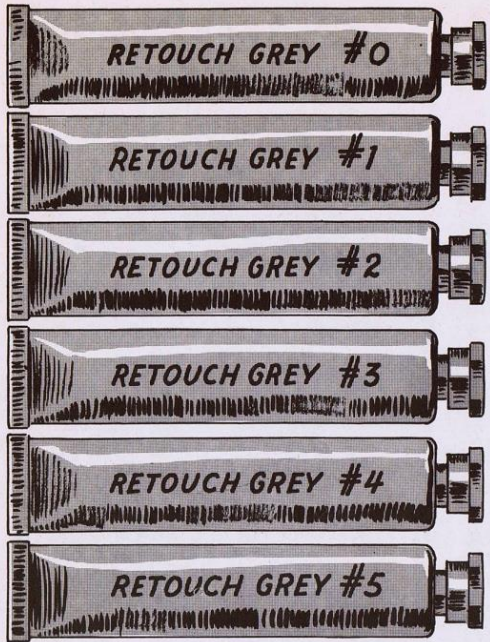


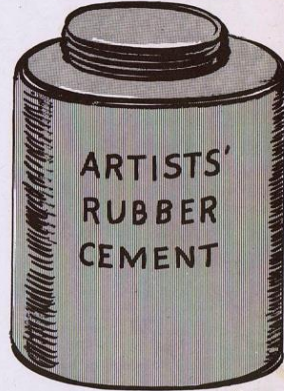




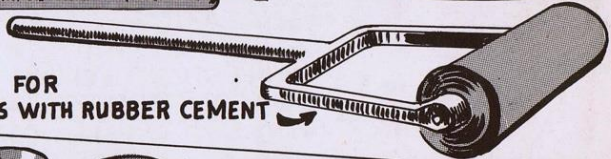
The Human Touch



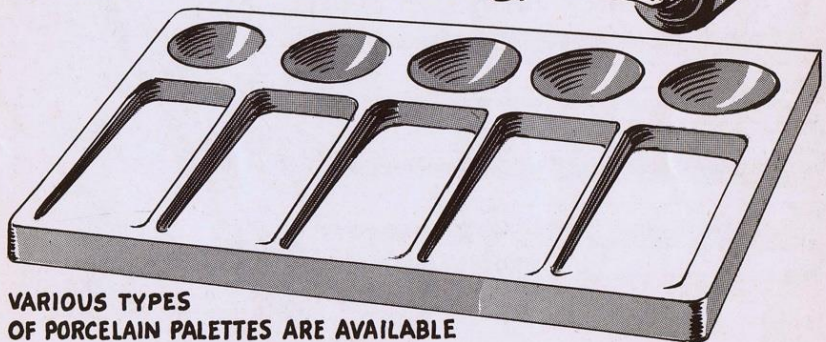
SOLD IN TUBES OR JARS



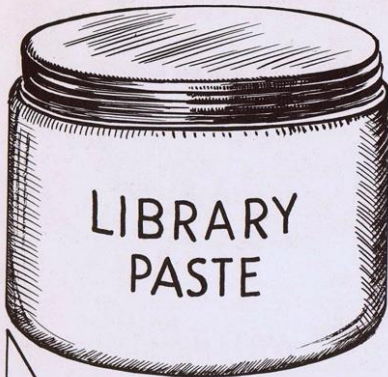
RUBBER ROLLER FOR MOUNTING PHOTOS WITH RUBBER CEMENT



VARIOUS TYPES OF PORCELAIN PALETTES ARE AVAILABLE

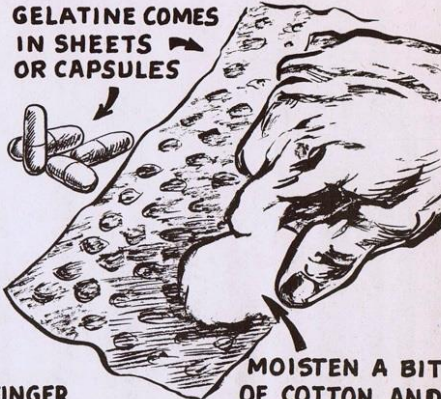


RETOUCH EQUIPMENT



LIBRARY PASTE

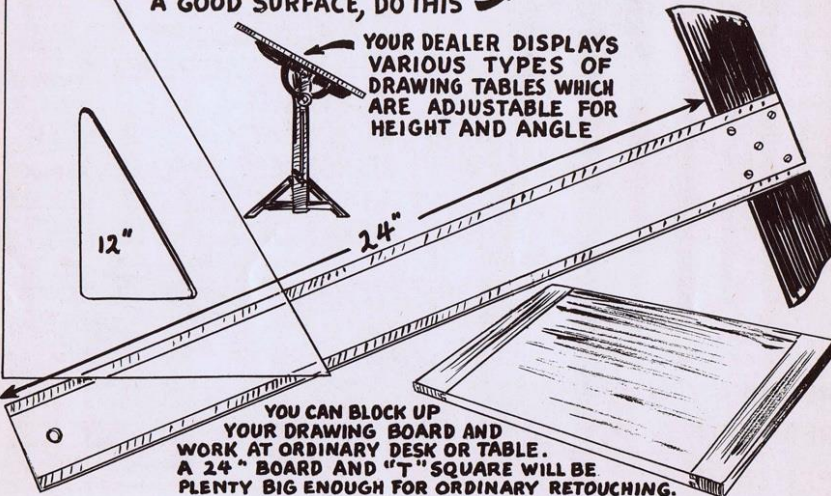
GELATINE COMES IN SHEETS OR CAPSULES



MOISTEN A BIT OF COTTON AND RUB GELATINE OVER THE SURFACE OF PHOTO AFTER YOU HAVE MOUNTED IT

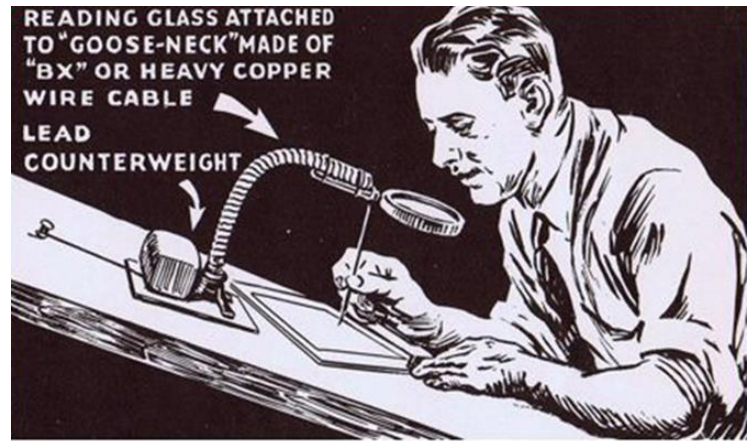
PASTE, GREASE AND FINGER PRINTS ON PHOTO, MAKE YOUR COLOR "CREEP" AS YOU APPLY IT: — SO FOR A GOOD SURFACE, DO THIS

YOUR DEALER DISPLAYS VARIOUS TYPES OF DRAWING TABLES WHICH ARE ADJUSTABLE FOR HEIGHT AND ANGLE

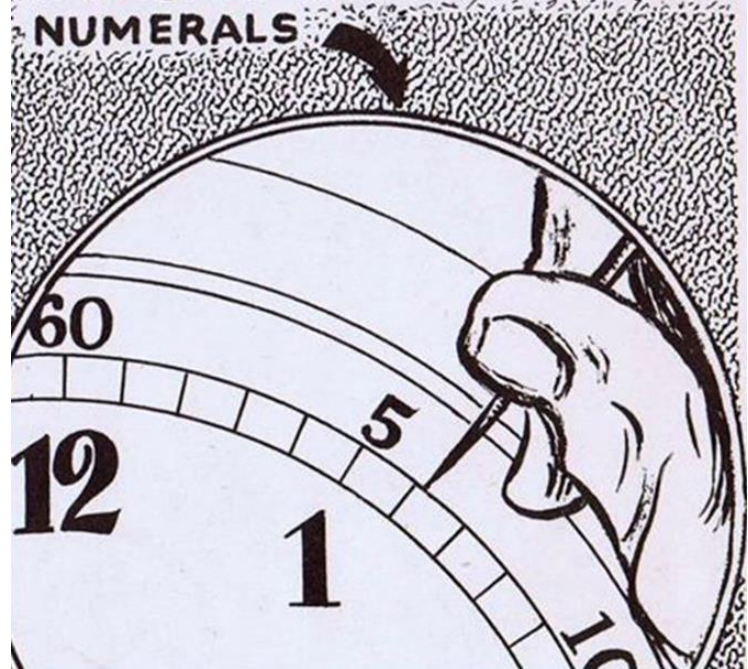


YOU CAN BLOCK UP YOUR DRAWING BOARD AND WORK AT ORDINARY DESK OR TABLE. A 24" BOARD AND "T" SQUARE WILL BE PLENTY BIG ENOUGH FOR ORDINARY RETOUCHING.

READING GLASS ATTACHED TO "GOOSE-NECK" MADE OF "BX" OR HEAVY COPPER WIRE CABLE
LEAD COUNTERWEIGHT



HERE'S WHAT YOU SEE PART OF PHOTO OF WATCH DIAL MAGNIFIED AND TIP OF YOUR BRUSH SNAPPING UP THE HAIRLINE CALIBRATIONS AND NUMERALS







universal

Editor Height 65.45



From Analog to AI









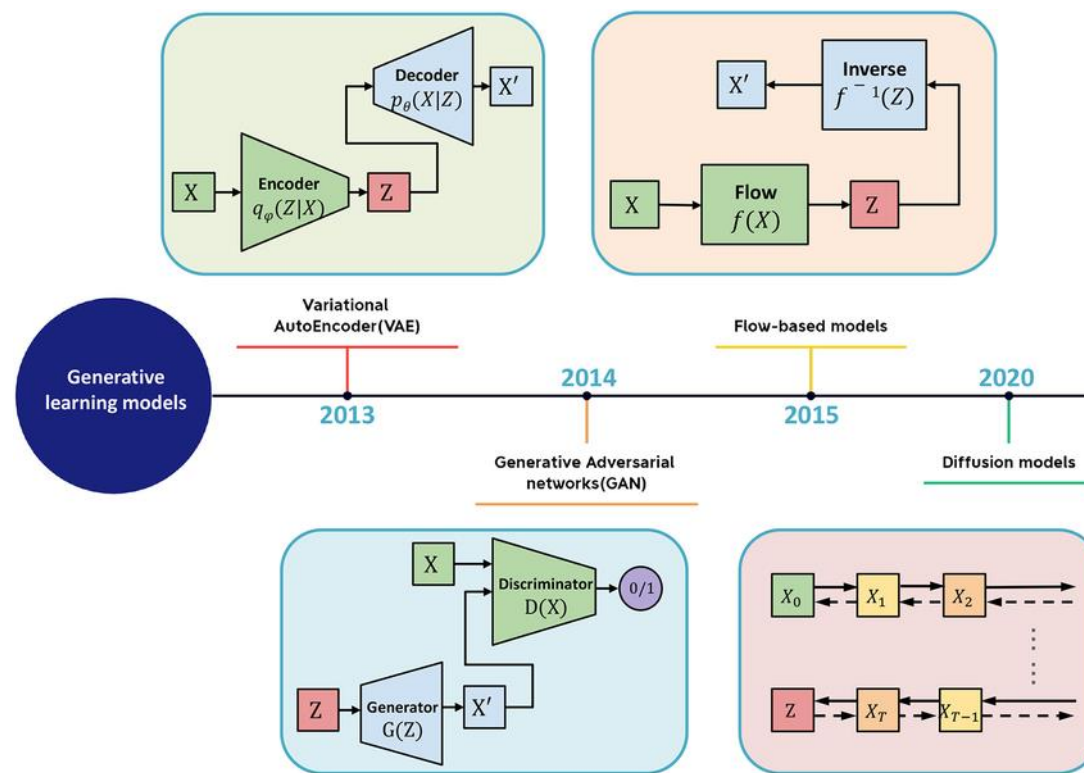
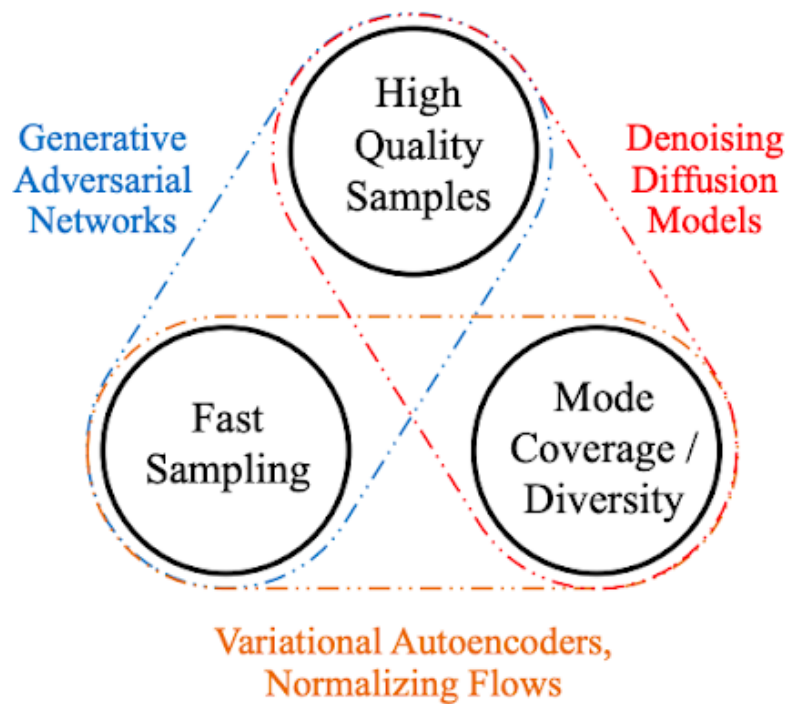
GenAI



AUTO RETOUCH



Turning Pixels to Pictures



Deep Learning requires large amounts of carefully **labeled data** which is **difficult** to acquire and **expensive** to annotate



(a) Texture image

81.4% **Indian elephant**
10.3% indri
8.2% black swan



(b) Content image

71.1% **tabby cat**
17.3% grey fox
3.3% Siamese cat



(c) Texture-shape cue conflict

63.9% **Indian elephant**
26.4% indri
9.6% black swan

Classification predictions of a ResNet-50 trained on ImageNet

Valuable (natural) image **features**
should not be specialized for solving
a particular supervised task, but
rather encapsulate richer
characteristics exploitable for **various**
downstream tasks

How Much Information is the Machine Given during Learning?

▶ “Pure” Reinforcement Learning (**cherry**)

- ▶ The machine predicts a scalar reward given once in a while.

▶ **A few bits for some samples**

▶ Supervised Learning (**icing**)

- ▶ The machine predicts a category or a few numbers for each input

- ▶ Predicting human-supplied data

▶ **10→10,000 bits per sample**

▶ Self-Supervised Learning (**cake génoise**)

- ▶ The machine predicts any part of its input for any observed part.

- ▶ Predicts future frames in videos

▶ **Millions of bits per sample**



Input: The man went to the [MASK]₁ . He bought a [MASK]₂ of milk .
Labels: [MASK]₁ = store; [MASK]₂ = gallon

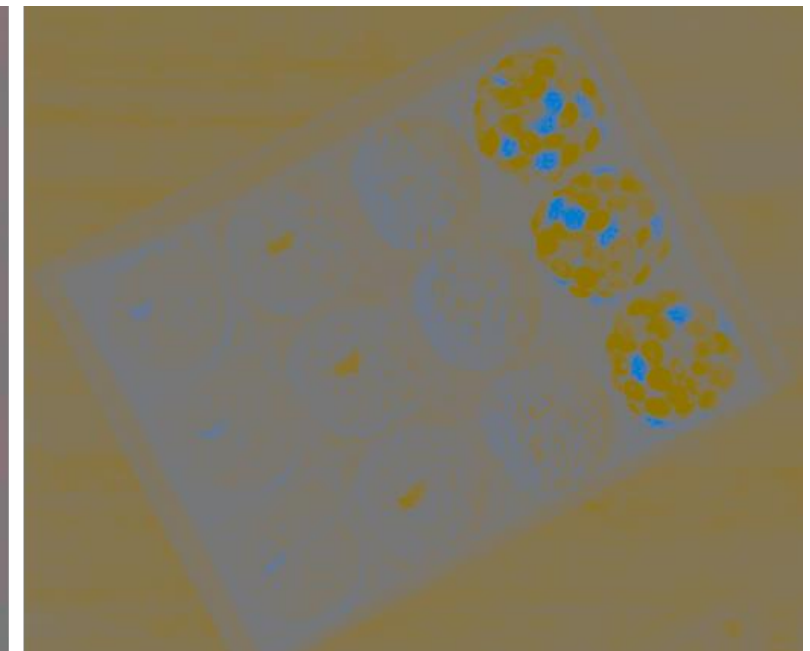
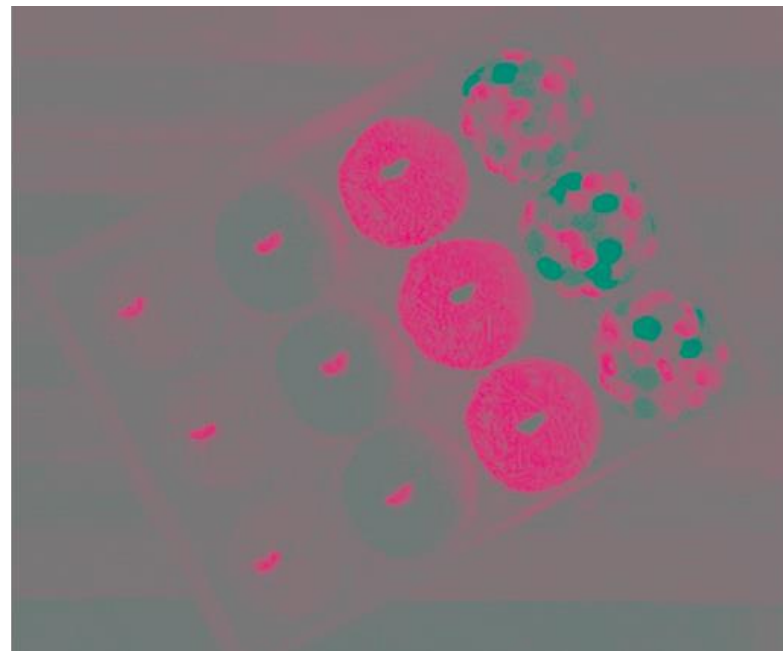
Missing word prediction task.

Sentence A = The man went to the store.
Sentence B = He bought a gallon of milk.
Label = IsNextSentence

Sentence A = The man went to the store.
Sentence B = Penguins are flightless.
Label = NotNextSentence

So What?

Let there be Color!



(240, 38, 53)



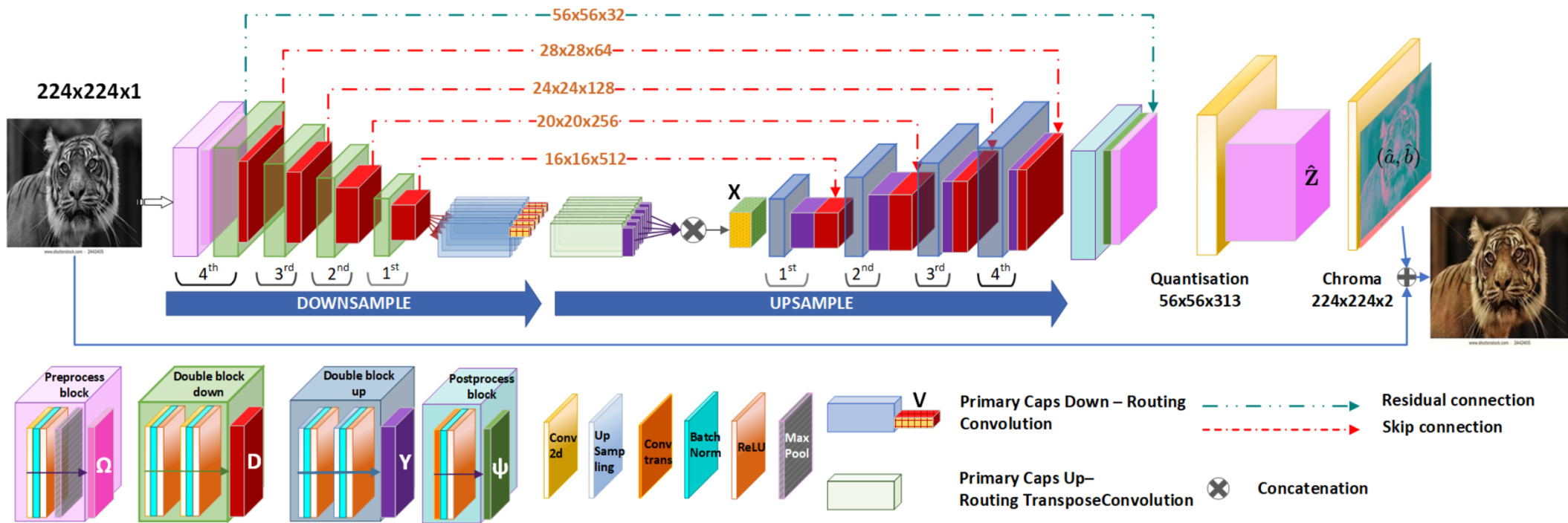
(100, 100, 100)



rgb2gray

(100)

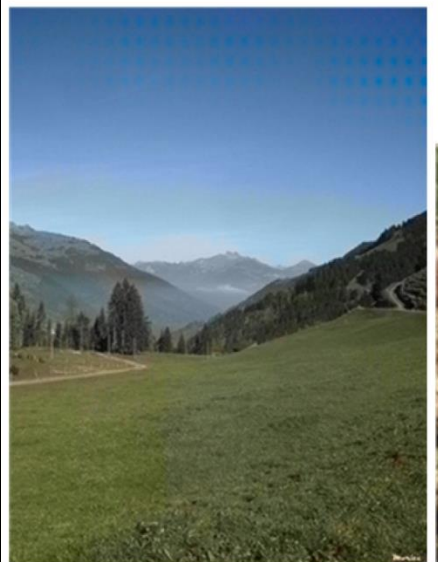
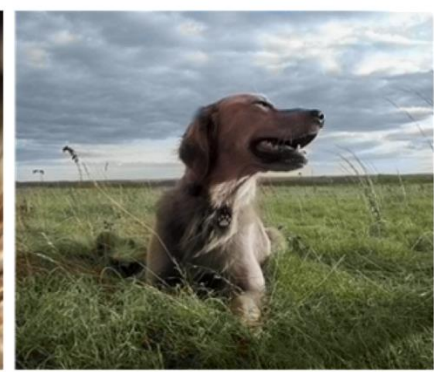




R. Pucci, C. Micheloni, G. L. Foresti, N. Martinel – *Is It a Plausible Colour? UCapsNet for Image Colourisation*. NeurIPS Workshop: Self-Supervised Learning – Theory and Practice (2021)

R. Pucci, C. Micheloni, N. Martinel – *Collaborative image and object level features for image colourisation*. CVPR (2021)

R. Pucci, C. Micheloni, G. L. Foresti, N. Martinel – *ProCCaps: Progressively Teaching Colourisation to Capsules*. WACV (2022)

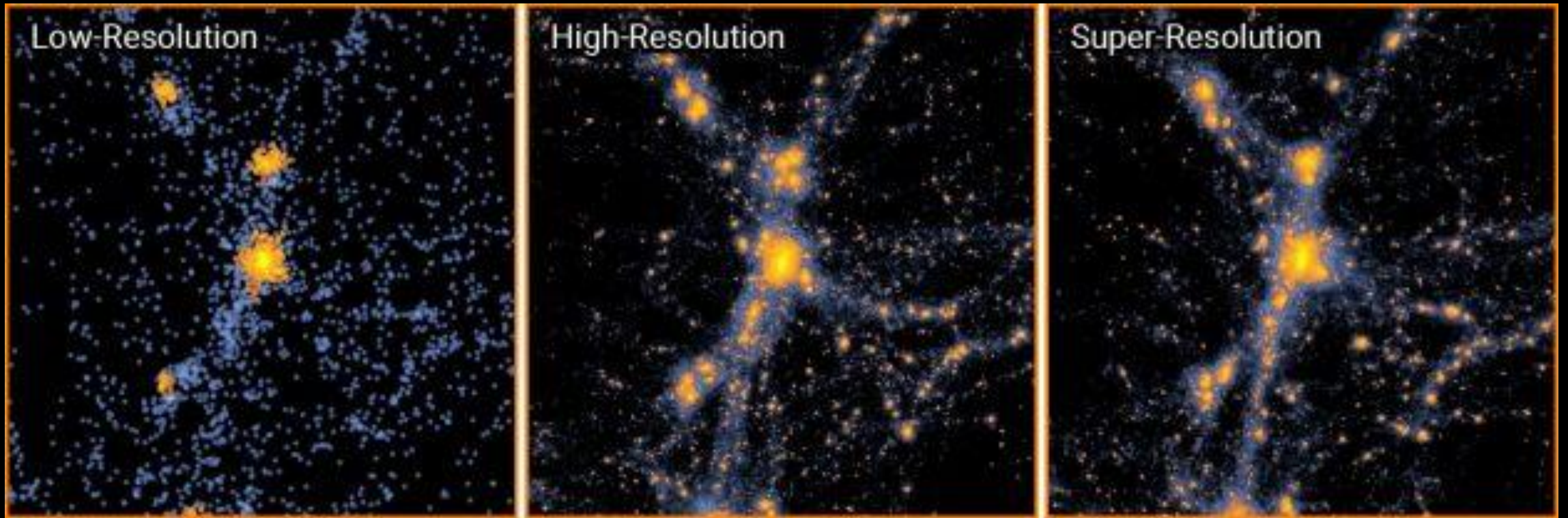




Henri Cartier Bresson, Ansel Adams, Alinari. Historical archives.



Where are the details?



Yin Li, Yueying Ni, Rupert A. C. Croft, Tiziana Di Matteo, Simeon Bird, and Yu Feng, *AI-assisted superresolution cosmological simulations*, PNAS 2021

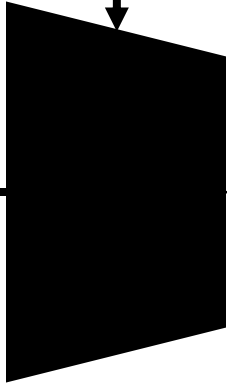


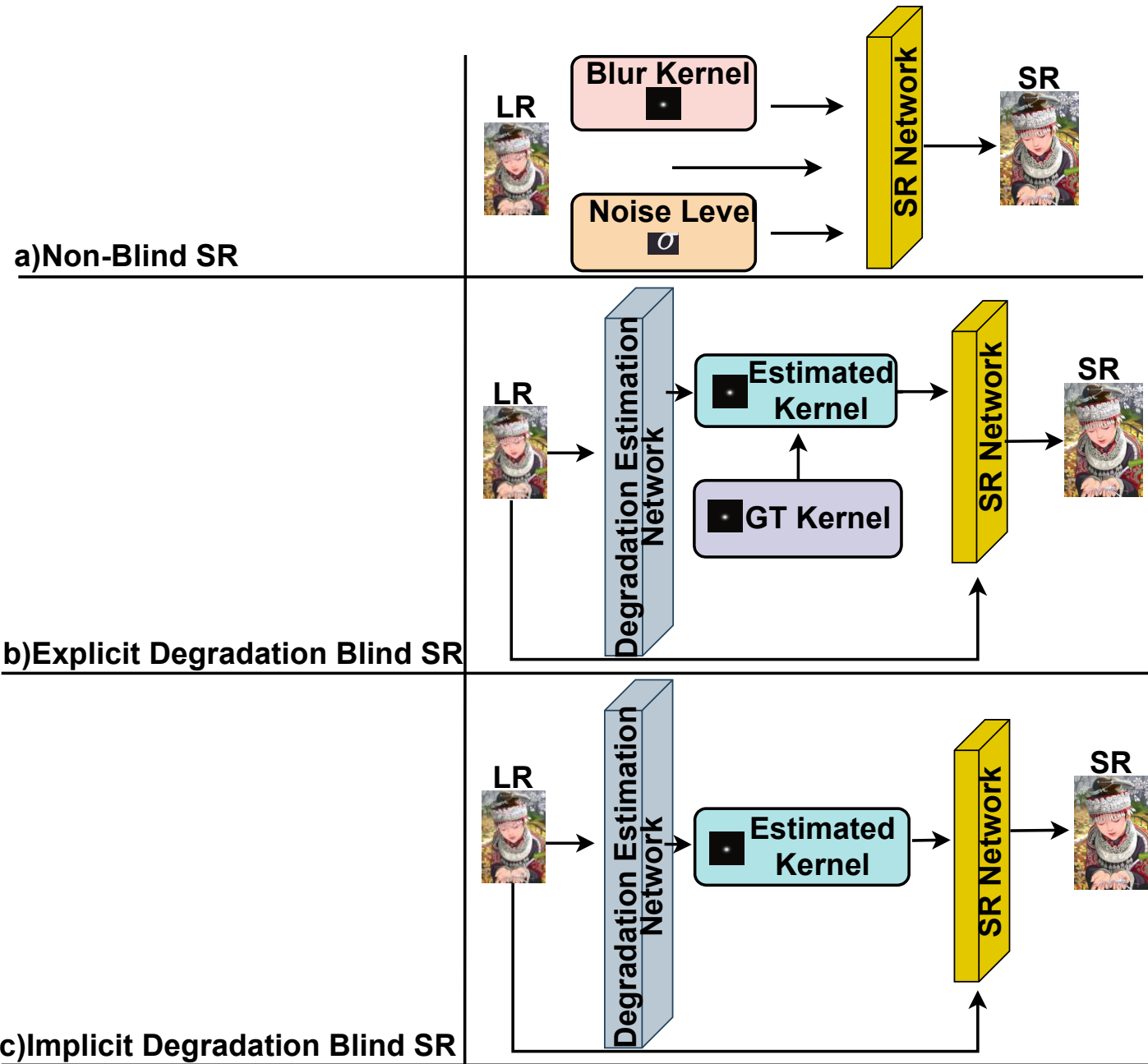
Artificial Degradation(s)

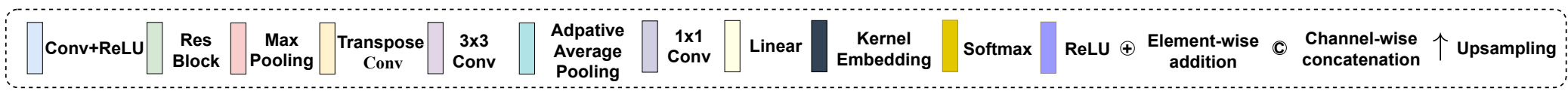
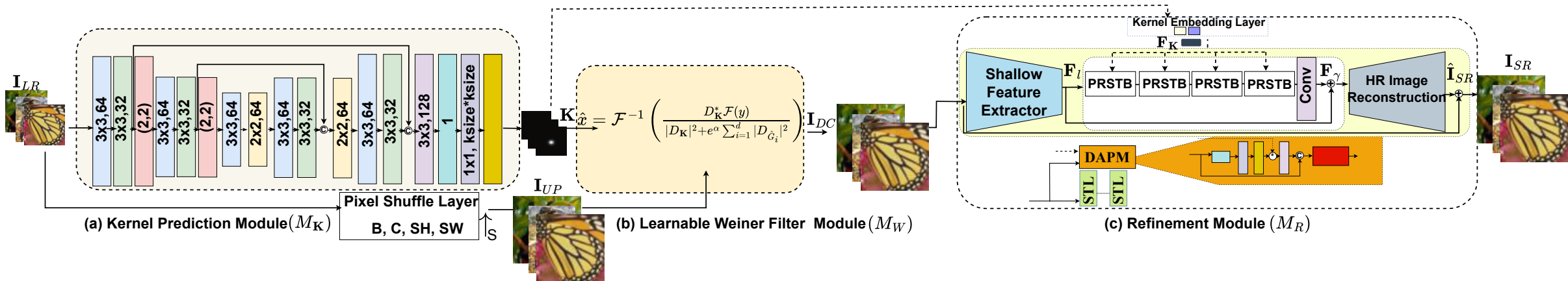
Downsampling



Minimize Loss Function







Now What?





Thanks!

niki.martinel@uniud.it



Machine Learning and Perception Lab
Università degli Studi di Udine