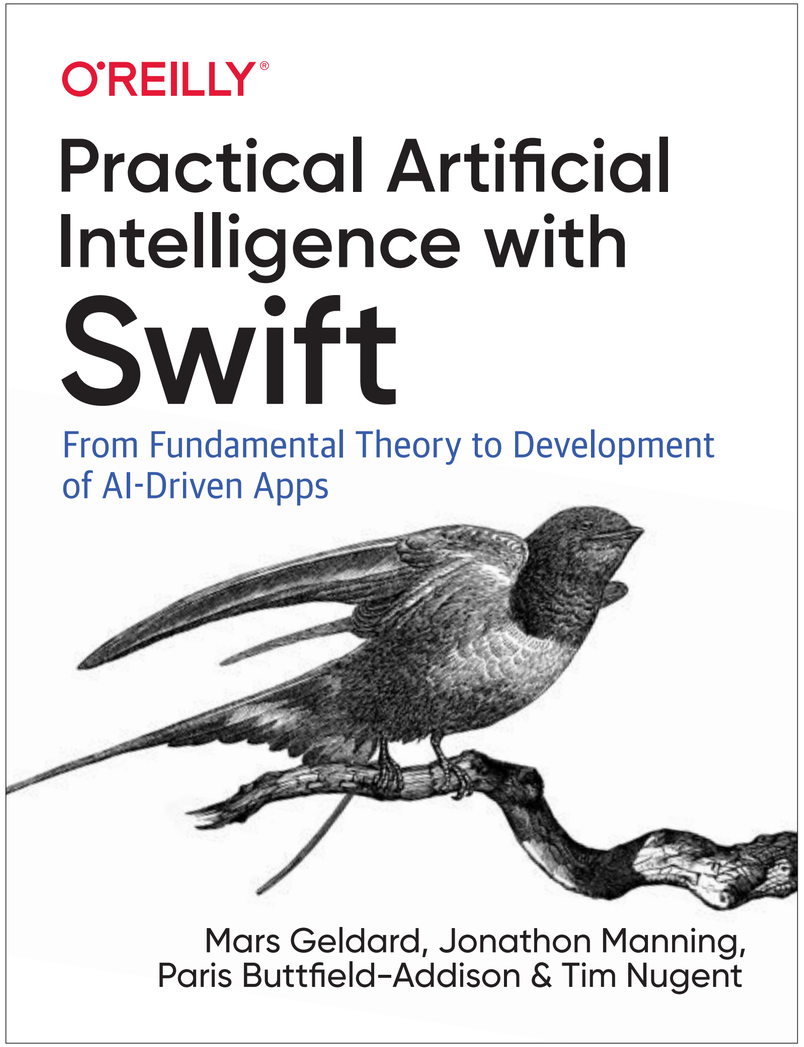
On-device Artificial Intelligence
Neural Style Transfer

with Mars Geldard &
Dr Paris Buttfield-Addison


O'REILLY®
Practical Artificial Intelligence with
Swift
From Fundamental Theory to Development of AI-Driven Apps
Mars Geldard, Jonathon Manning,
Paris Buttfield-Addison & Tim Nugent

@parisba

@themartianlife

Neural Style Transfer

Neural Style Transfer

(Image A Content + Image B Style = Image C)

NST is just our case study

This is really a talk about on-device ML

This isn’t really an Apple talk

They’re just the ~~biggest~~ most interesting player... for now


turi
create intelligence™


ML

Goals of this talk

- Discuss how useful, effective, and sensible the idea of on-device artificial intelligence is
- Have a brief diversion to discuss with Style Transfer is, and gloss over how it works
- Demonstrate that on-device AI works, by implementing Style Transfer for it on iOS
- Show off how useful task-focused approaches to AI can be, and how useful Turi Create is

Part 1

On-device Machine Learning

Part 2

Neural Style Transfer

Part 3

Demonstration

Part 4

The Future

Part 1

On-device Machine Learning

This is the big takeaway of our talk…

On-device AI

On-device artificial intelligence...

... usually means on-device Machine Learning

ML refresher

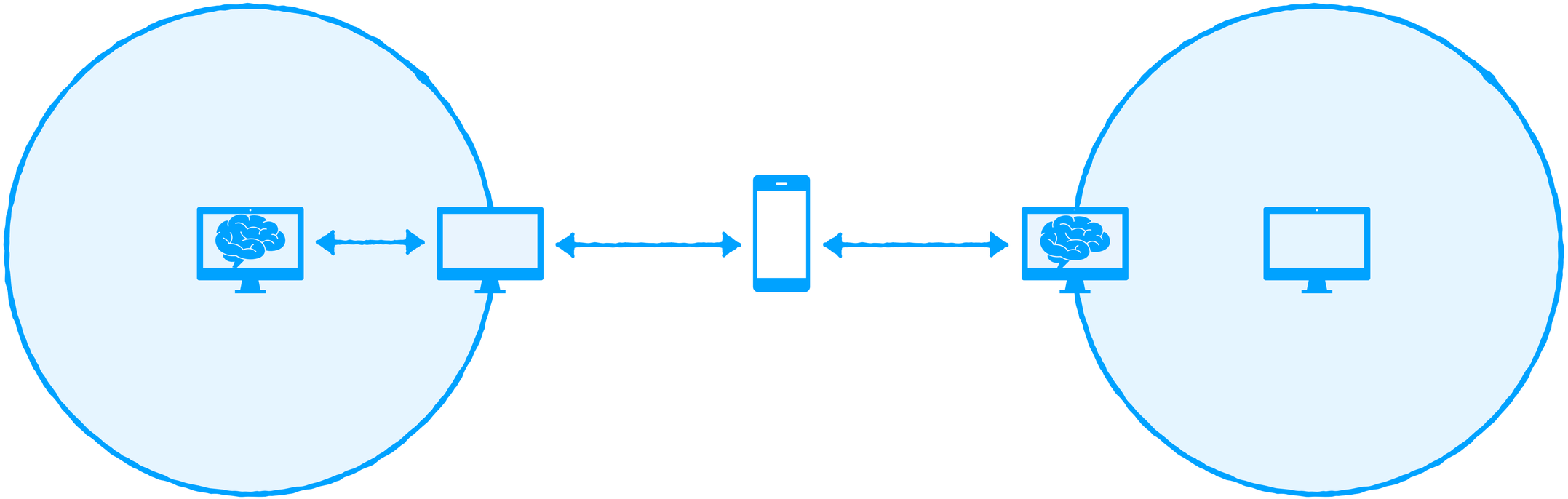
Training and Inference

On-device machine learning...

... usually means on-device consultation of a pre-trained model (inference)

On-device inference

This is just edge computing



“Inference on the edge”

… is another phrase for “on-device ML”

What can you do on device?

What can you do on device?

- Image recognition
- Object localisation
- Speech/character recognition/translation
- Gesture recognition
- Text prediction/classification

Benefits?

- Less (laggy) network requests
- High-speed lag-free user experiences
- Reliability (works offline)
- Cheap(er)
- Privacy

Negatives

- Bigger apps
- Battery use, maybe
- Creation of initial training data
- Model training/retraining
- App updates need to ship the model (or download the model)

Training AND Inference?

- Much harder to do with current hardware, but still possible
- iOS's Photos app
- FaceID + TouchID
- Set of conditions that must be met for the model to attempt training with new data

Part 1

On-device Machine Learning

Part 2

Neural Style Transfer

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Demonstration

Part 4

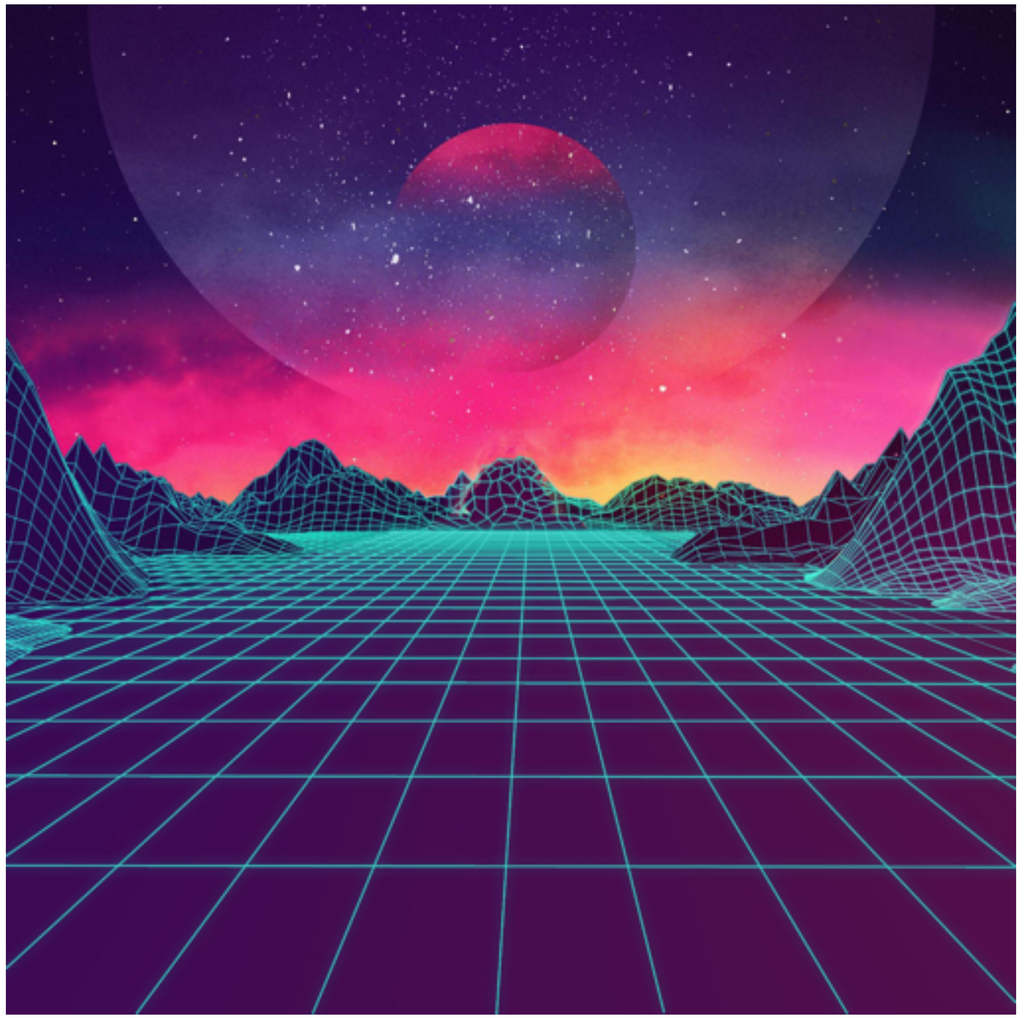
The Future

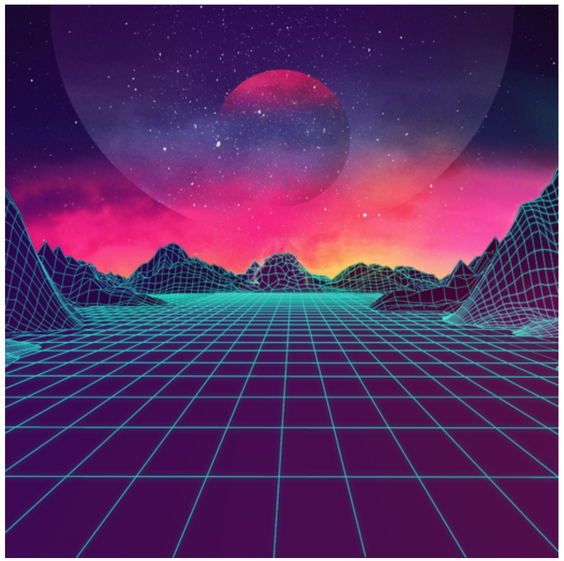
Part 2

Neural Style Transfer

“Style Transfer is a task wherein the stylistic elements of a style image are imitated onto a new image while preserving the content of the new image.”

–TuriCreate documentation





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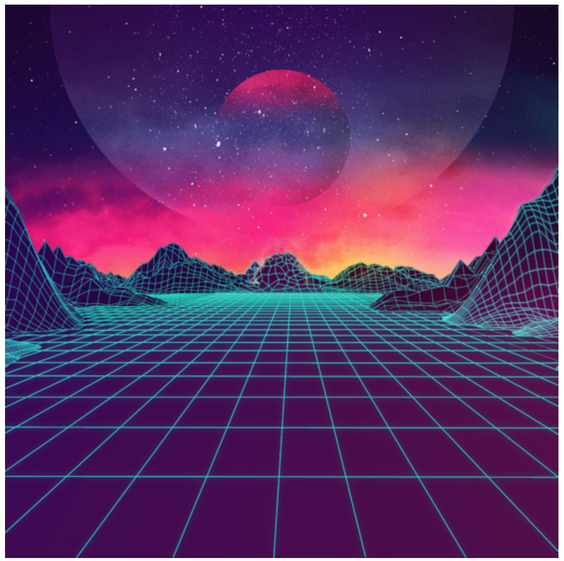

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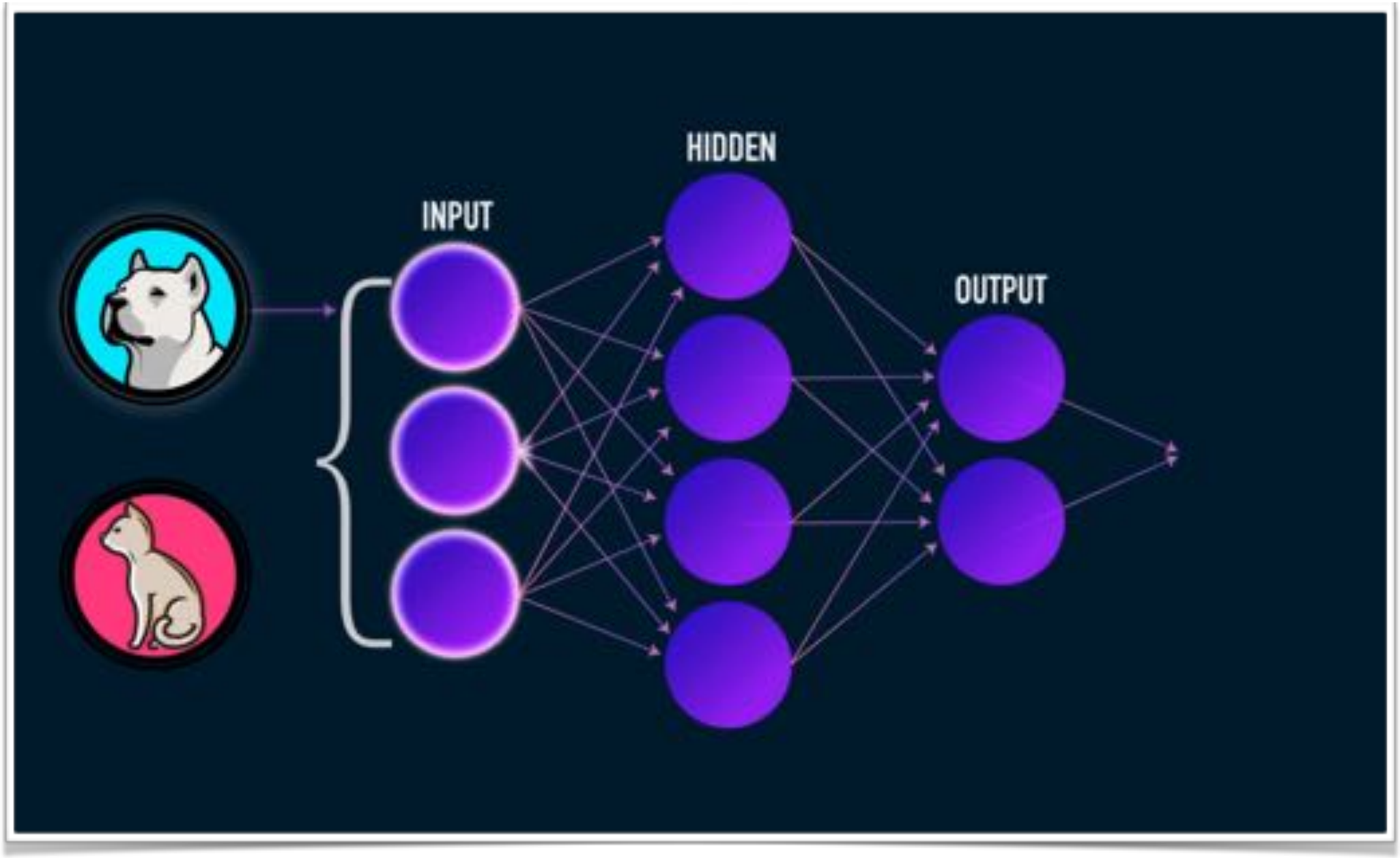
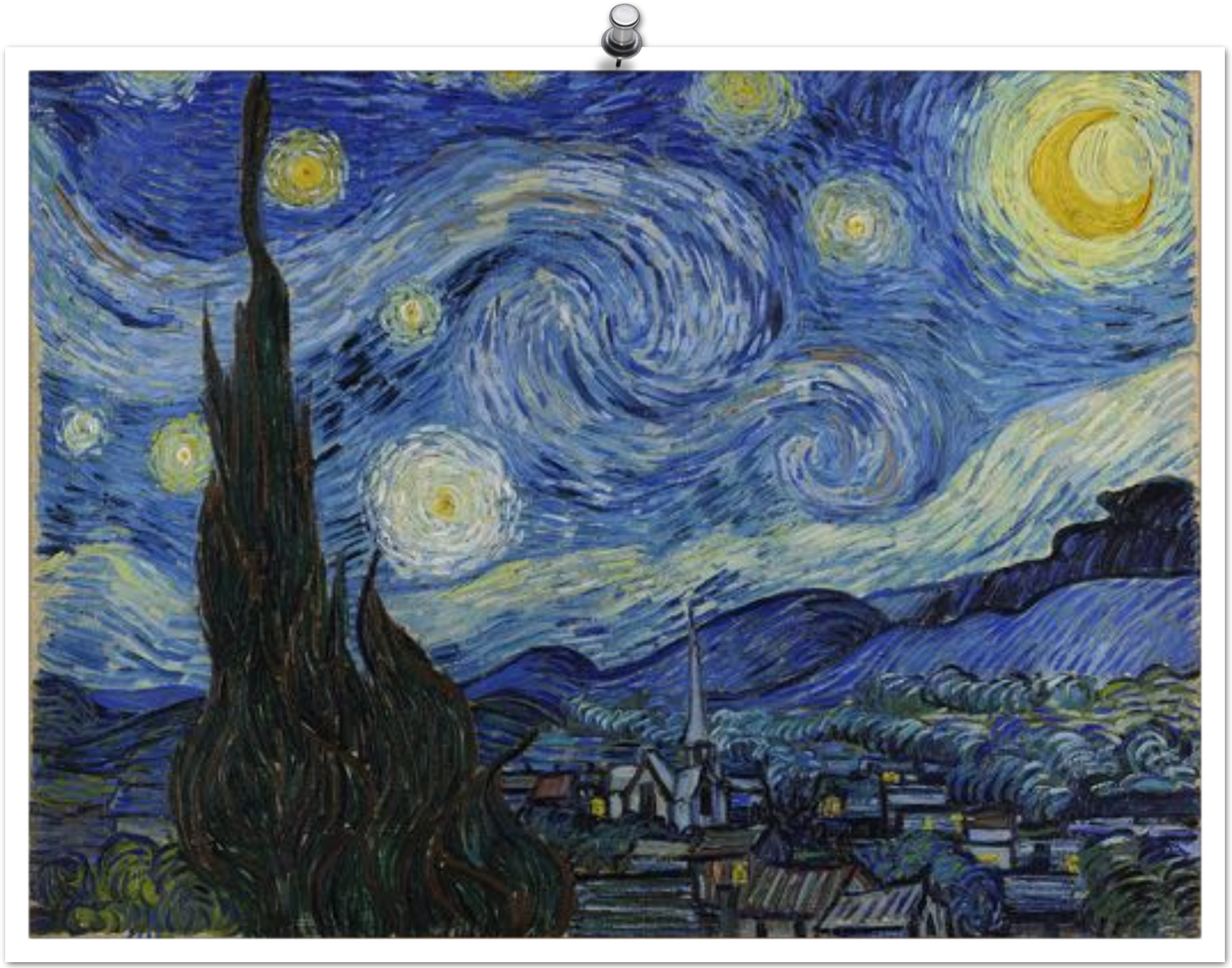
OK, great. How’s it work?

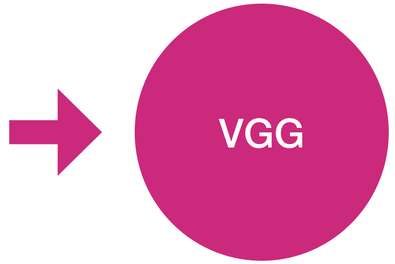
Technically, what’s going on?

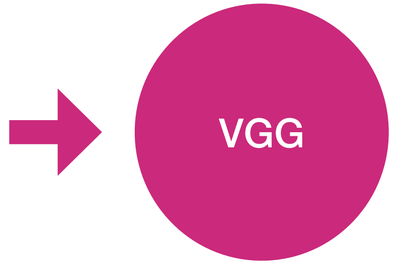
Neural Network refresher

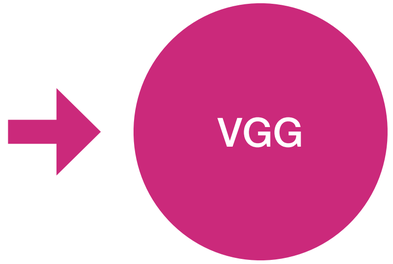

HIDDEN
INPUT
OUTPUT

Using a model to generate?




VGG


VGG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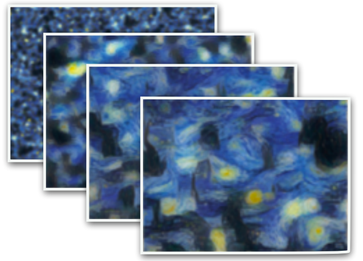

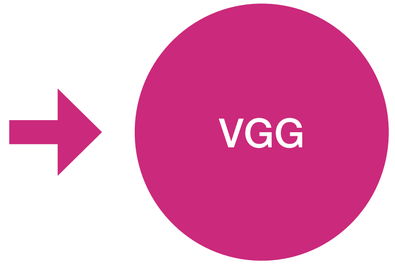
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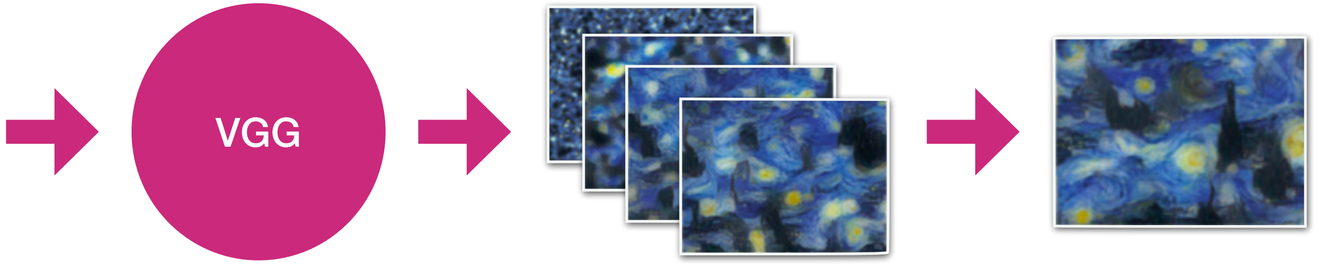
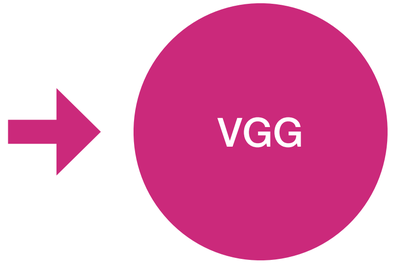

VGG


VGG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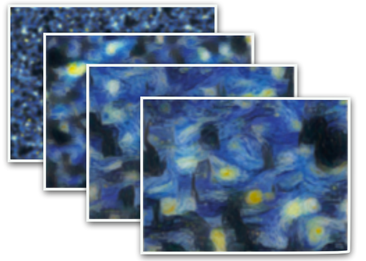
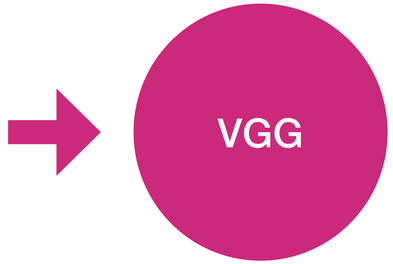
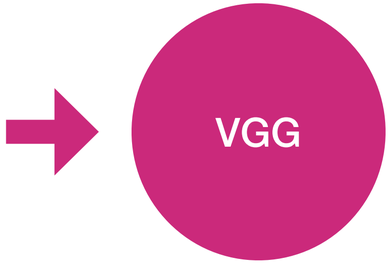
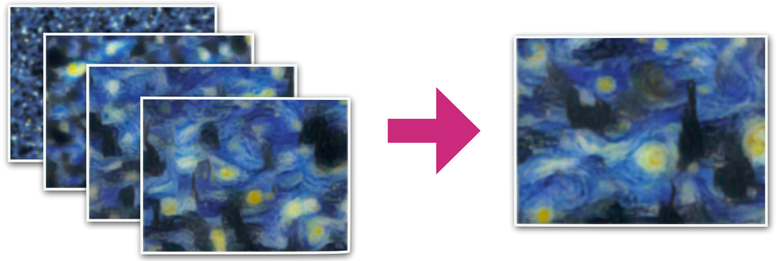
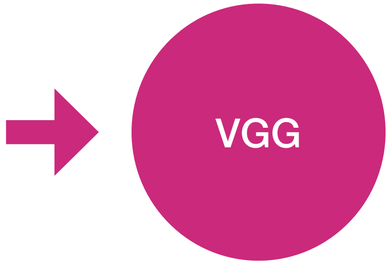



VGG



Style reconstructions

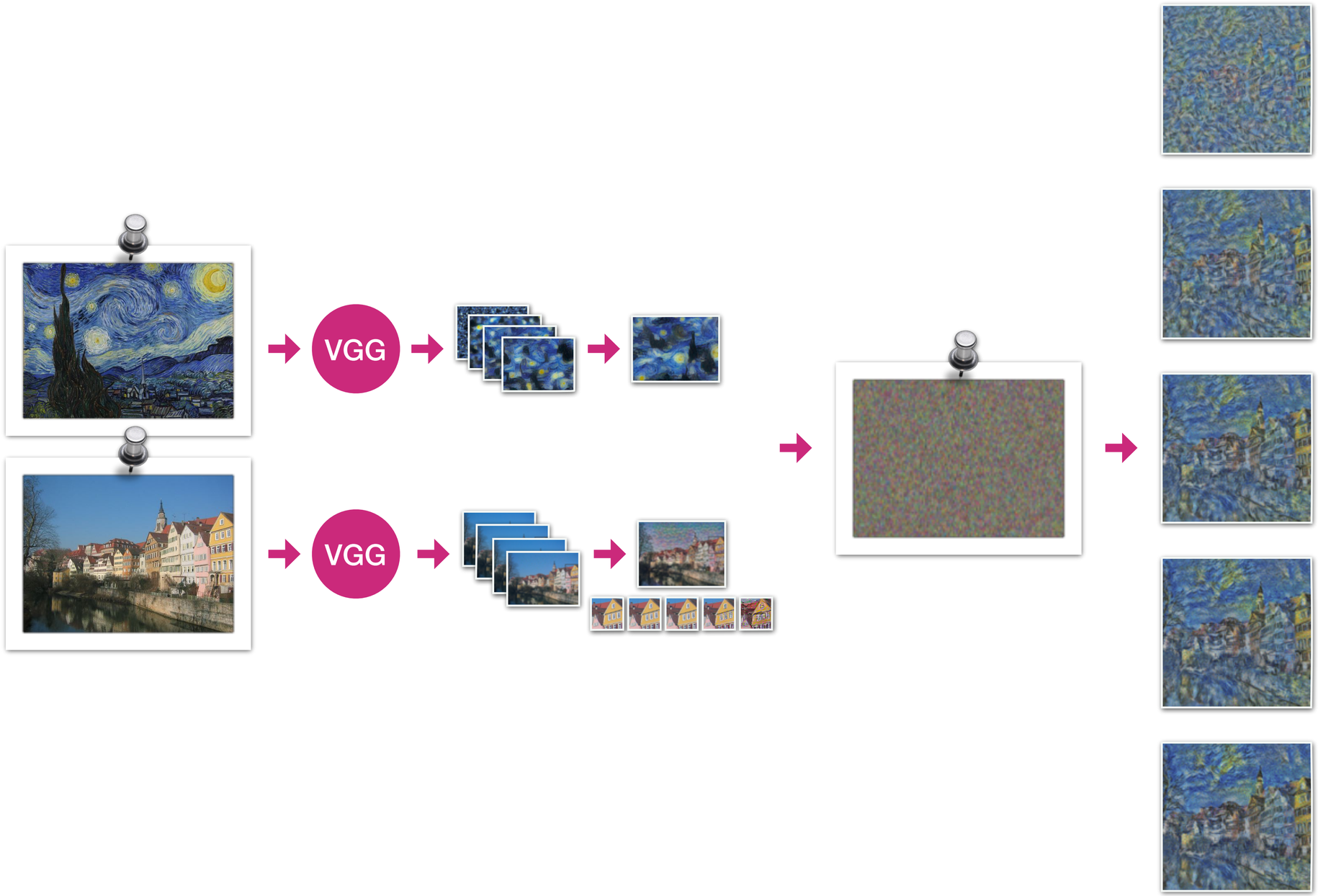


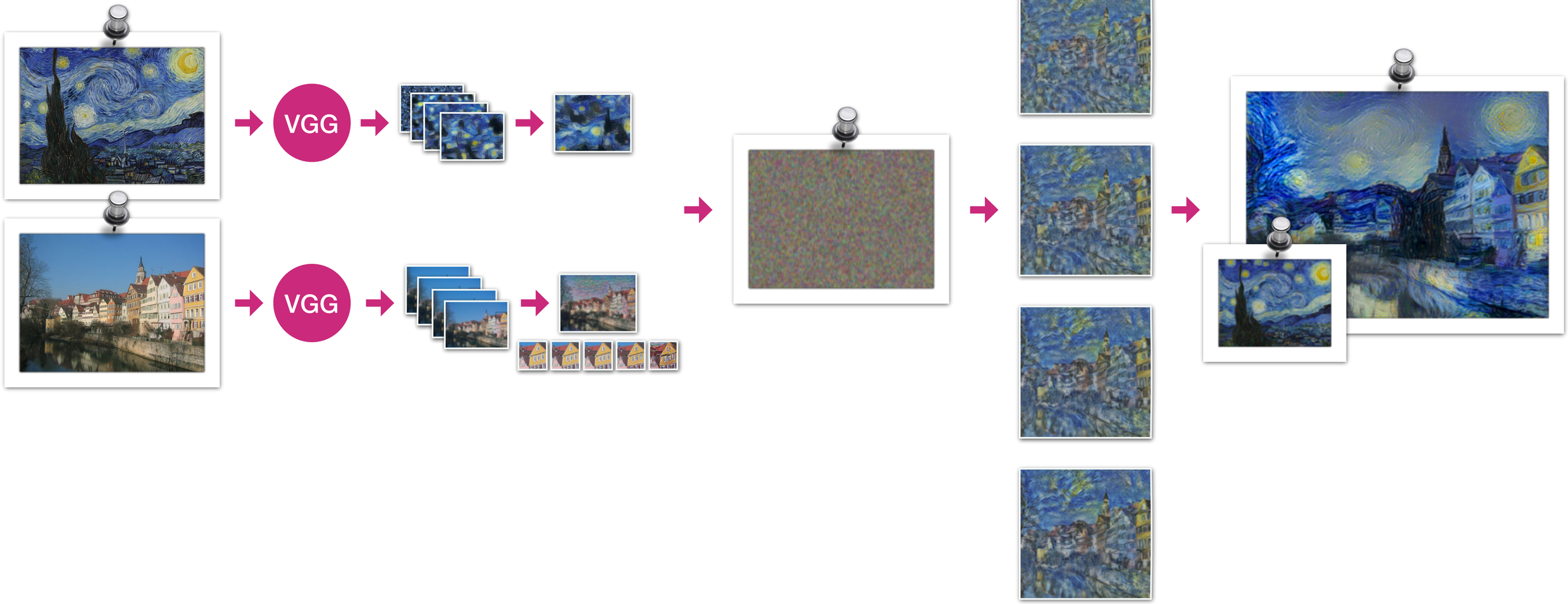


Content reconstructions


VGG
VGG


VGG
VGG


VGG
VGG


VGG
VGG

A Neural Algorithm of Artistic Style

Leon A. Gatys,[1,2,3*] Alexander S. Ecker,[1,2,4,5] Matthias Bethge[1,2,4]

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and Institute of Theoretical Physics, University of Tübingen, Germany
[2]Bernstein Center for Computational Neuroscience, Tübingen, Germany
[3]Graduate School for Neural Information Processing, Tübingen, Germany
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In fine art, especially painting, humans have mastered the skill to create unique visual experiences through composing a complex interplay between the content and style of an image. Thus far the algorithmic basis of this process is unknown and there exists no artificial system with similar capabilities. However, in other key areas of visual perception such as object and face recognition near-human performance was recently demonstrated by a class of biologically inspired vision models called Deep Neural Networks.[1,2] Here we introduce an artificial system based on a Deep Neural Network that creates artistic images of high perceptual quality. The system uses neural representations to separate and recombine content and style of arbitrary images, providing a neural algorithm for the creation of artistic images. Moreover, in light of the striking similarities between performance-optimised artificial neural networks and biological vision,[3–7] our work offers a path forward to an algorithmic understanding of how humans create and perceive artistic imagery.

So what?

That’s nice, but it makes sense. Why does this talk have ‘on-device’ in the title?
What are these Australians ranting about?

Quick and efficient

If it’s going mobile, if it’s going on-device, it needs to be better.

The Old Way

Using a neural network… but not really training.

An Old Way

- Trained classifier as a feature detector: texture synthesis
  - e.g. using a network to extract features from a texture image.
- Checking how close the synthesised image is to a content image with respect to the features extracted by the classifier
- Repeat.
- Feedforward network, going from content to new styled image in one pass, but only works on a single style.

It’s always the same problem…

As it turns out!

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Published as a conference paper at ICLR 2017

A LEARNED REPRESENTATION FOR ARTISTIC STYLE

Vincent Dumoulin & Jonathon Shlens & Manjunath Kudlur
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ABSTRACT

The diversity of painting styles represents a rich visual vocabulary for the construction of an image. The degree to which one may learn and parsimoniously capture this visual vocabulary measures our understanding of the higher level features of paintings, if not images in general. In this work we investigate the construction of a single, scalable deep network that can parsimoniously capture the artistic style of a diversity of paintings. We demonstrate that such a network generalizes across a diversity of artistic styles by reducing a painting to a point in an embedding space. Importantly, this model permits a user to explore new painting styles by arbitrarily combining the styles learned from individual paintings. We hope that this work provides a useful step towards building rich models of paintings and offers a window on to the structure of the learned representation of artistic style.

1 INTRODUCTION

A pastiche is an artistic work that imitates the style of another one. Computer vision and more recently machine learning have a history of trying to automate pastiche, that is, render an image in the style of another one. This task is called *style transfer*, and is closely related to the texture synthesis task. While the latter tries to capture the statistical relationship between the pixels of a source image which is assumed to have a stationary distribution at some scale, the former does so while also attempting to preserve some notion of content.

On the computer vision side, Efros & Leung (1999) and Wei & Levoy (2000) attempt to "grow" textures one pixel at a time using non-parametric sampling of pixels in an examplar image. Efros & Freeman (2001) and Liang et al. (2001) extend this idea to "growing" textures one patch at a time, and Efros & Freeman (2001) uses the approach to implement "texture transfer", i.e. transfering the texture of an object onto another one. Kwatra et al. (2005) approaches the texture synthesis problem from an energy minimization perspective, progressively refining the texture using an EM-like algorithm. Hertzmann et al. (2001) introduces the concept of "image analogies": given a pair of "unfiltered" and "filtered" versions of an examplar image, a target image is processed to create an analogous "filtered" result. More recently, Frigo et al. (2016) treats style transfer as a local texture transfer (using an adaptive patch partition) followed by a global color transfer, and Elad & Milanfar (2016) extends Kwatra's energy-based method into a style transfer algorithm by taking content similarity into account.

On the machine learning side, it has been shown that a trained classifier can be used as a feature extractor to drive texture synthesis and style transfer. Gatys et al. (2015a) uses the VGG-19 network (Simonyan & Zisserman, 2014) to extract features from a texture image and a synthesized texture. The two sets of features are compared and the synthesized texture is modified by gradient descent so that the two sets of features are as close as possible. Gatys et al. (2015b) extends this idea to style transfer by adding the constraint that the synthesized image also be close to a content image with respect to another set of features extracted by the trained VGG-19 classifier.

While very flexible, this algorithm is expensive to run due to the optimization loop being carried. Ulyanov et al. (2016a), Li & Wand (2016) and Johnson et al. (2016) tackle this problem by introducing a *feedforward style transfer network*, which is trained to go from content to pastiche image in one pass. However, in doing so some of the flexibility of the original algorithm is lost: the style transfer network is tied to a single style, which means that separate networks have to be trained

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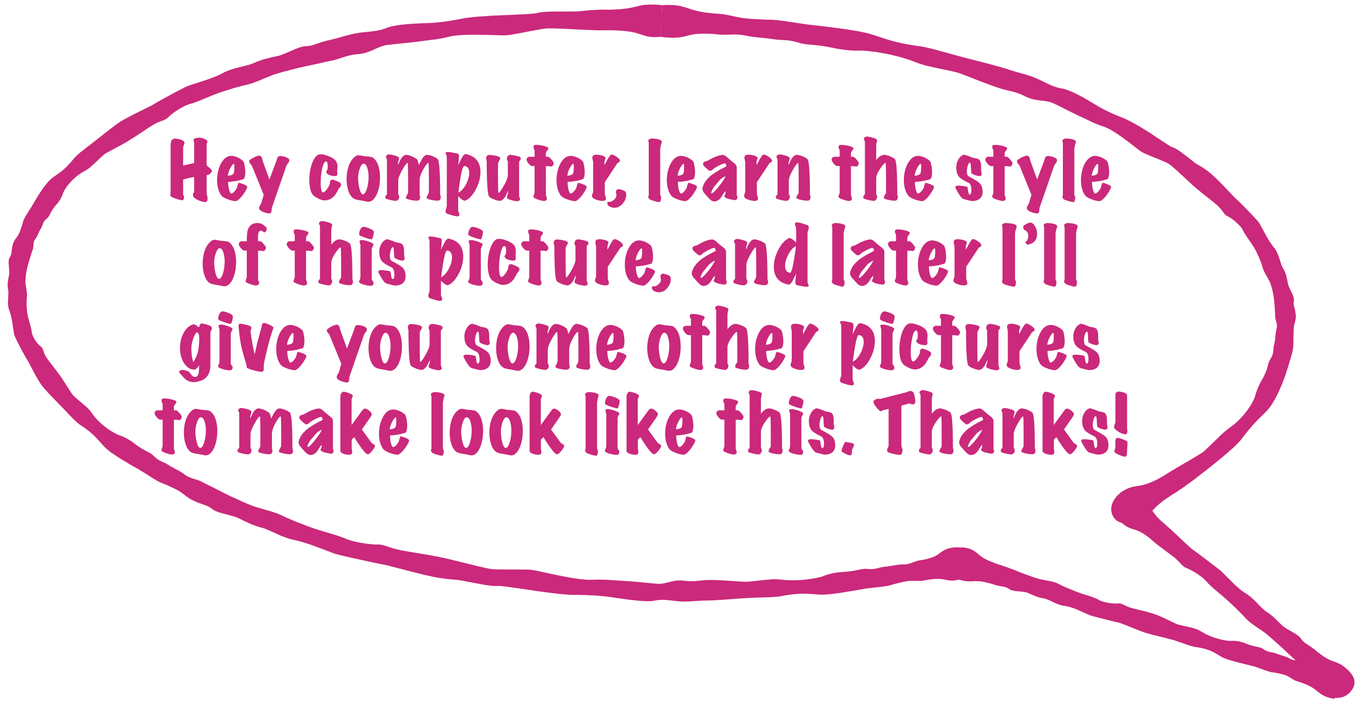
The New Way

The New Way


Hey computer, learn the style
of this picture, and later I'll
give you some other pictures
to make look like this. Thanks!

The New Image

Activations in the neural network that are similar
to both the style and to the content activations.

A million approaches

- Turi Create + Core ML + Swift iOS app
- Keras + Core ML Tools + Core ML + Swift iOS app
- PyTorch + Core ML Tools + Core ML + Swift iOS app
- TensorFlow + Core ML Tools + Core ML + Swift iOS app
- …. and many others!


turi
create intelligence™

Part 1

On-device Machine Learning

Part 2

Neural Style Transfer

Part 3

Demonstration

Part 4

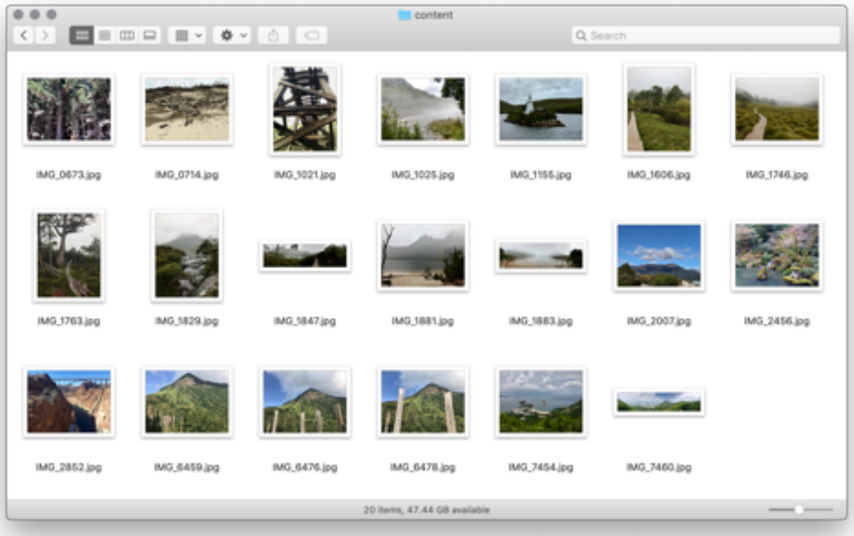
The Future

Part 3

Demonstration

Data Preparation

Step 1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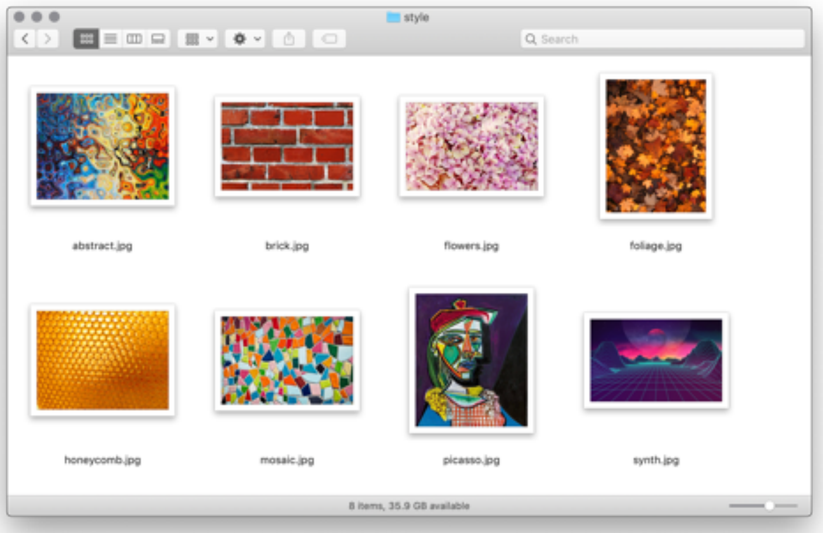
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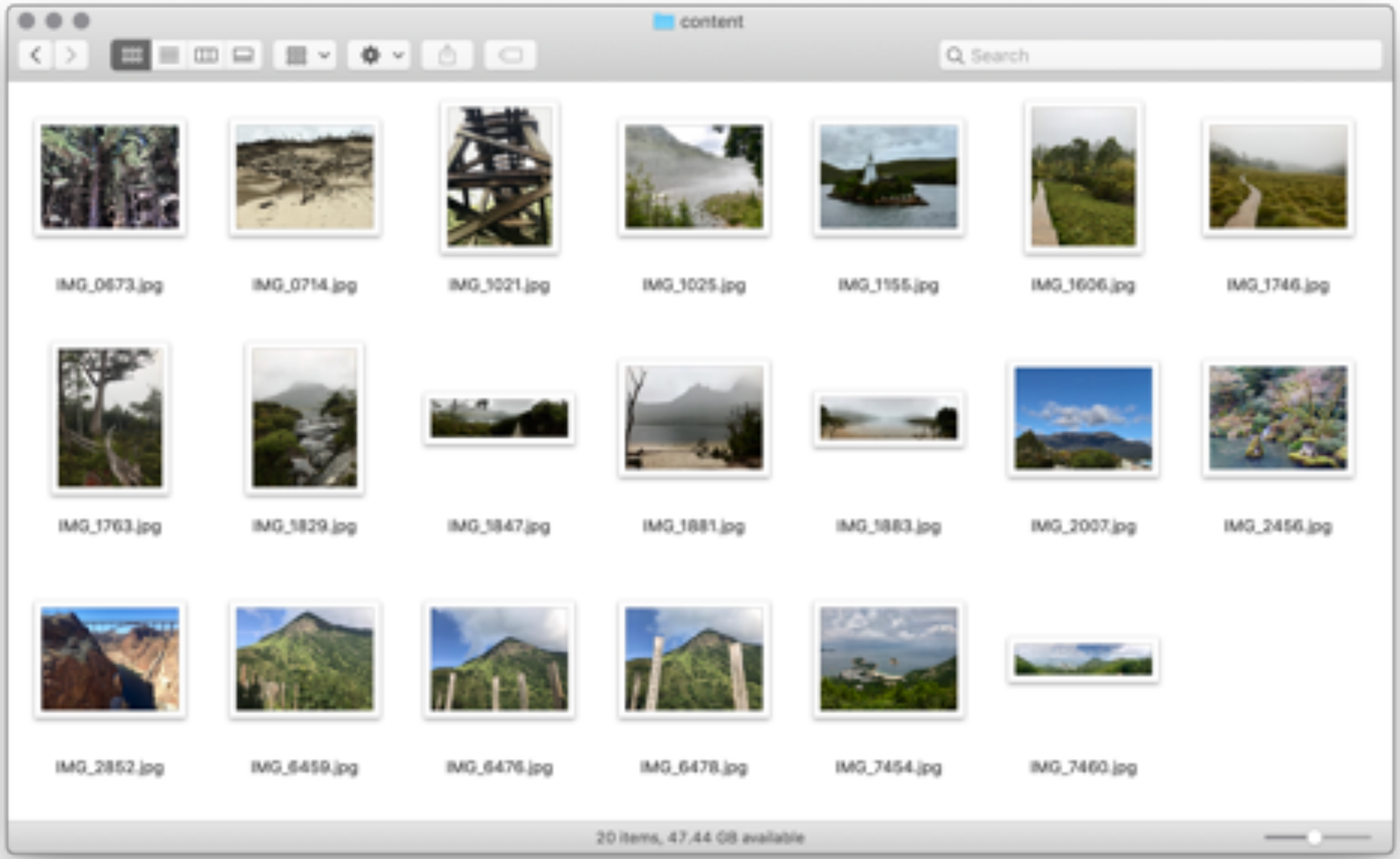
8 items, 35.9 GB available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IMG_0673.jpg
IMG_0714.jpg
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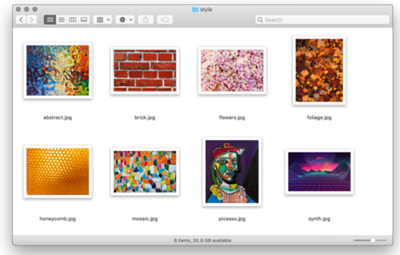
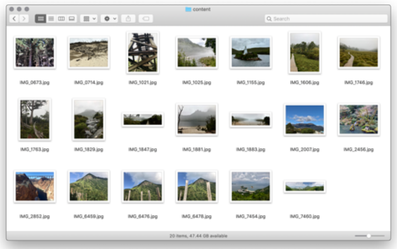
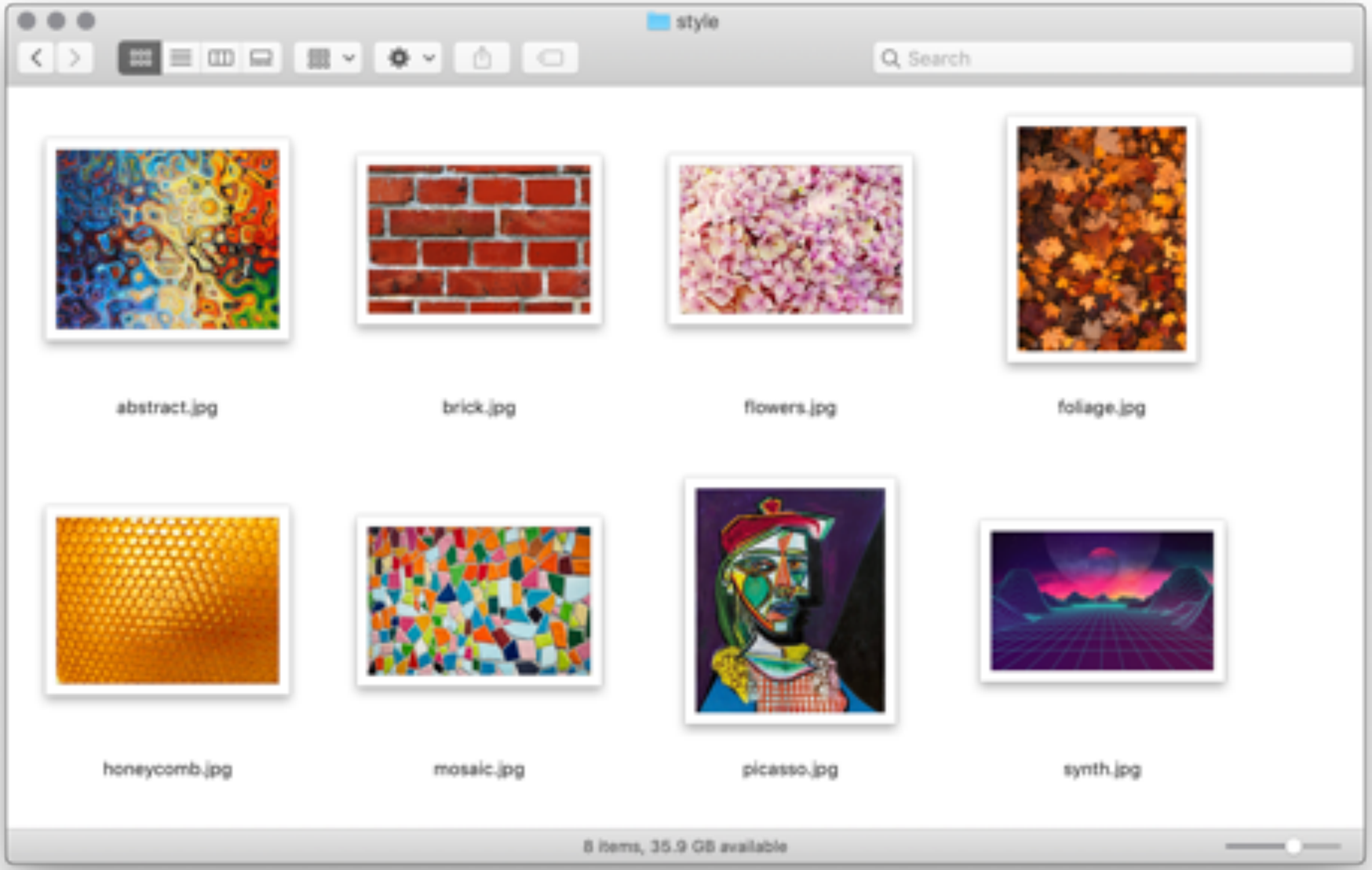
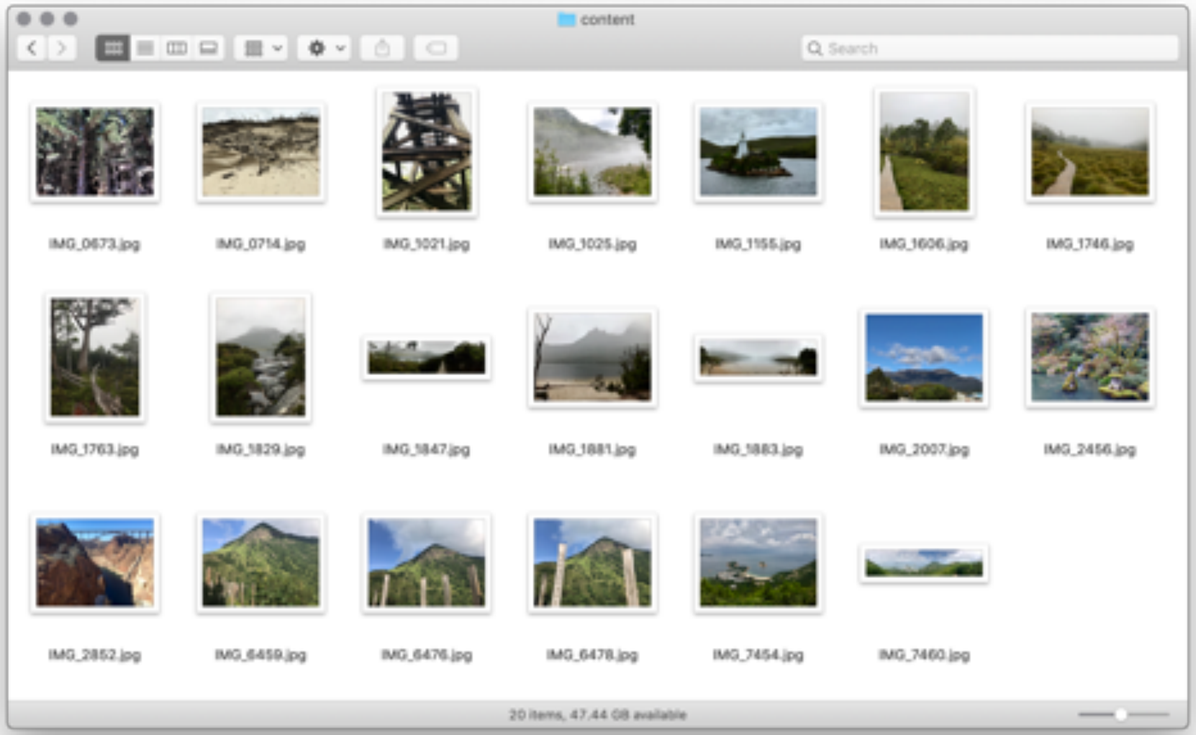
20 items, 47.44 GB available






style
Search
abstract.jpg
brick.jpg
flowers.jpg
foliage.jpg
honeycomb.jpg
mosaic.jpg
picasso.jpg
synth.jpg
8 items, 35.9 GB available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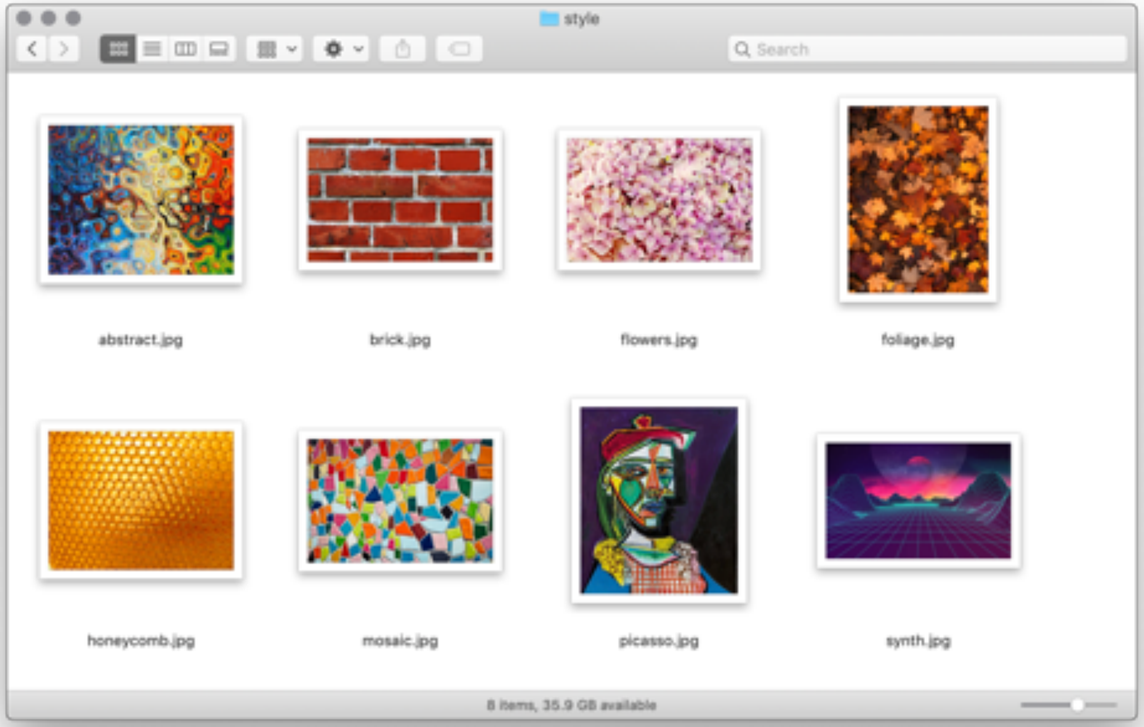
style
Search
abstract.jpg
brick.jpg
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foliage.jpg
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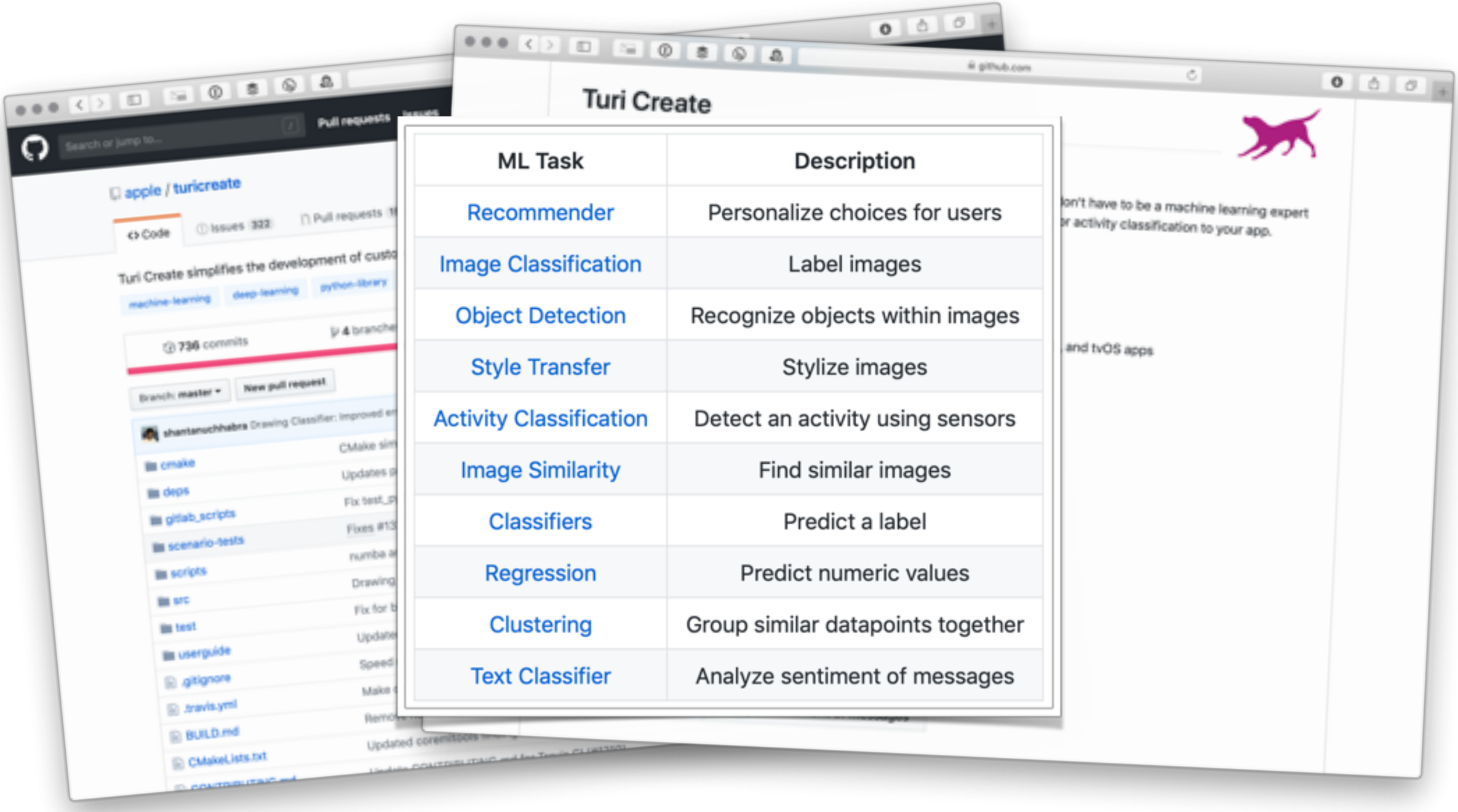
Training

Step 2



ML Task	Description
Recommender	Personalize choices for users
Image Classification	Label images
Object Detection	Recognize objects within images
Style Transfer	Stylize images
Activity Classification	Detect an activity using sensors
Image Similarity	Find similar images
Classifiers	Predict a label
Regression	Predict numeric values
Clustering	Group similar datapoints together
Text Classifier	Analyze sentiment of messages

```
import turicreate as tc

# Load the style and content images
styles = tc.load_images('style/')
content = tc.load_images('content/')

# Create a StyleTransfer model
model = tc.style_transfer.create(styles, content, max_iterations=2000)

# Load some test images
test_images = tc.load_images('test/')

# Stylize the test images
stylized_images = model.stylize(test_images)

# Save the model for later use in Turi Create
model.save('DemoNST.model')

# Export for use in Core ML
model.export_coreml('DemoNST.mlmodel')
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```


turicreate-training — train.py — 80×24
(venv) Hyperion:turicreate-training desplesda$ ./train.py


NST — python train_nst.py — python — python • python train_nst.py — 119×30
python train_nst.py
Using 'image' in style_dataset as feature column and using 'image' in content_dataset as feature column
Downloading https://docs-assets.developer.apple.com/turicreate/models/resnet-16.params
Download completed: /var/folders/sz/9p_l7vsn4zn0f4051by7yh9m0000gn/T/model_cache/resnet-16.params
Downloading https://docs-assets.developer.apple.com/turicreate/models/vgg16-conv1_1-4_3.params
Download completed: /var/folders/sz/9p_l7vsn4zn0f4051by7yh9m0000gn/T/model_cache/vgg16-conv1_1-4_3.params
1	20.058	7.5
2	19.391	29.7
3	22.495	52.2
4	25.156	74.5
5	24.308	97.4
6	23.609	126.4
7	23.020	153.1
8	25.688	179.0
9	24.263	203.8
10	22.451	230.1
11	21.359	260.5
12	20.486	292.7
13	19.633	319.2
14	18.834	342.8
15	21.639	367.2
16	20.758	392.9
17	23.566	418.9
18	22.874	444.5

Training

Training

Super fast

Training in the cloud

Many options!

- https://notebooks.azure.com
- https://colab.research.google.com
- https://www.paperspace.com
- https://www.floydhub.com/

Demo

Quick & Easy to Make & Deploy

Maybe not so quick to run…

Get our code!

https://github.com/thesecretlab/ReinforceConf2019

https://lab.to/NSTDemoJupyter

Part 1

On-device Machine Learning

Part 2

Neural Style Transfer

Part 3

Demonstration

Part 4

The Future

Part 4

The Future

What’s next for on-device AI?

- Privacy focus!
- Bringing AI-driven solutions to disconnected areas
- Better tools
- Task focused tools
- Smooth mobile experiences

Privacy

“I have done nothing wrong, so I have nothing to hide.”

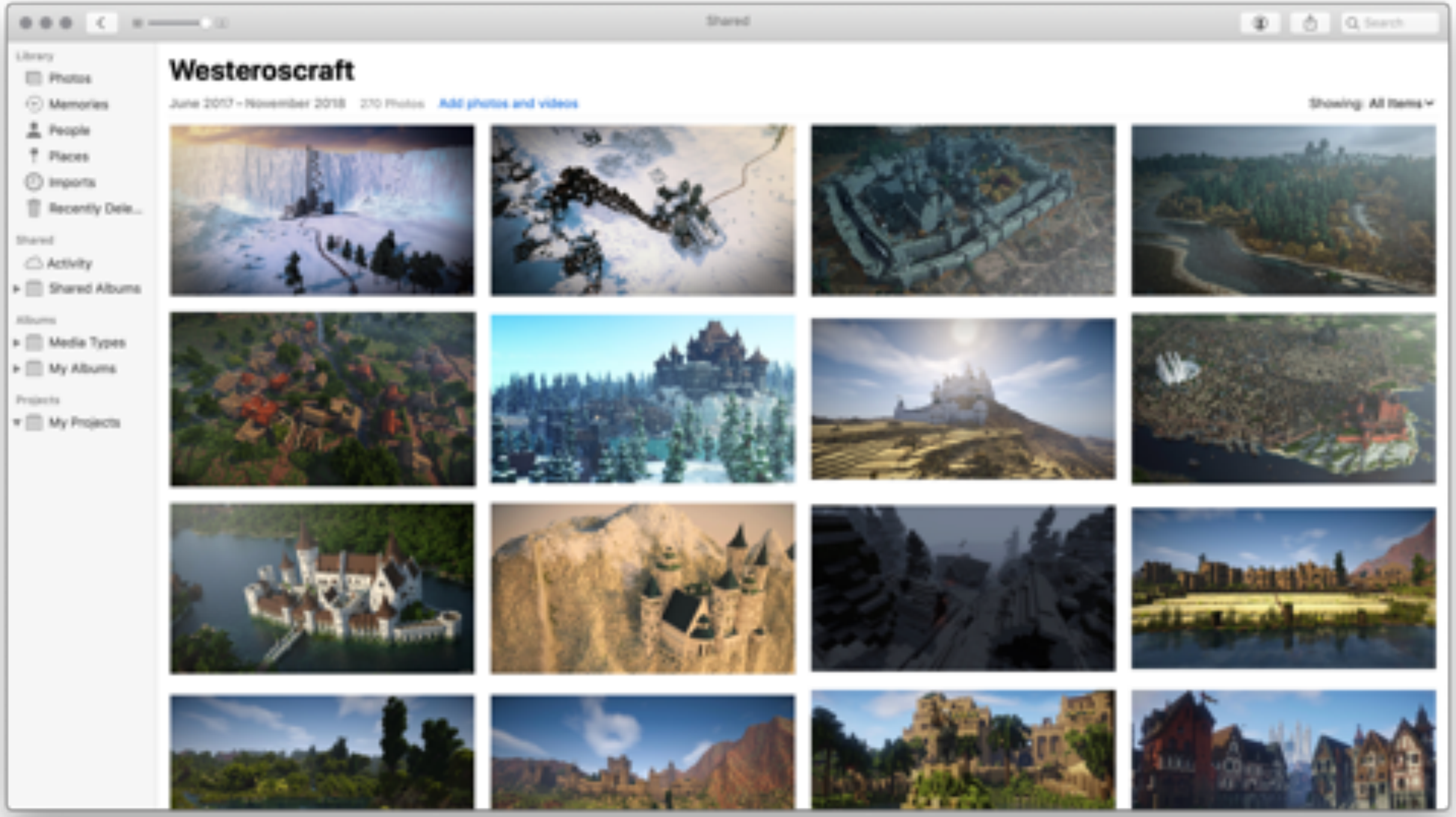
–Almost everyone we have ever spoken to under the age of 25, on personal privacy

“My problem with [statements like these] is that they accept the premise that privacy is about hiding a wrong. It's not.

Privacy is an inherent human right, and a requirement for maintaining the human condition with dignity and respect.”

–Bruce Schneier, computer security expert and cryptographer

Let’s look at a (bad) example


Shared
Search
Library
Photos
Memories
People
Places
Imports
Recently Dele...
Shared
Activity
Shared Albums
Albums
Media Types
My Albums
Projects
My Projects
Westeroscraft
June 2017 – November 2018
270 Photos
Add photos and videos
Showing: All Items

Let’s pretend this is SUPER embarrassing

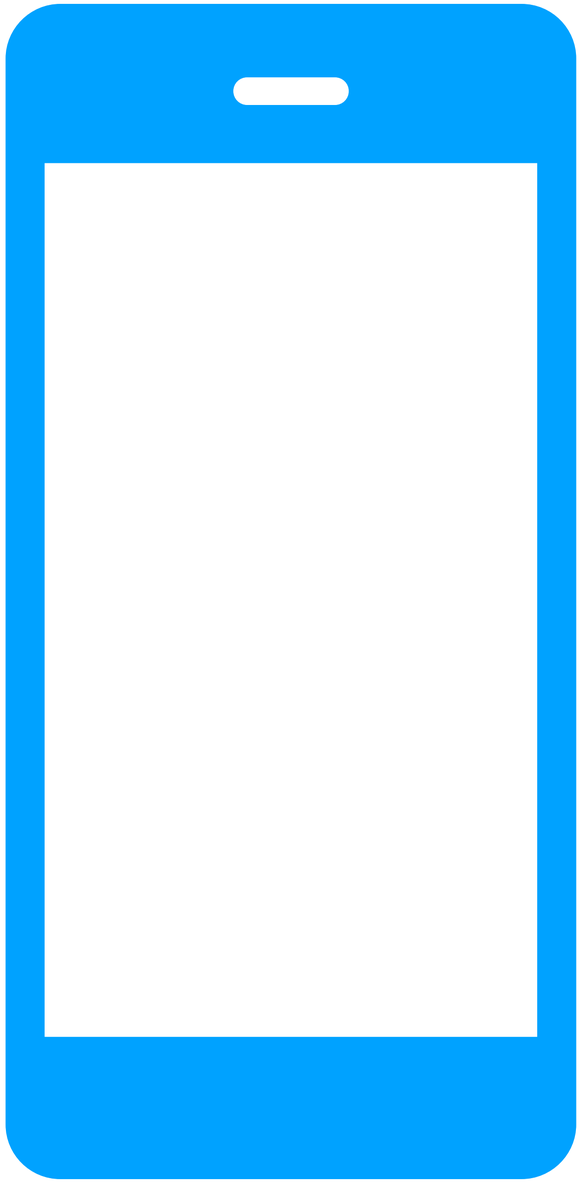
(even it’s not; it’s obviously really cool 😐)

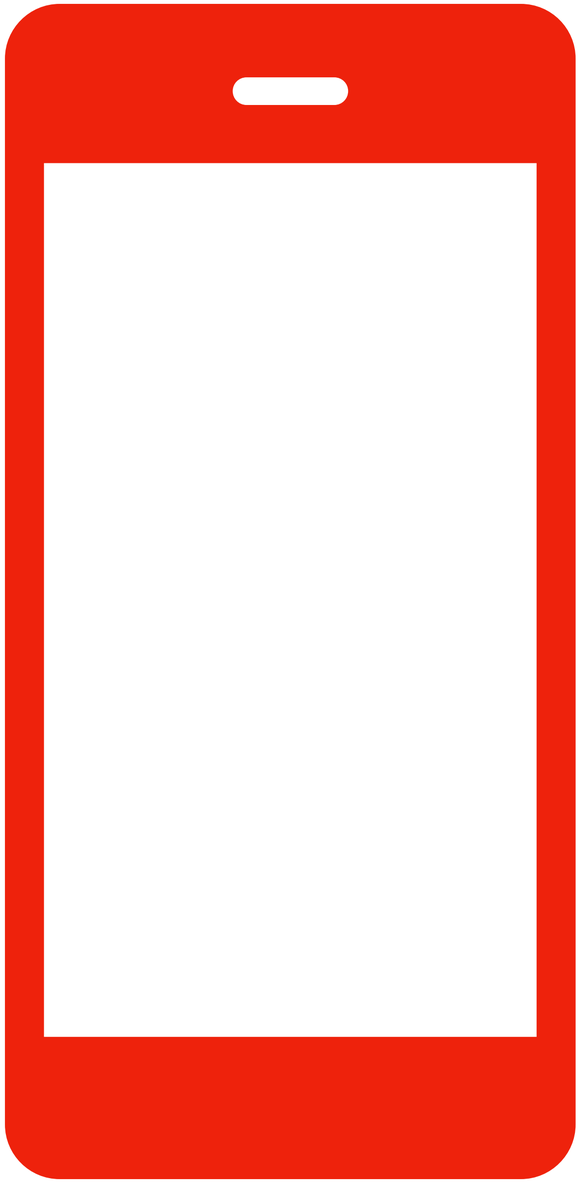
Schmapple

Schmandroid

DISCLAIMER

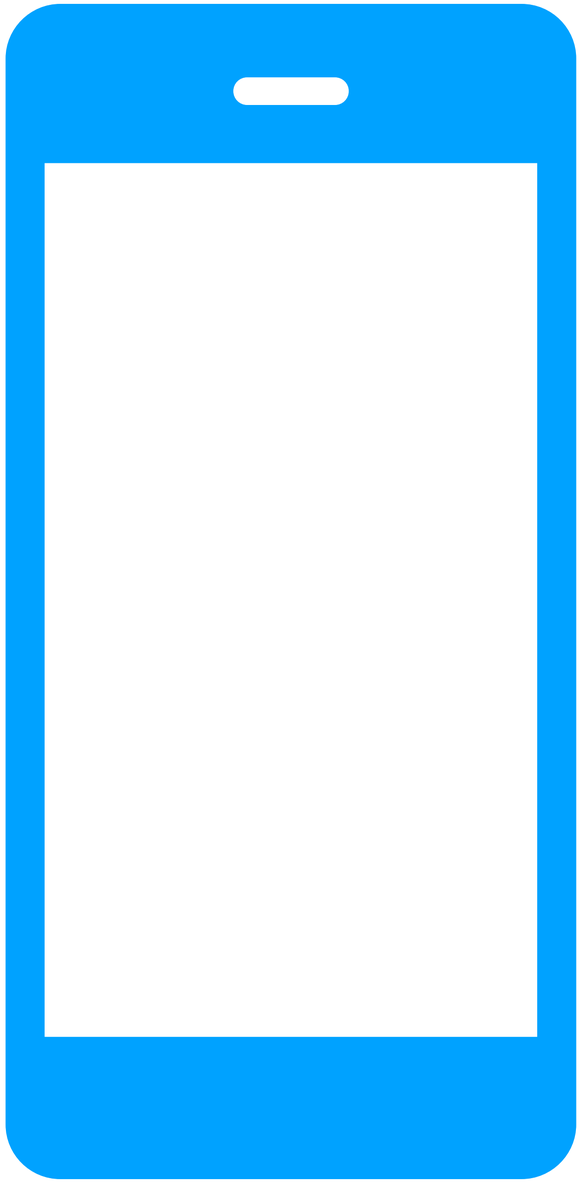
Schmapple

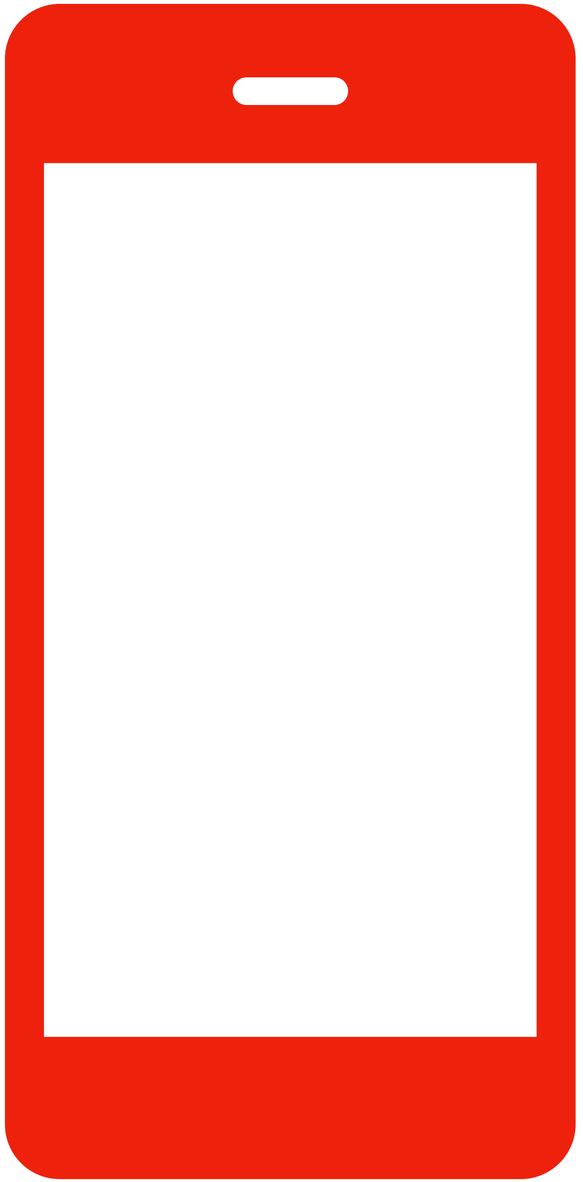




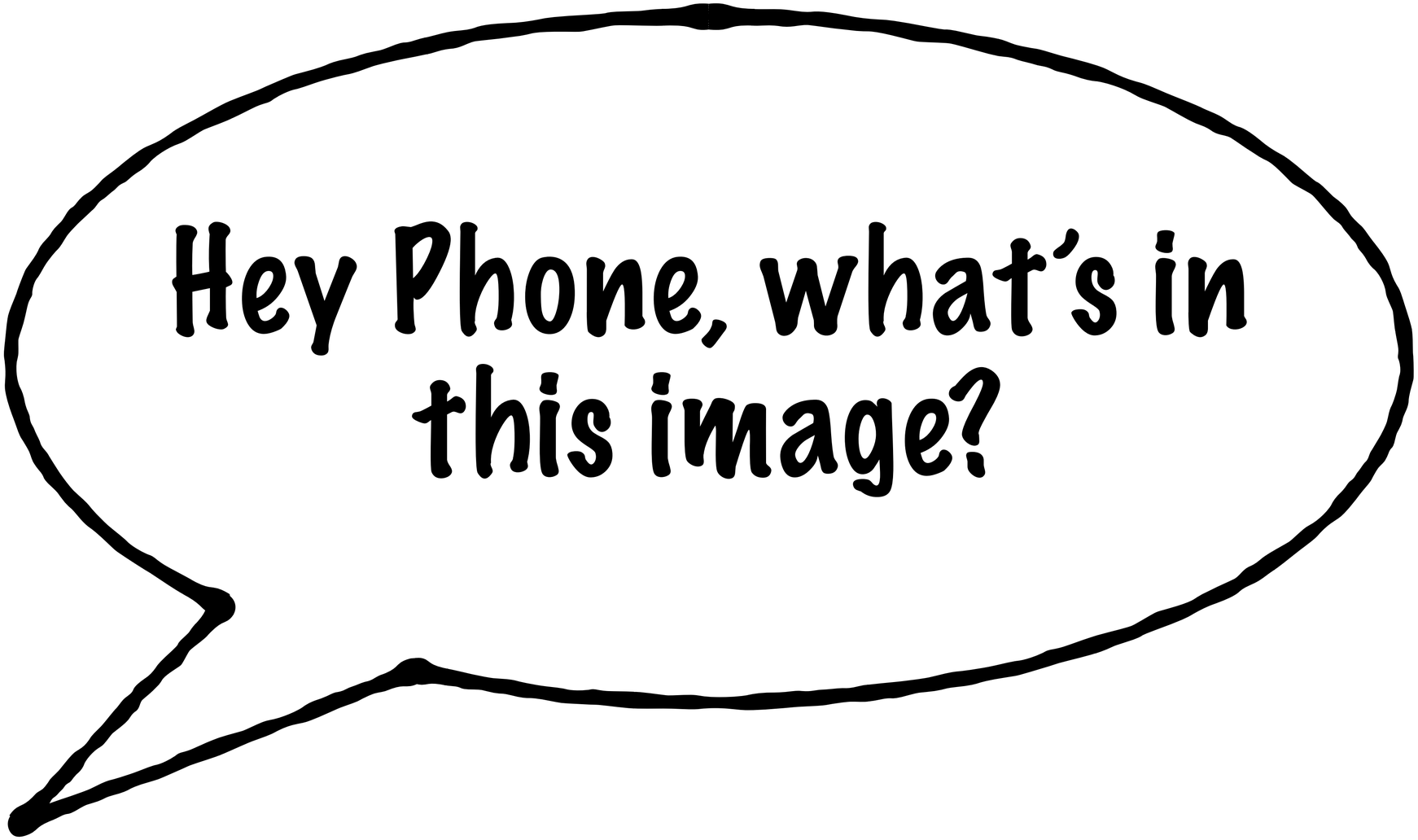
Schmandroid

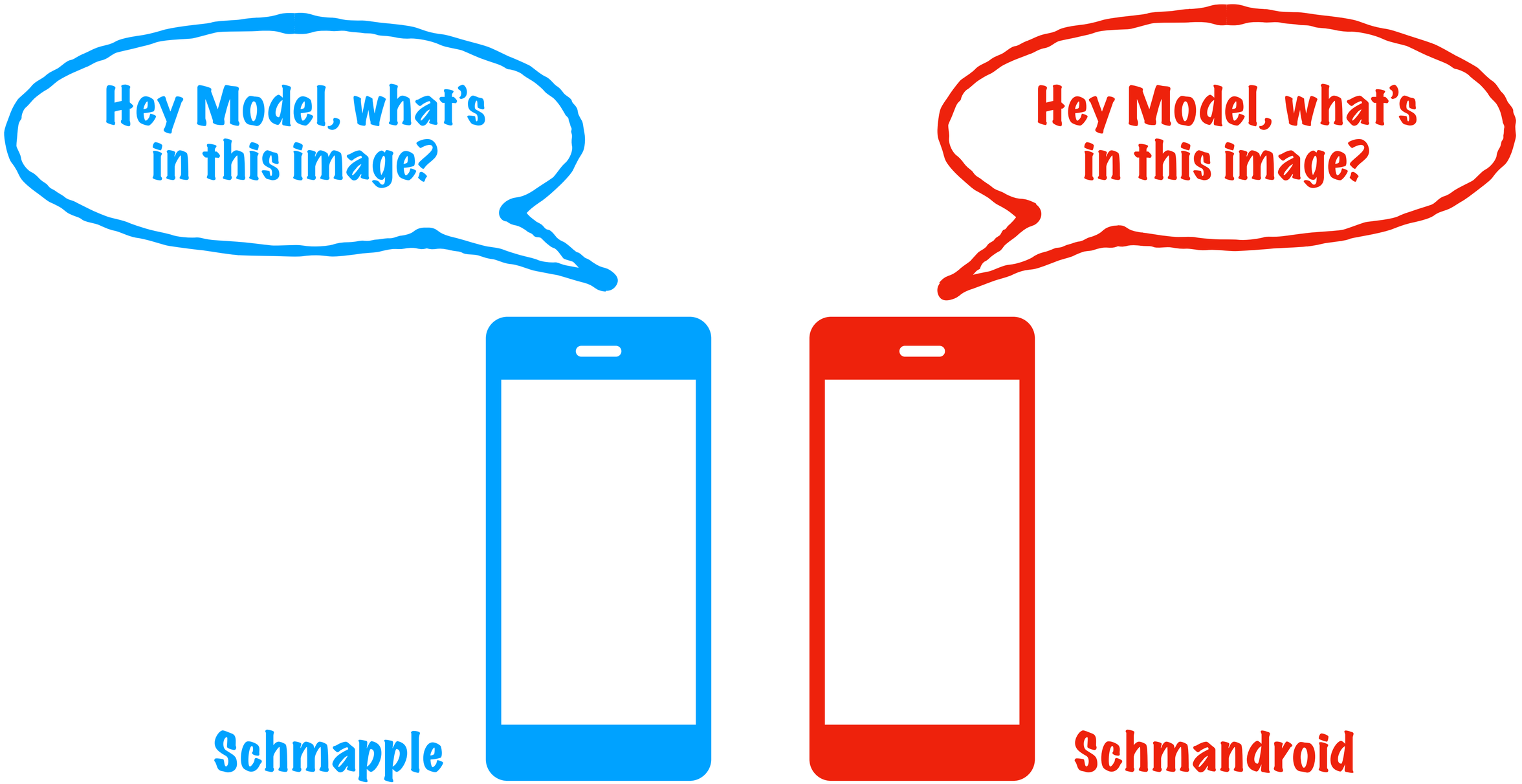
On-device

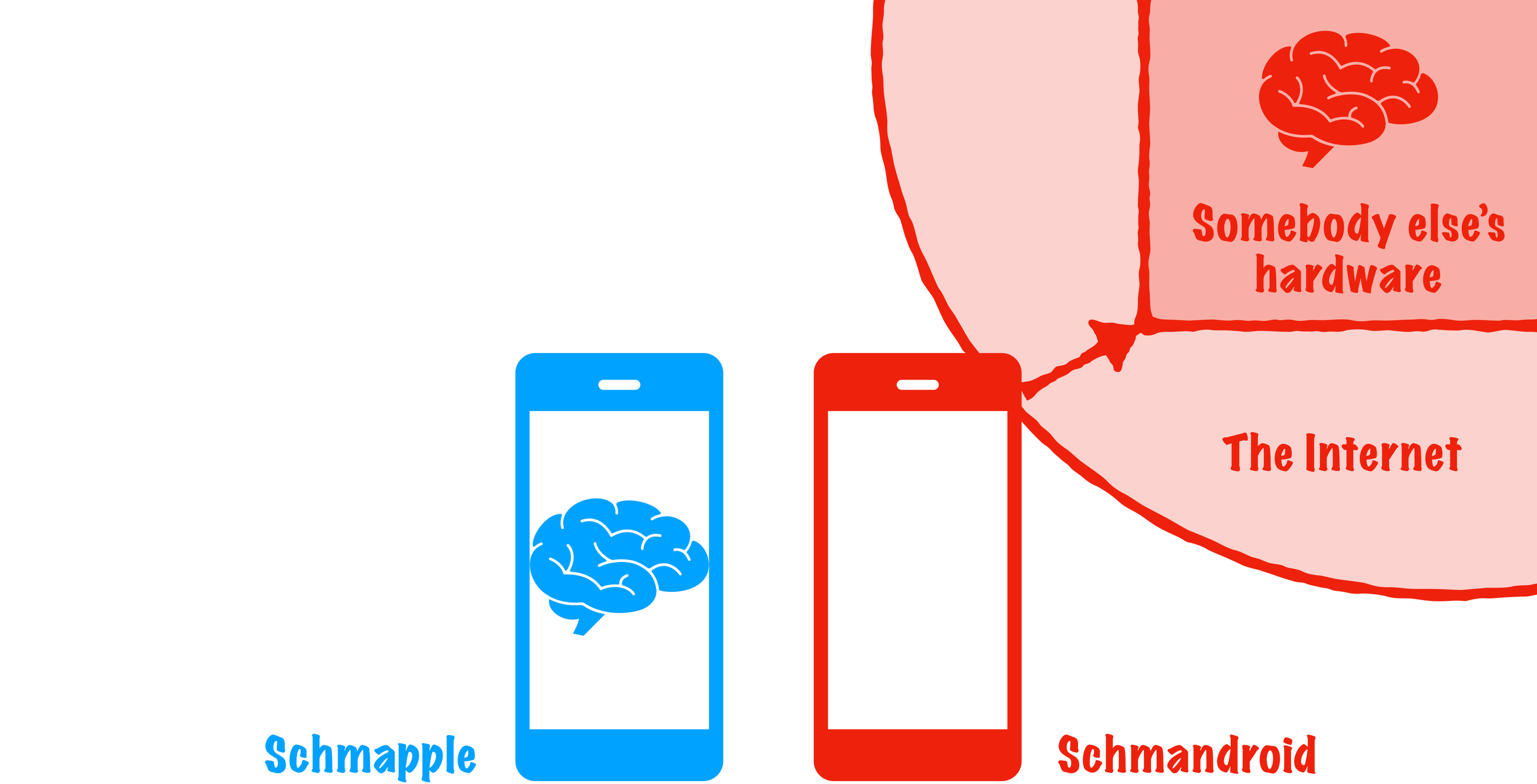


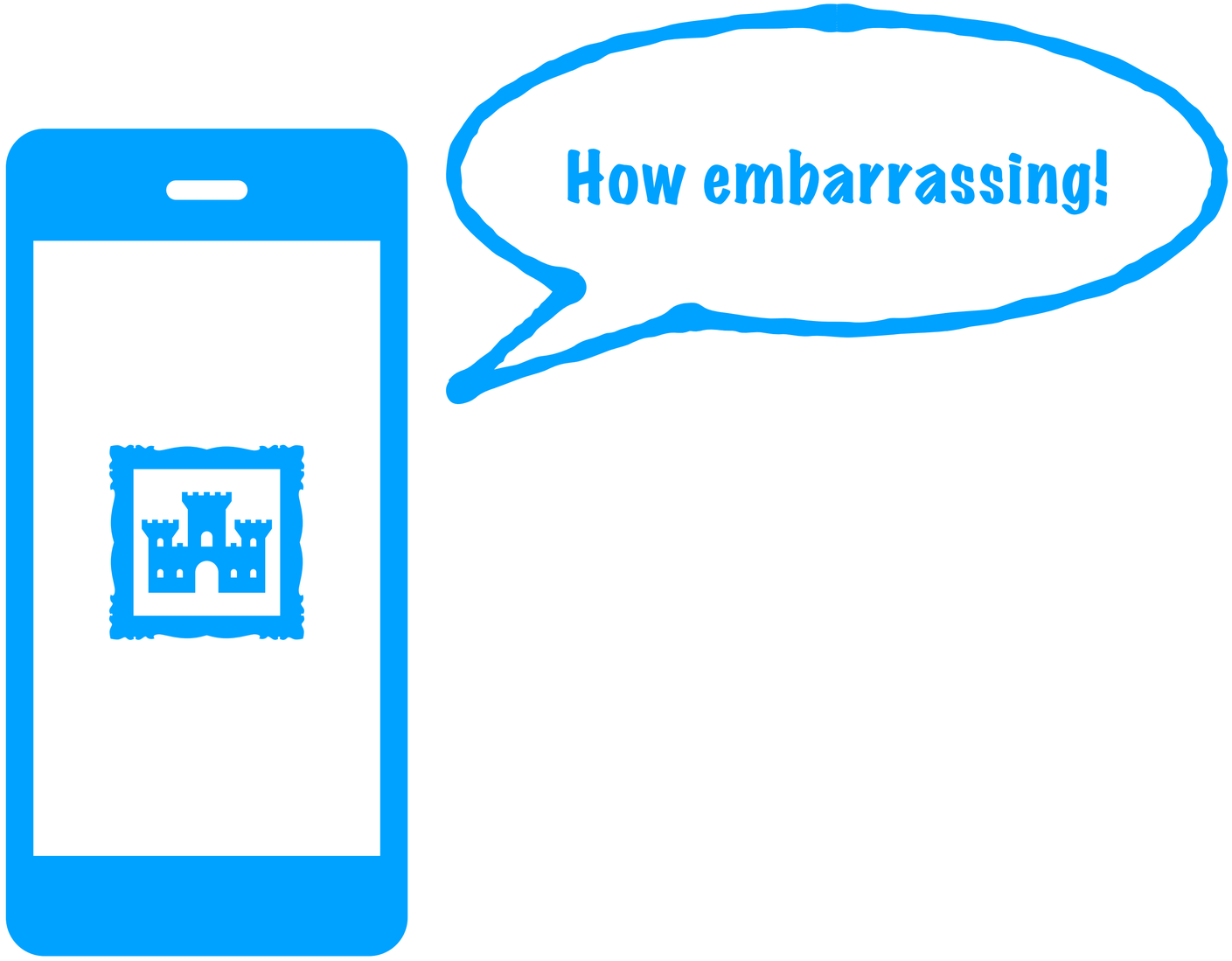


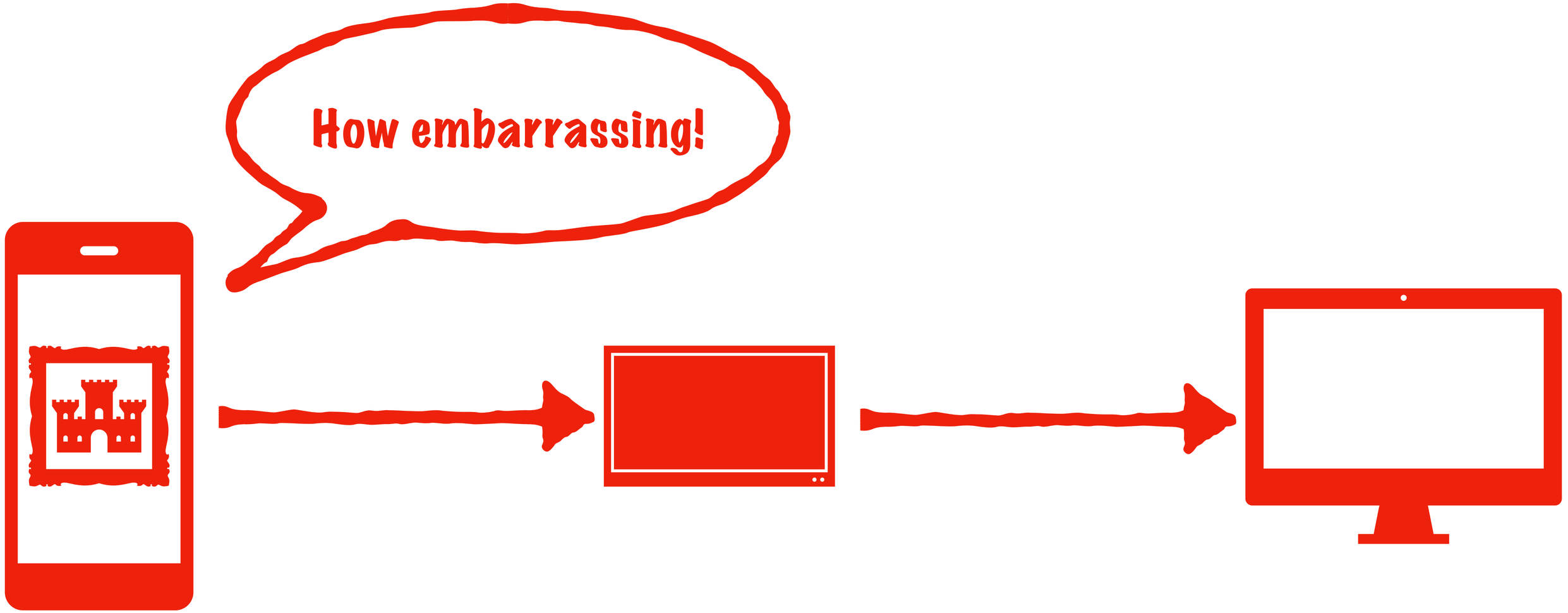
Not


Hey Phone, what's in this image?


Hey Model, what's in this image?
Hey Model, what's in this image?
Schmapple
Schmandroid


Somebody else's hardware
The Internet
Schmapple
Schmandroid


How embarrassing!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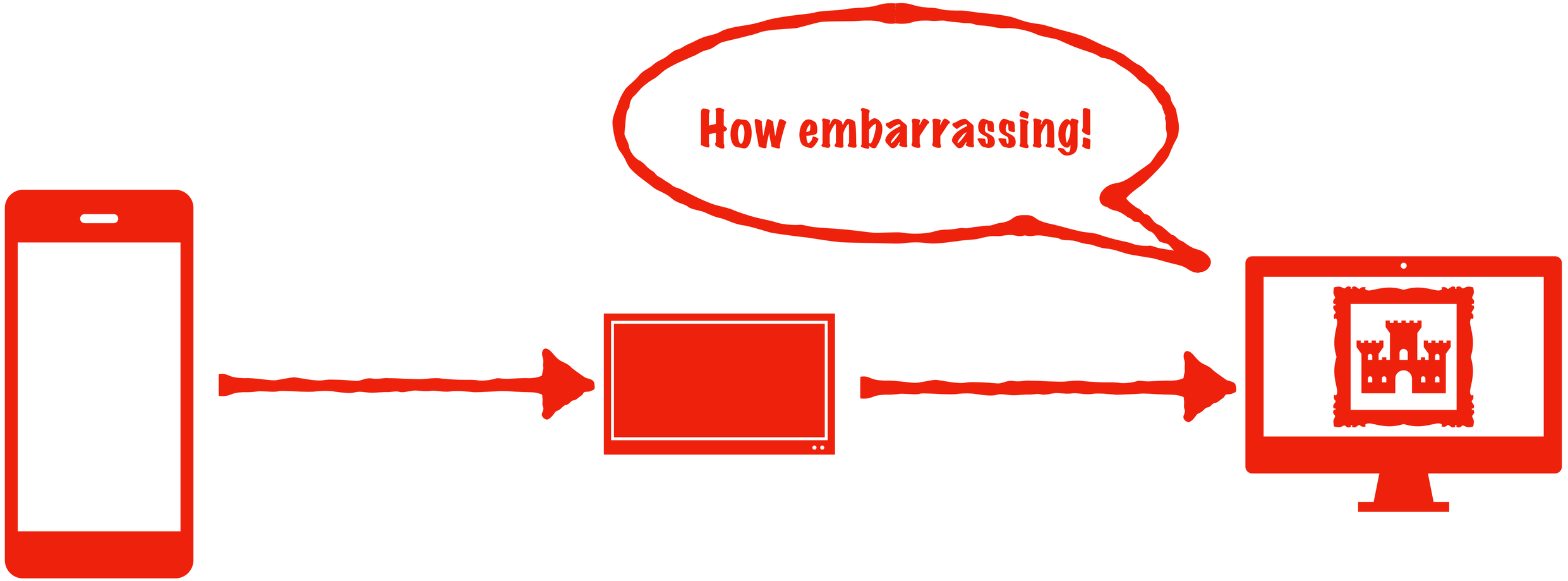
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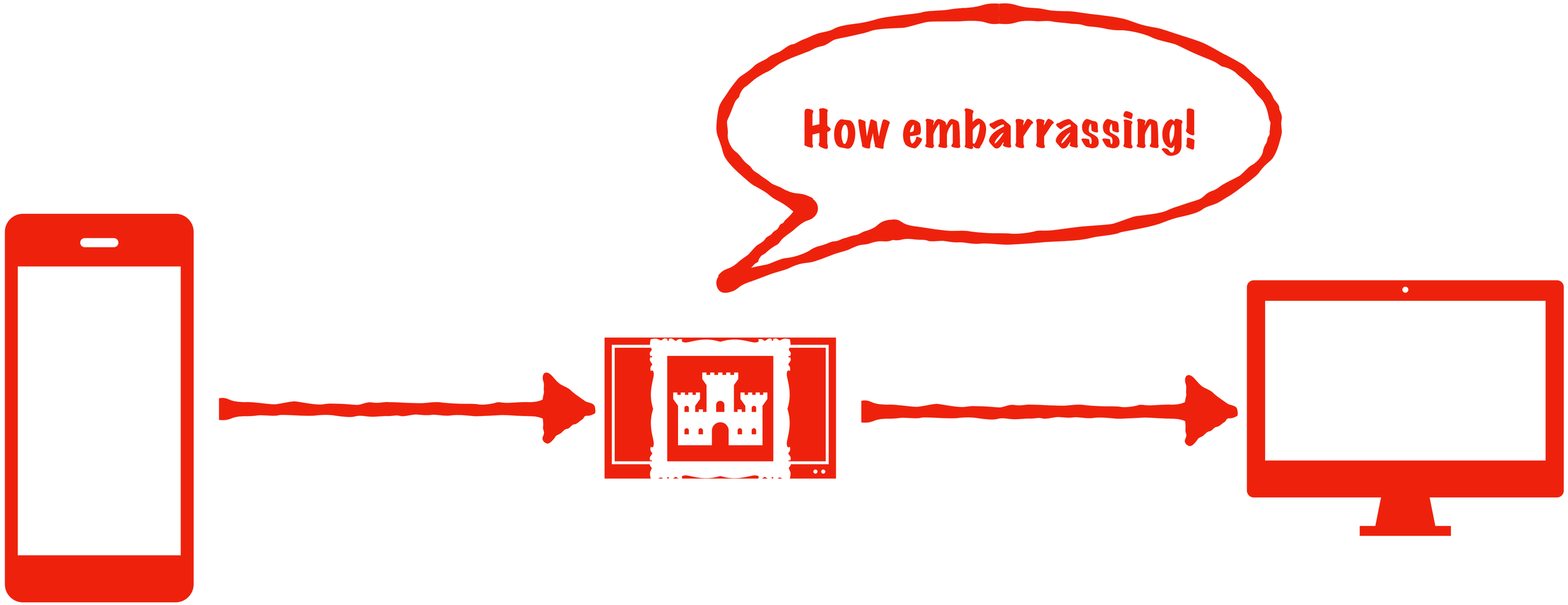
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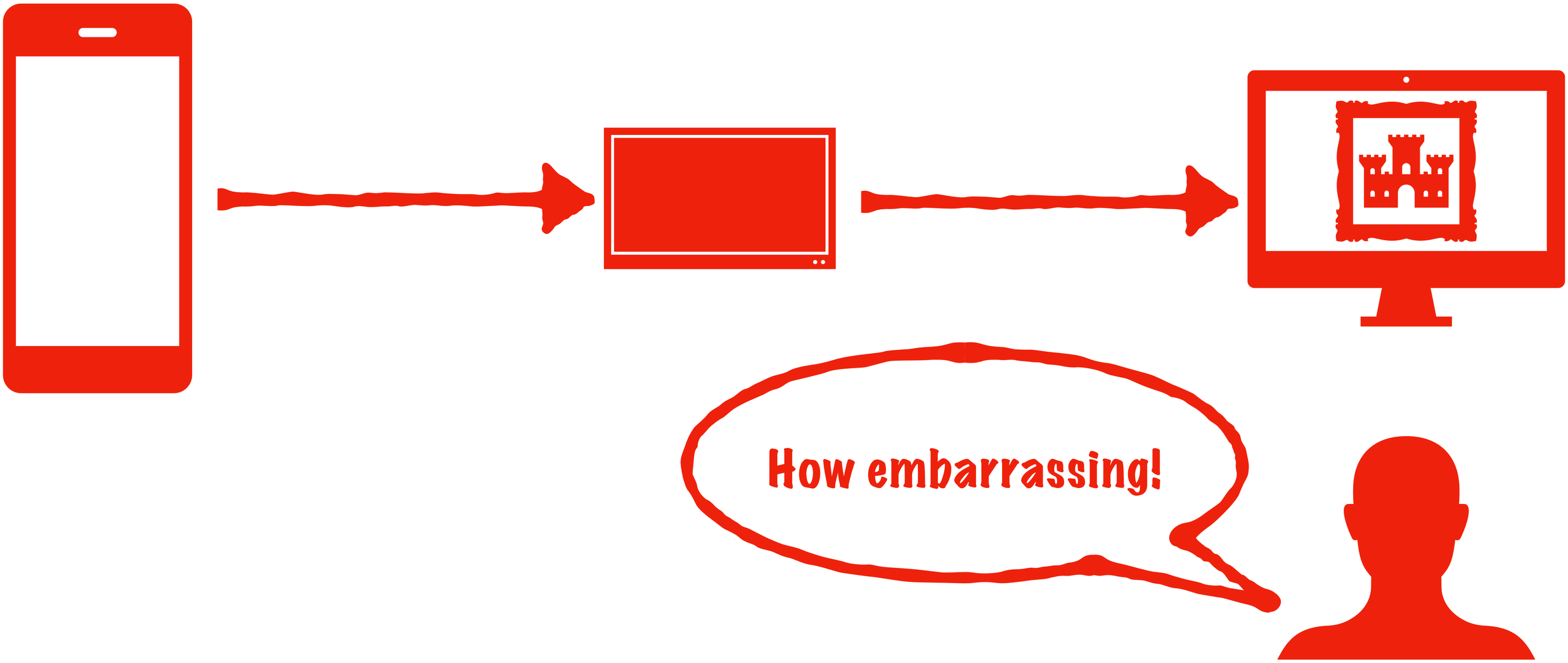
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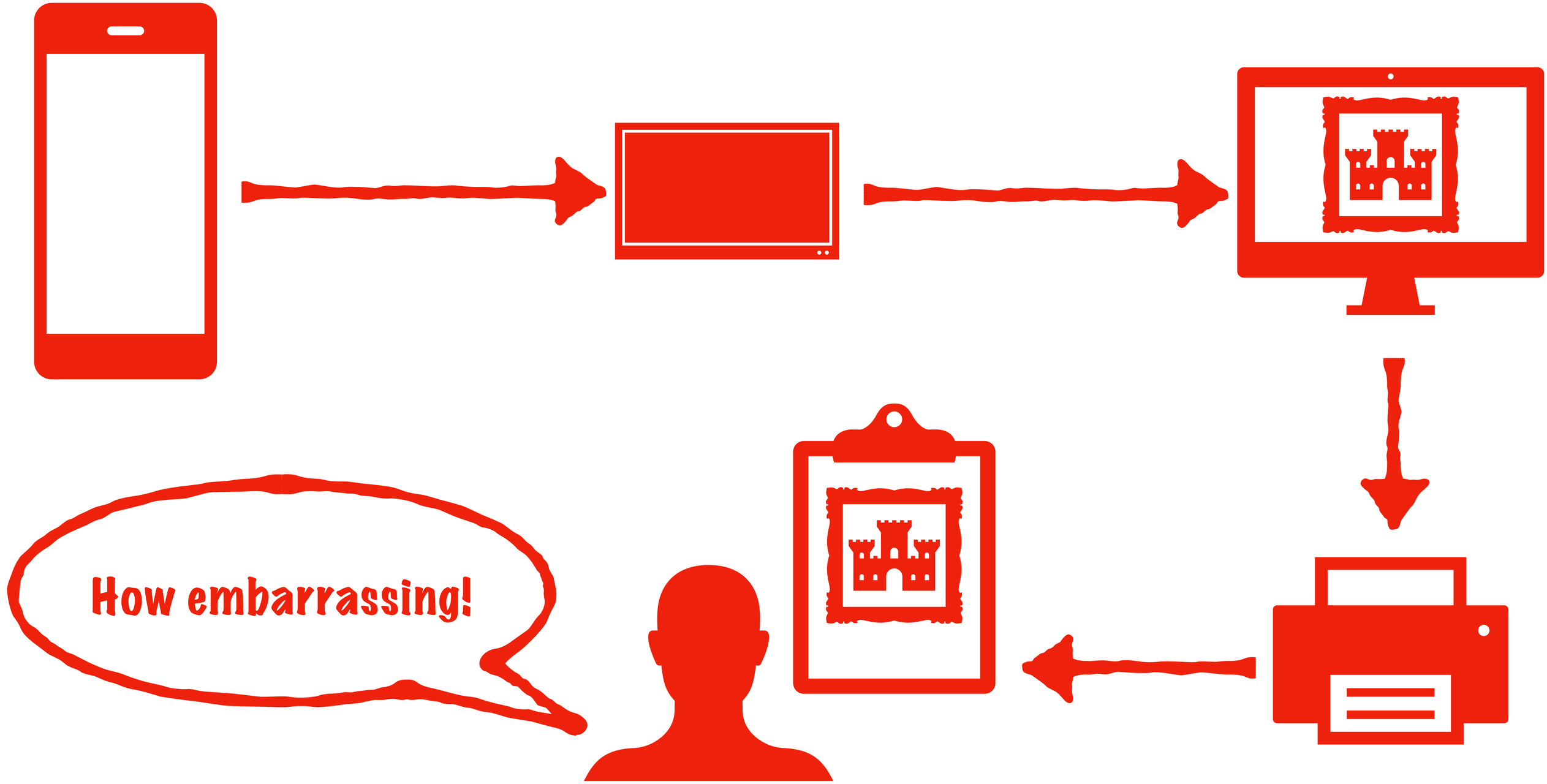
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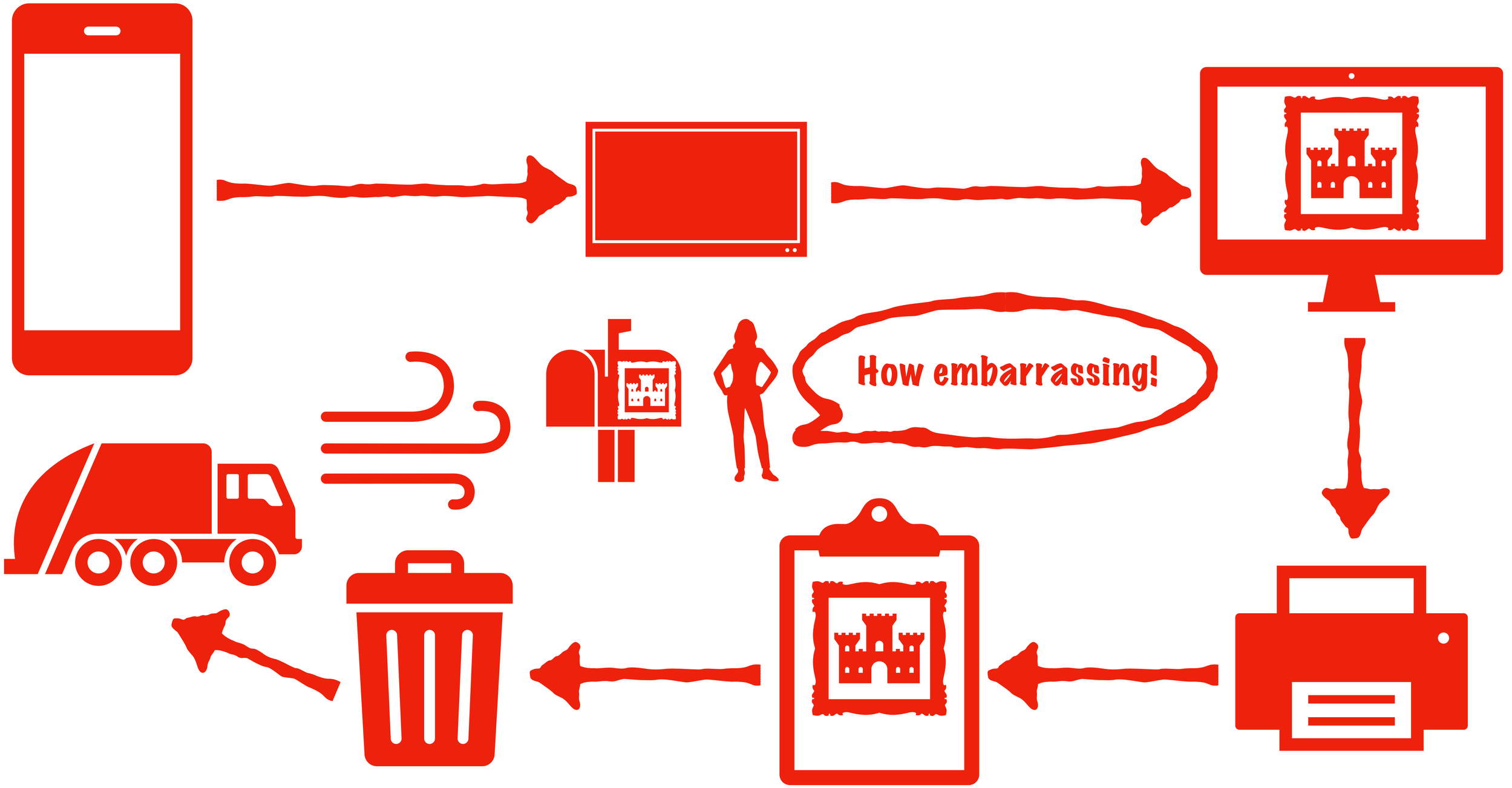
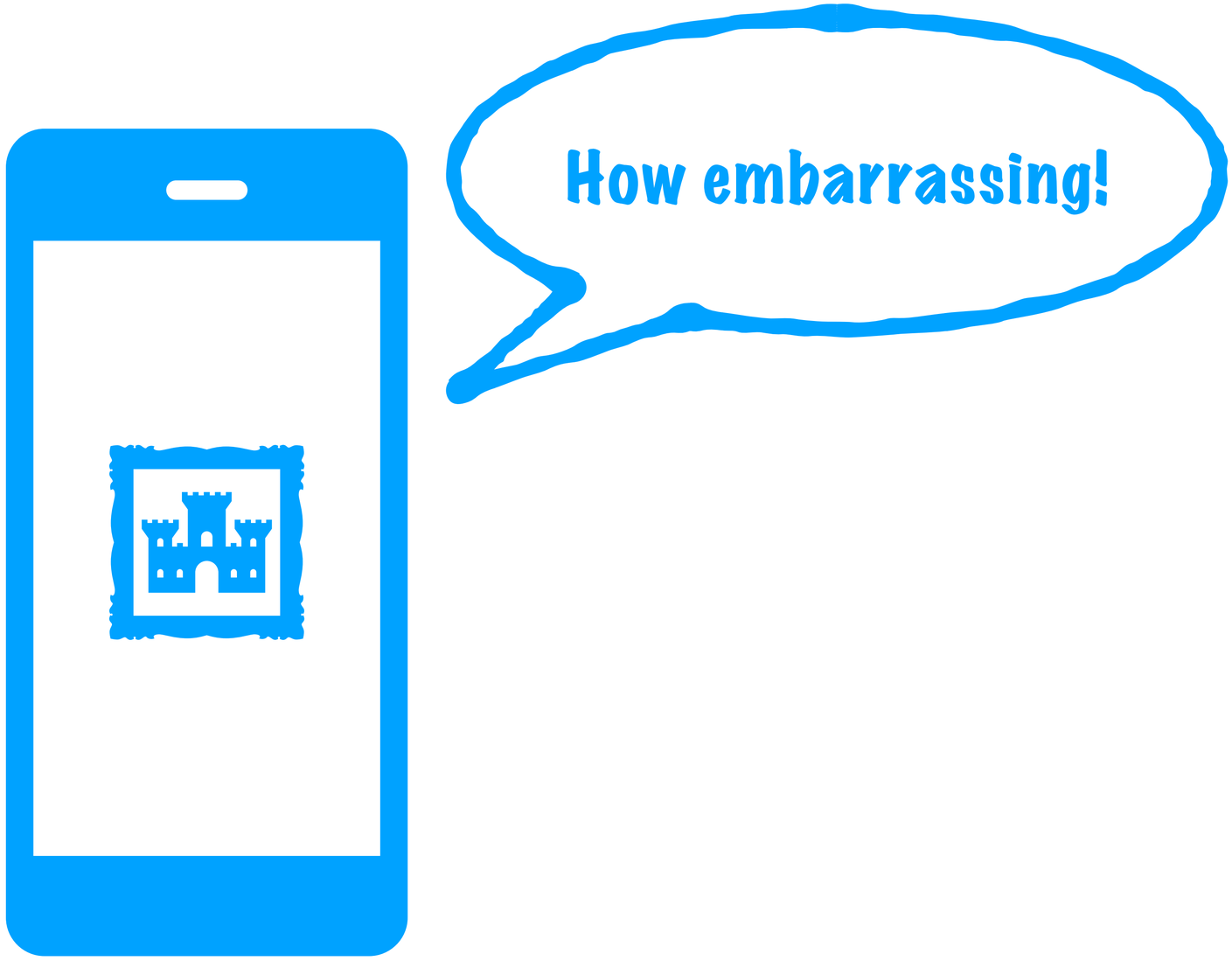

How embarrassing!

No Control

(which might terrify you)


How embarrassing!

Inability to share

==

As good as secret

MDacne - Custom Acne Treatment

12+

Acne Treatment Crafted For You

MDalgorithms Inc.

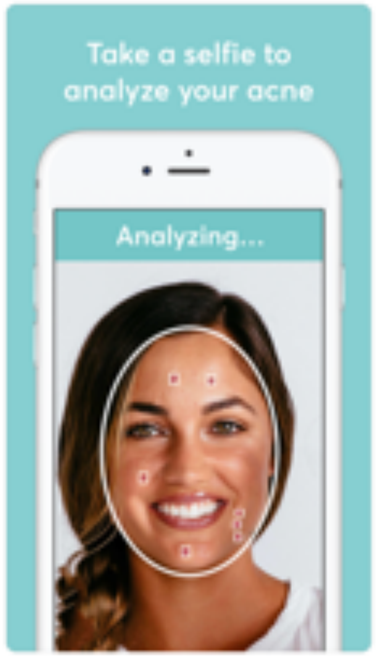
#6 in Medical

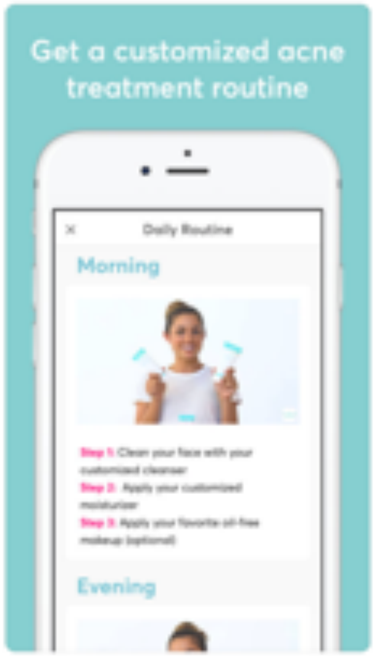
★★★★½ 4.3, 1.6K Ratings

Free

Screenshots

iPhone iPad





Privacy 👍

“Disconnected AI”


Hey Model, should I brake?

PlantVillage

Nuru

We have built an AI assistant called Nuru, which is Swahili for light. Nuru is an Artificially Intelligent that has been developed with the UN FAO, CGIAR, and other publicly funded institutions. As an assistant Nuru has learned to diagnose multiple diseases in Cassava, fall armyworm infections in African Maize, potato disease and wheat disease. She is also diagnosing spotted lanternfly pests in Pennsylvania.

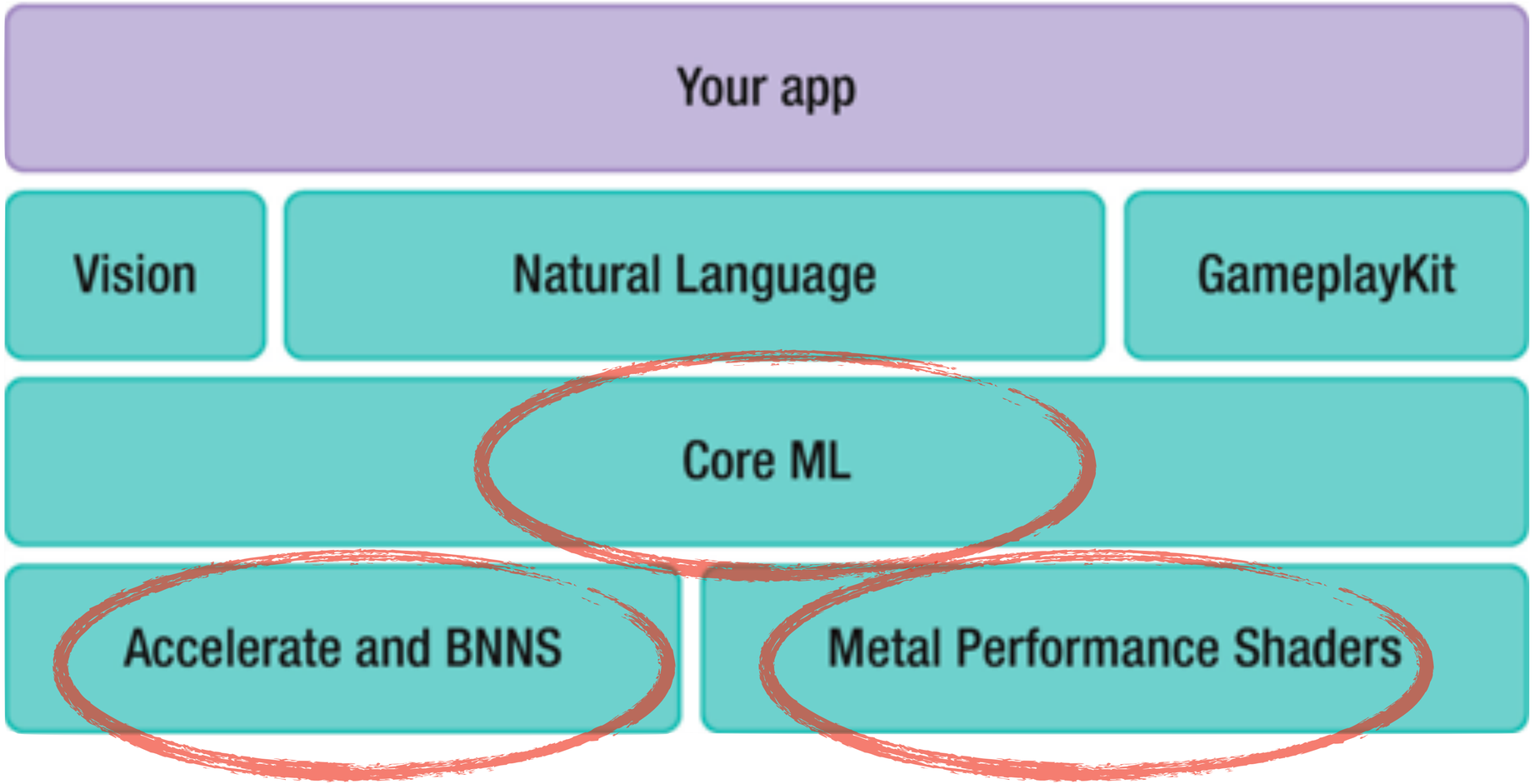
Explain it with $$$


DEMOS
Tap to change

Privacy and Security

GDPR compliance is easier!

Tools

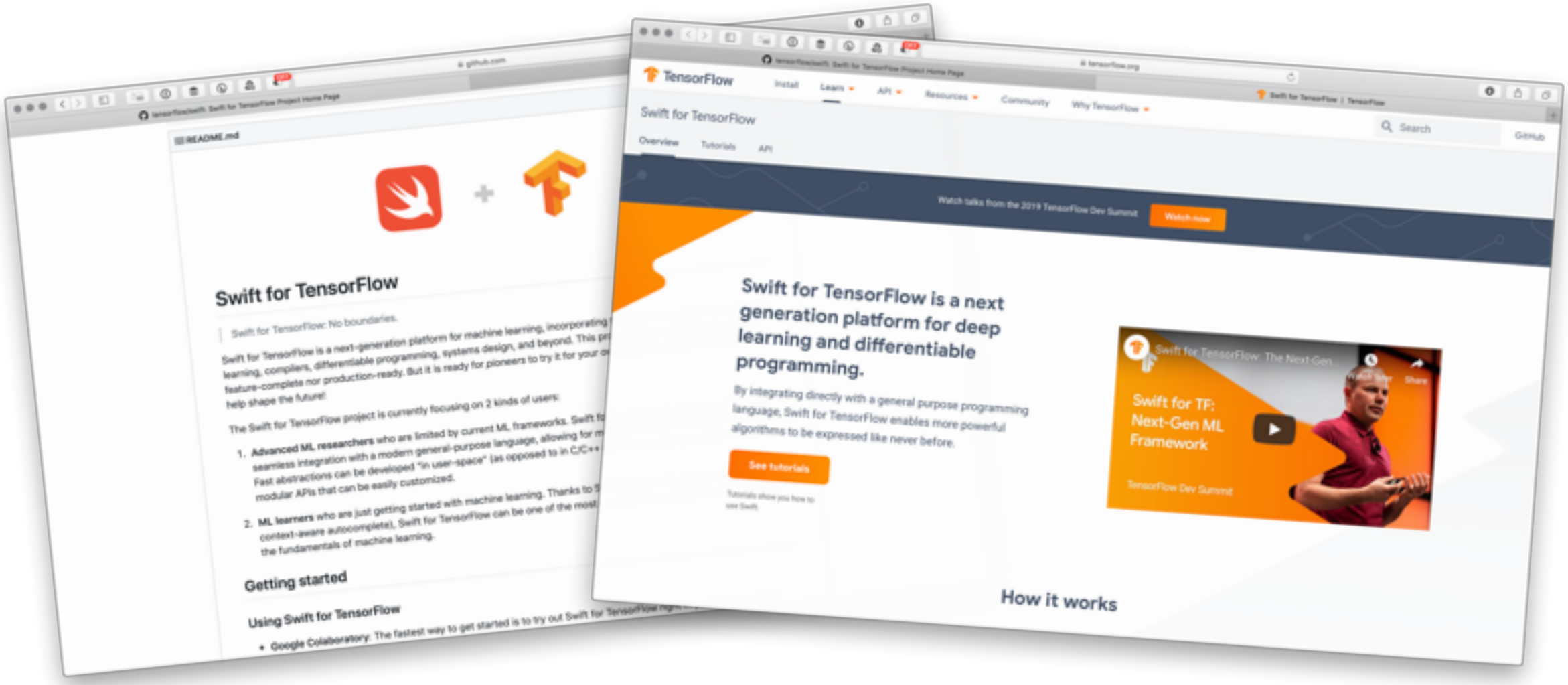

Your app
Vision
Natural Language
GameplayKit
Core ML
Accelerate and BNNS
Metal Performance Shaders

XGBoost

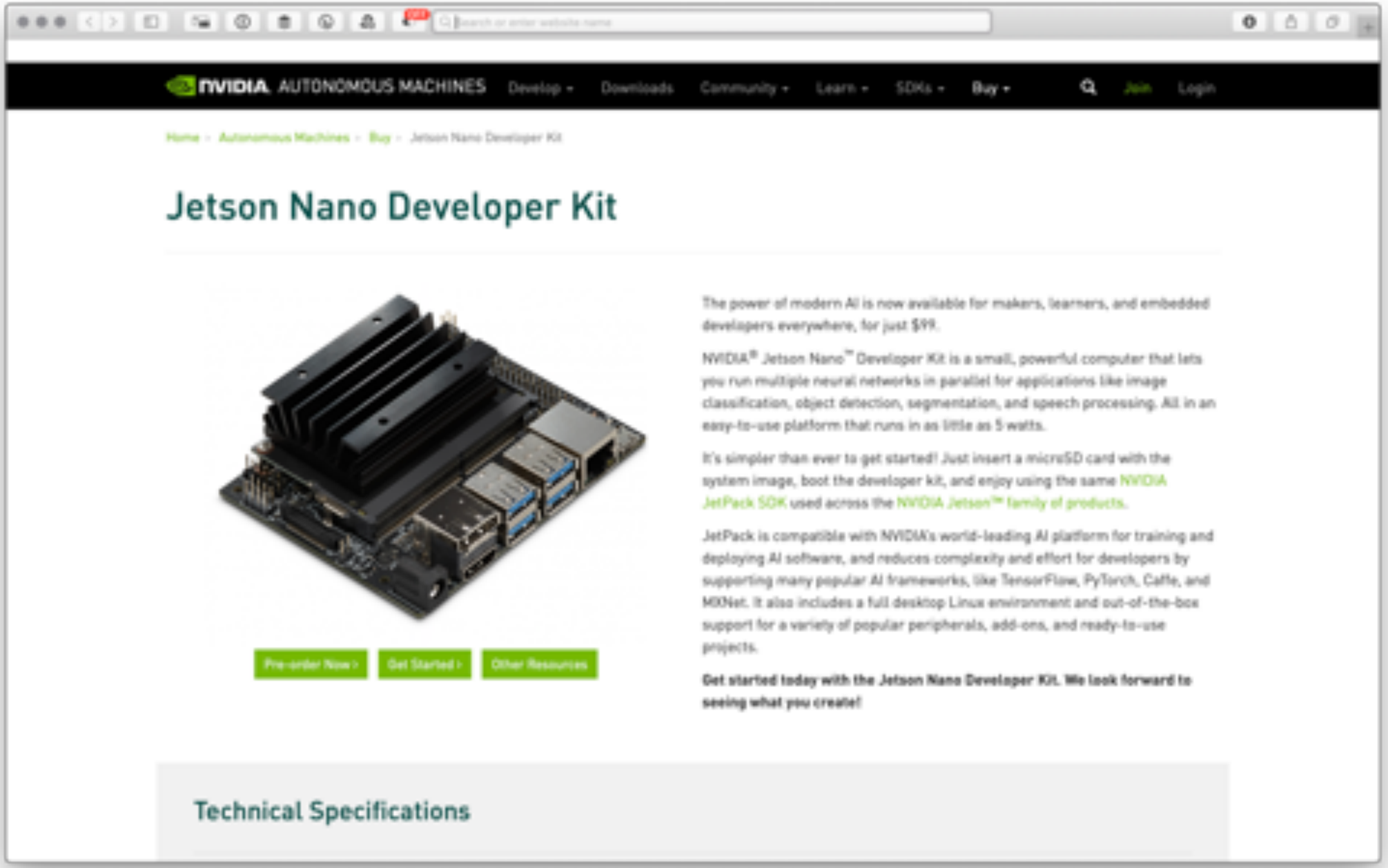
turi

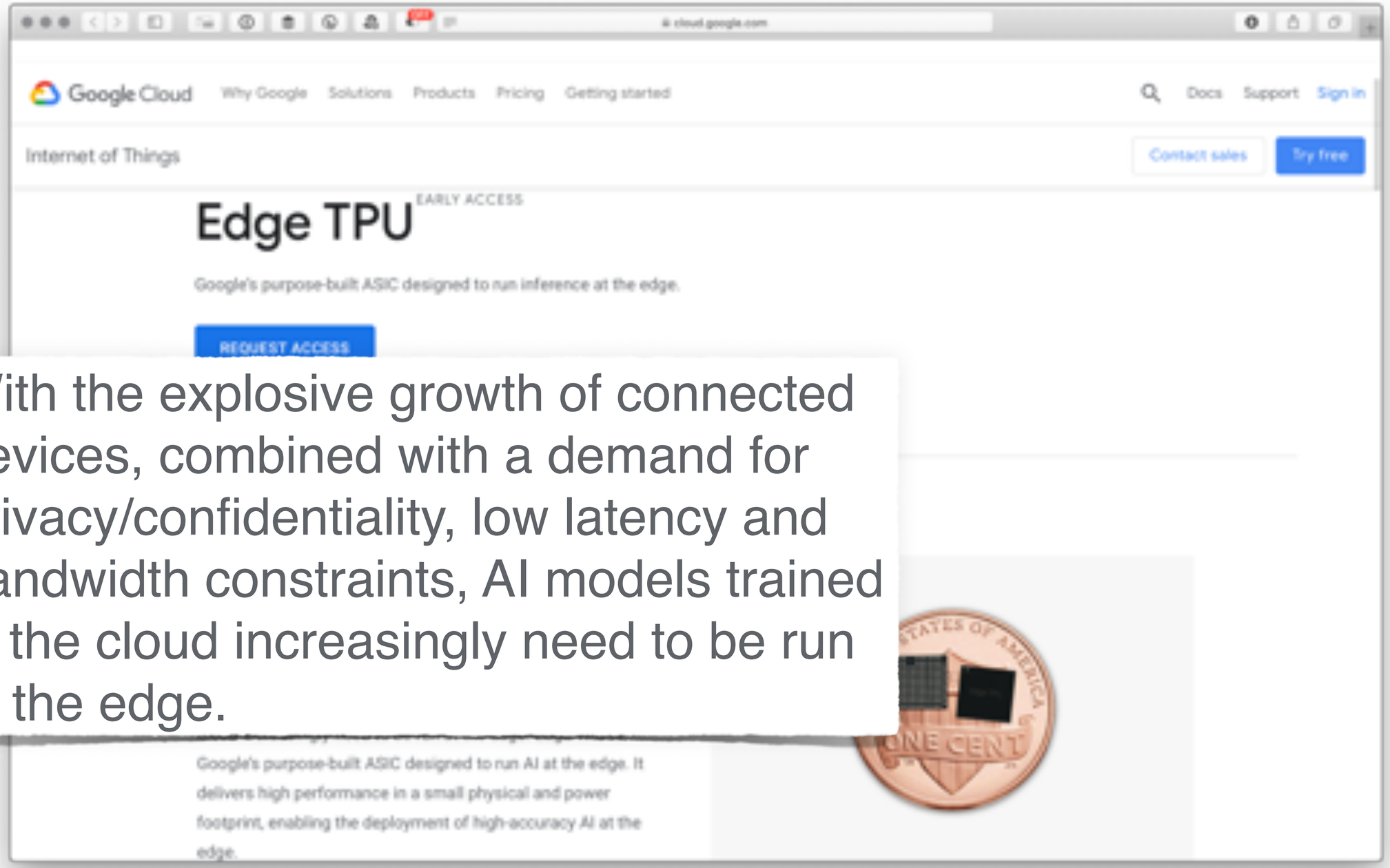
K

Caffe


README.md
Swift for TensorFlow
Swift for TensorFlow: No boundaries.
Swift for TensorFlow is a next-generation platform for machine learning, incorporating
learning, compilers, differentiable programming, systems design, and beyond. This pr
feature-complete nor production-ready. But it is ready for pioneers to try it for your o
help shape the future!
The Swift for TensorFlow project is currently focusing on 2 kinds of users:
1. Advanced ML researchers who are limited by current ML frameworks. Swift fo
seamless integration with a modern general-purpose language, allowing for m
Fast abstractions can be developed "in user-space" (as opposed to in C/C++
modular APIs that can be easily customized.
2. ML learners who are just getting started with machine learning. Thanks to S
context-aware autocomplete), Swift for TensorFlow can be one of the most
the fundamentals of machine learning.
Getting started
Using Swift for TensorFlow
Google Colaboratory: The fastest way to get started is to try out Swift for
TensorFlow
Install
Learn
API
Resources
Community
Why TensorFlow
Swift for TensorFlow
Overview
Tutorials
API
Search
GitHub
Watch talks from the 2019 TensorFlow Dev Summit
Watch now
Swift for TensorFlow is a next generation platform for deep learning and differentiable programming.
By integrating directly with a general purpose programming language, Swift for TensorFlow enables more powerful algorithms to be expressed like never before.
See tutorials
Tutorials show you how to use Swift.
Swift for TensorFlow: The Next-Gen...
Share
Swift for TF: Next-Gen ML Framework
TensorFlow Dev Summit
How it works

Hardware


NVIDIA AUTONOMOUS MACHINES
Develop
Downloads
Community
Learn
SDKs
Buy
Join
Login
Home › Autonomous Machines › Buy › Jetson Nano Developer Kit
Jetson Nano Developer Kit
The power of modern AI is now available for makers, learners, and embedded developers everywhere, for just $99.
NVIDIA® Jetson Nano™ Developer Kit is a small, powerful computer that lets you run multiple neural networks in parallel for applications like image classification, object detection, segmentation, and speech processing. All in an easy-to-use platform that runs in as little as 5 watts.
It's simpler than ever to get started! Just insert a microSD card with the system image, boot the developer kit, and enjoy using the same NVIDIA JetPack SDK used across the NVIDIA Jetson™ family of products.
JetPack is compatible with NVIDIA's world-leading AI platform for training and deploying AI software, and reduces complexity and effort for developers by supporting many popular AI frameworks, like TensorFlow, PyTorch, Caffe, and MXNet. It also includes a full desktop Linux environment and out-of-the-box support for a variety of popular peripherals, add-ons, and ready-to-use projects.
Get started today with the Jetson Nano Developer Kit. We look forward to seeing what you create!
Pre-order Now ›
Get Started ›
Other Resources
Technical Specifications

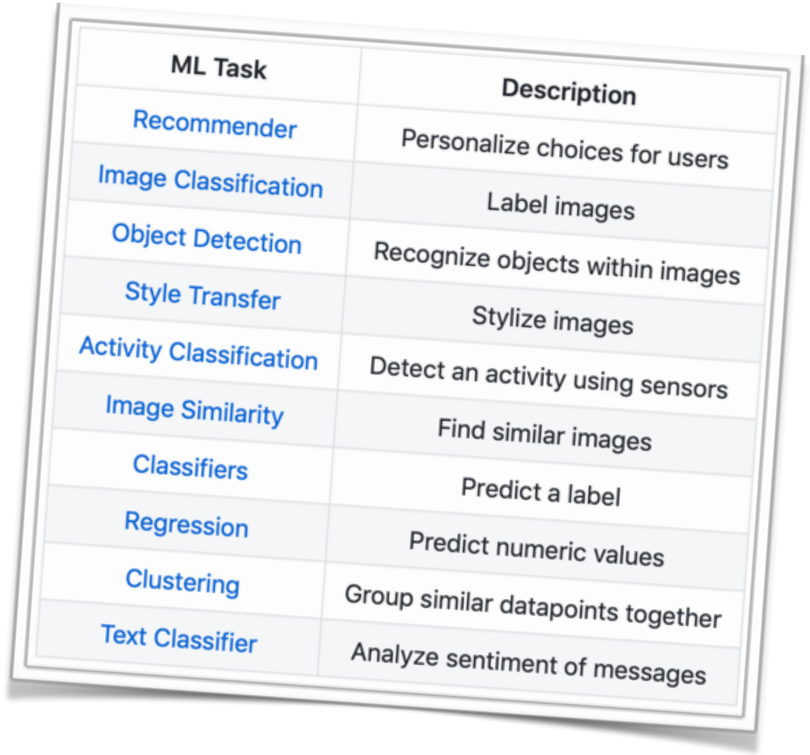


With the explosive growth of connected devices, combined with a demand for privacy/confidentiality, low latency and bandwidth constraints, AI models trained in the cloud increasingly need to be run at the edge.

Tensor Processing Unit

https://en.wikipedia.org/wiki/Tensor_processing_unit

Task-based AI/ML



ML Task	Description
Recommender	Personalize choices for users
Image Classification	Label images
Object Detection	Recognize objects within images
Style Transfer	Stylize images
Activity Classification	Detect an activity using sensors
Image Similarity	Find similar images
Classifiers	Predict a label
Regression	Predict numeric values
Clustering	Group similar datapoints together
Text Classifier	Analyze sentiment of messages

Task-based AI/ML

New interest and motivations

+ better software

+ better hardware

+ task focused frameworks

=> On-device ML 👍

Part 1

On-device Machine Learning

Part 2

Neural Style Transfer

Part 3

Demonstration

Part 4

The Future

Thank You!

Goals of this talk

- Discuss how useful, effective, and sensible the idea of on-device artificial intelligence is
- Have a brief diversion to discuss with Style Transfer is, and gloss over how it works
- Demonstrate that on-device AI works, by implementing Style Transfer for it on iOS
- Show off how useful task-focused approaches to AI can be, and how useful Turi Create is

Great resources

(You should check them out)

- https://developer.apple.com/videos/play/wwdc2018/712/
- https://github.com/apple/turicreate/
- https://github.com/alexsosn/iOS_ML
- https://www.manning.com/books/grokking-deep-learning
- https://medium.com/artists-and-machine-intelligence/neural-artistic-style-transfer-a-comprehensive-look-f54d8649c199

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