "Art" by Learning About Styles and Deviating from Style Norms

Ahmed Elgammal, Bingchen Liu, Mohamed Elhoseiny, Marian Mazzone

We propose a new system for generating art. The system generates art by looking at art and learning about style; and becomes creative by increasing the arousal potential of the generated art by deviating from the learned styles. We build over Generative Adversarial Networks (GAN), which have shown the ability to learn to generate novel images simulating a given distribution. We argue that such networks are limited in their ability to generate creative products in their original design. We propose modifications to its objective to make it capable of generating creative art by maximizing deviation from established styles and minimizing deviation from art distribution. We conducted experiments to compare the response of human subjects to the generated art with their response to art created by artists. The results show that human subjects could not distinguish art generated by the proposed system from art generated by contemporary artists and shown in top art fairs. Human subjects even rated the generated images higher on various scales.

Comments: This paper is an extended version of a paper published on the eighth International Conference on Computational Creativity (ICCC), held in Atlanta, GA, June 20th-June 22nd, 2017

Subjects: Artificial Intelligence (cs.AI)

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References & Citations

- NASA ADS
- Google Scholar
- Semantic Scholar

2 blog links (what is this?)

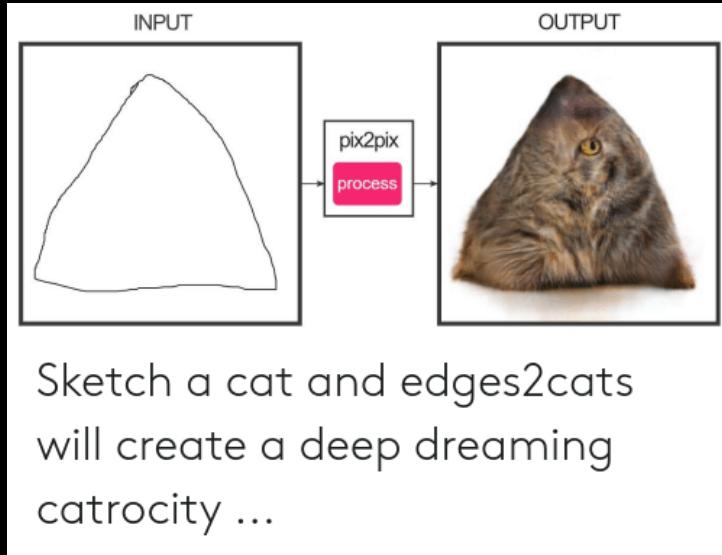
DBLP - CS Bibliography

listing | bibtex

Ahmed M. Elgammal
Bingchen Liu
Marian Mazzone

CAN: Creative Adversarial Networks, Generating "Art" by Learning About Styles and Deviating from Style Norms – [A. Elgammal](#), (2017)

PDF: <https://arxiv.org/pdf/1706.07068.pdf>



The end