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Repurposing neural networks

An introduction to transfer learning

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This presentation will cover:

- A speedy introduction to dense and convolutional neural networks (CNN)
- An analysis of what the layers in a CNN “see”
- A case study where a pretrained CNN is repurposed for a different domain
- A case study where a pretrained CNN is used to generate images

The fundamentals

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The fundamentals

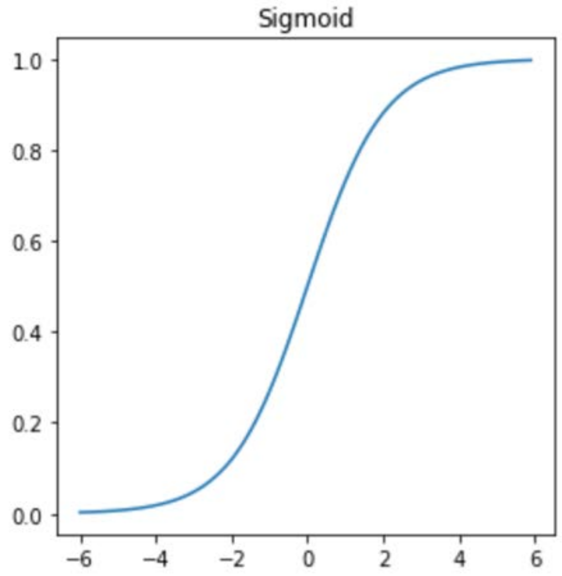
Logistic regression

Logistic regression **maps values from [–infinity, +infinity] to a fixed range of [0, 1]** in such a way that can be interpreted as a probability.

The prediction of a logistic regression model is binary; it **models the probability of belonging to a single class**.

$$\sigma(t) = \frac{1}{1 + e^{-t}}$$

$$t = \log\left(\frac{p}{1-p}\right) \approx w_0 + w_1 x_1 + \cdots + w_n x_n = \mathbf{w}^T \mathbf{x}$$



The fundamentals

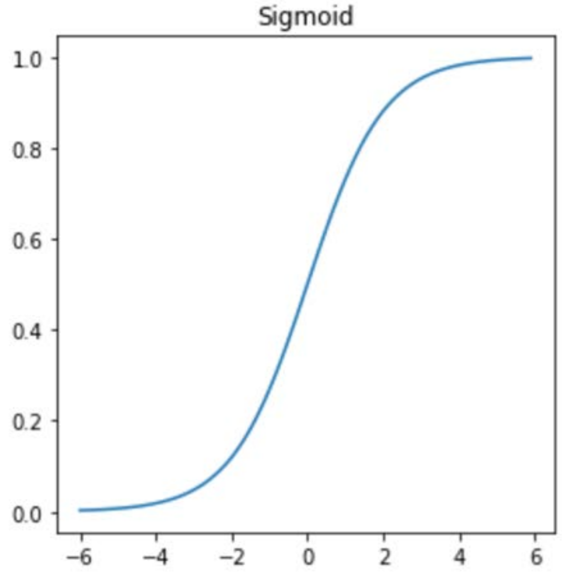
Multi-class logistic regression

Multi-class logistic regression (softmax regression) normalises the predictions of multiple logistic regressions such that the sum of each regression is 1.

It models the probability of an belonging to one of several classes.

$$\sigma(t)_k = \frac{e^{t_k}}{\sum_{i=1}^{K} e^{t_i}}$$

$$t = \log\left(\frac{p}{1-p}\right) \approx w_0 + w_1 x_1 + \cdots + w_n x_n = \mathbf{w}^T \mathbf{x}$$



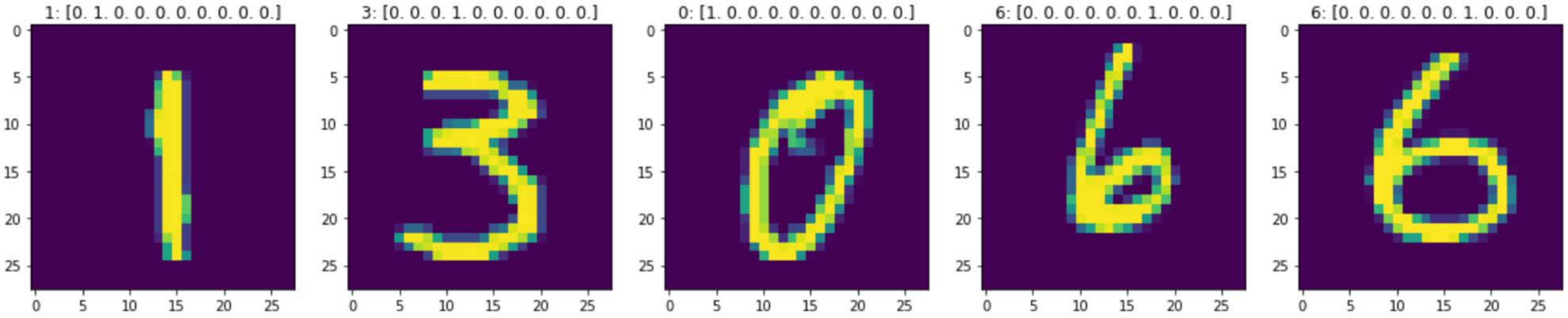
The fundamentals

Multi-class logistic regression

$$\sigma(t)_k = \frac{e^{t_k}}{\sum_{i=1}^{K} e^{t_i}}$$

A set of weights corresponding to each pixel exist for each digit (0-9) that predict the probability of a given image being a given digit.

$$t = \log\left(\frac{p}{1-p}\right) \approx w_0 + w_1 x_1 + \cdots + w_n x_n = \mathbf{w}^T \mathbf{x}$$



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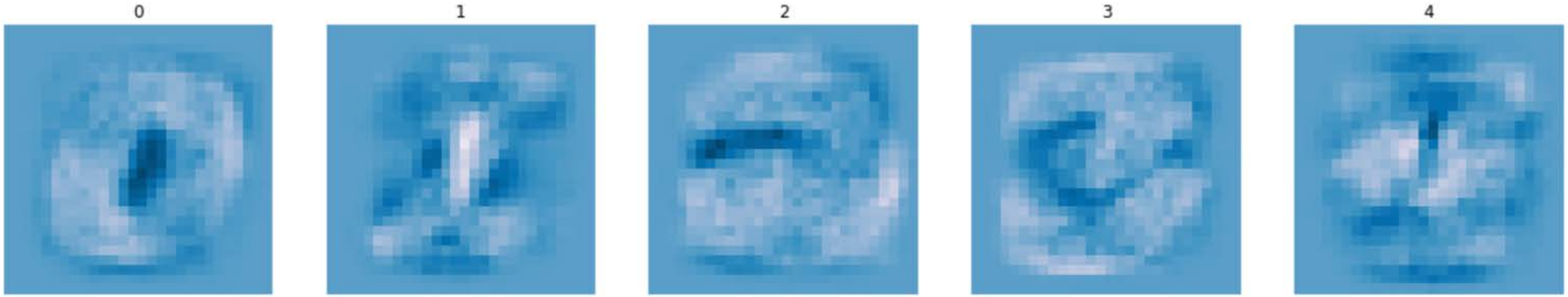
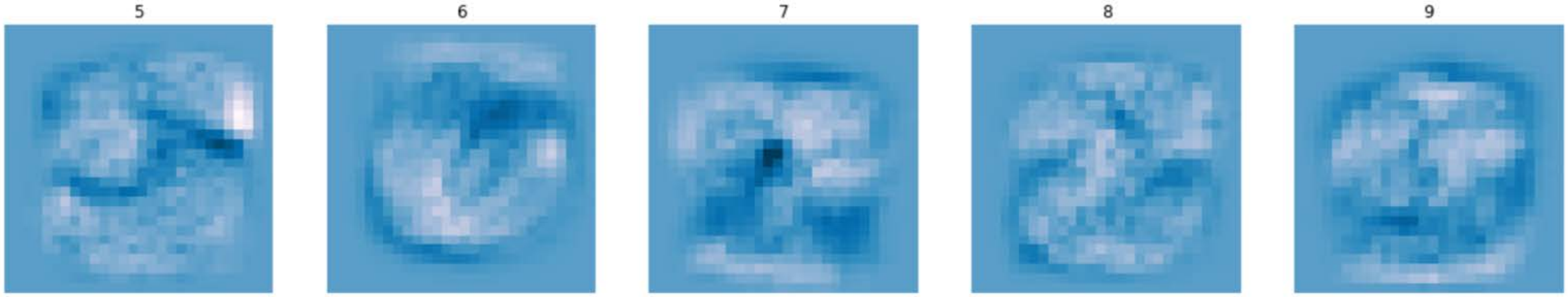
The fundamentals

Multi-class logistic regression



The weights look like this! White indicates a positively for a given digit, black is a negative indication



The fundamentals

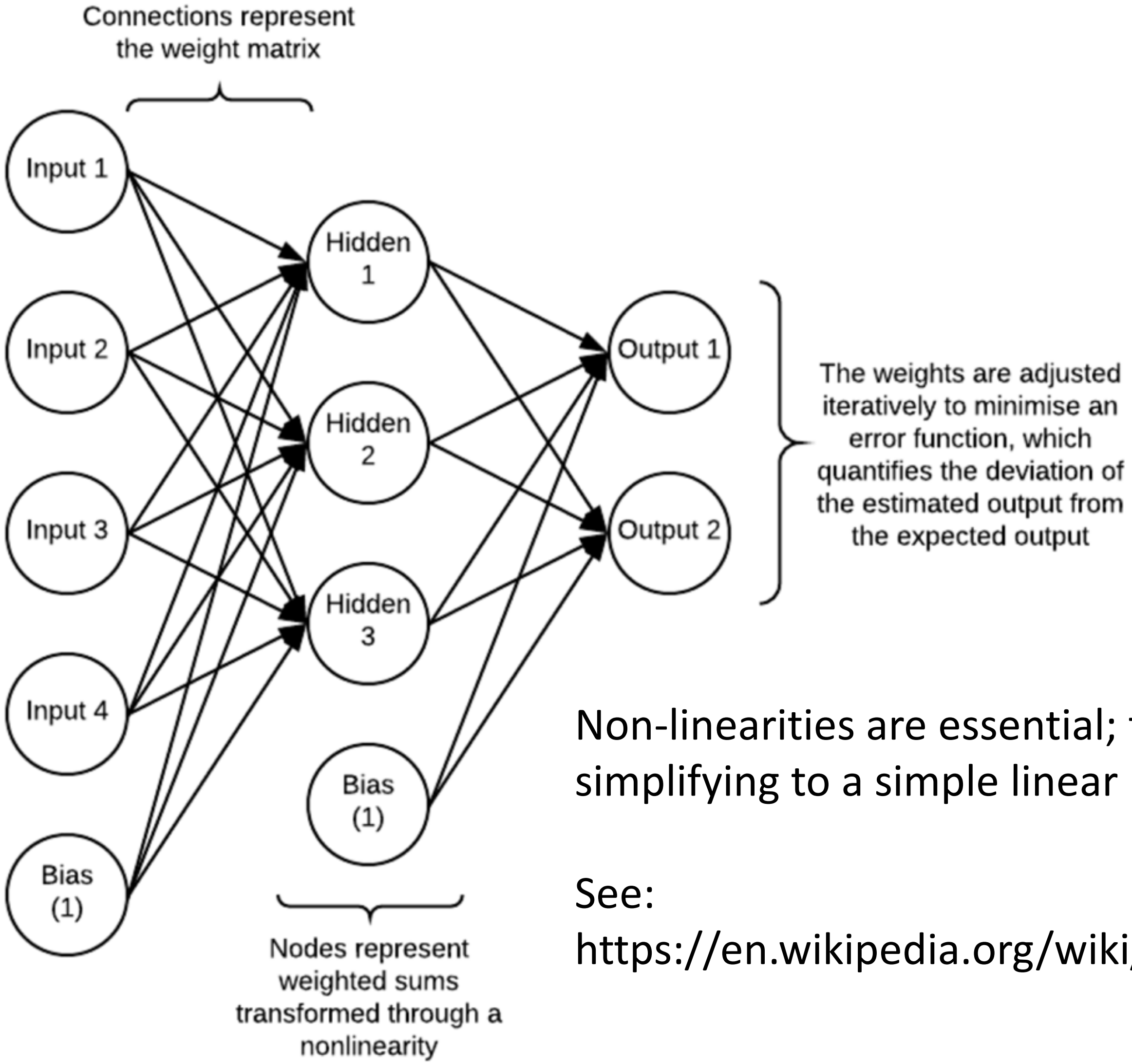
Optimisation

The parameters *w* can be optimised using *gradient descent*; this involves incrementally adjusting *w* by examining their derivative with respect to an error function (loss function, *J*) to make the error as small as possible.

$$\mathbf{w}_{t+1} = \mathbf{w}_t - \eta \frac{\partial J}{\partial \mathbf{w}}$$

The fundamentals

Logistic regressions can be stacked together to account for more complex relationships

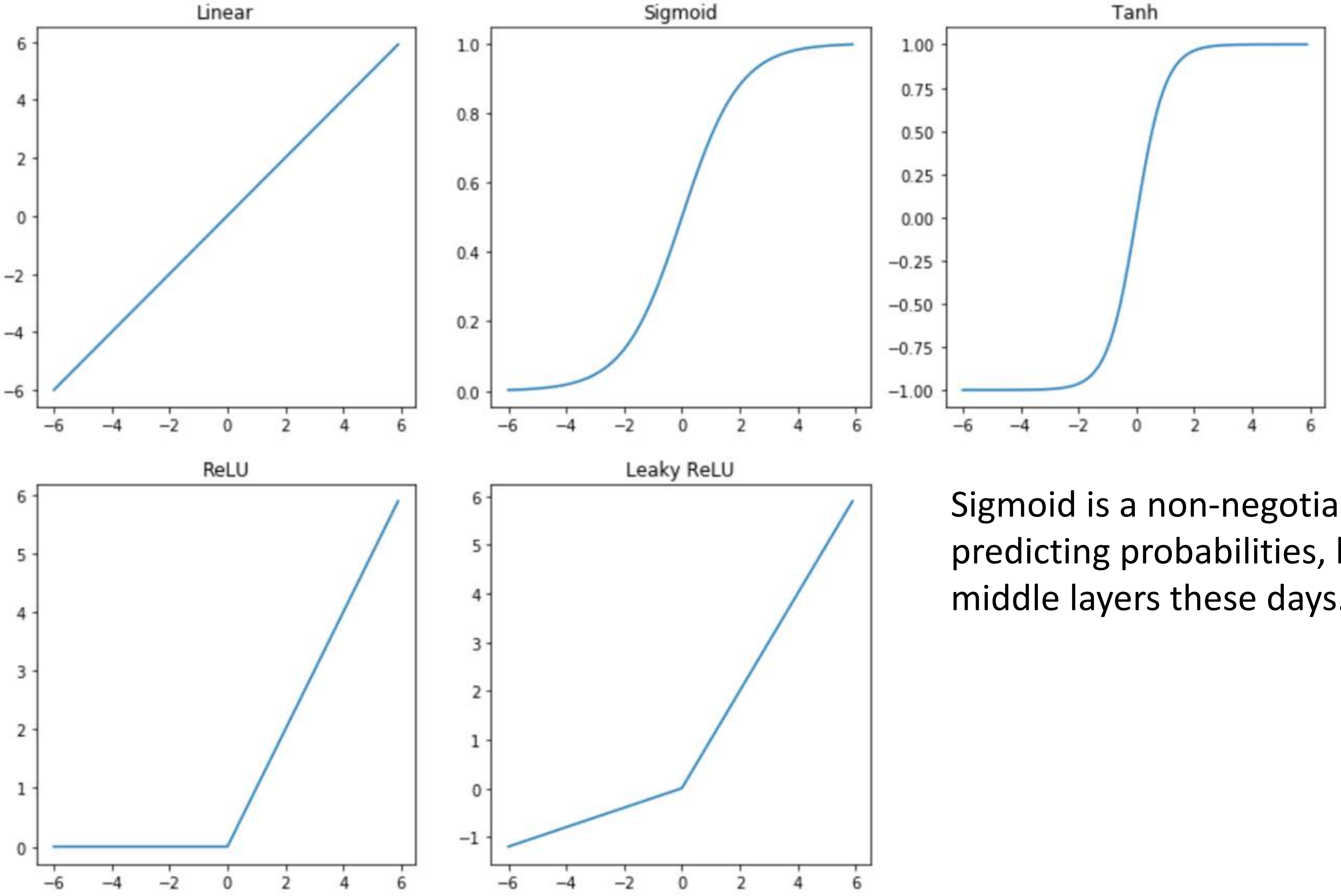


Non-linearities are essential; they prevent the network from simplifying to a simple linear regression.

See:
https://en.wikipedia.org/wiki/Universal_approximation_theorem

The fundamentals

There are many non-linearities to choose from



Sigmoid is a non-negotiable for the output of networks predicting probabilities, but ReLU is more common for the middle layers these days.

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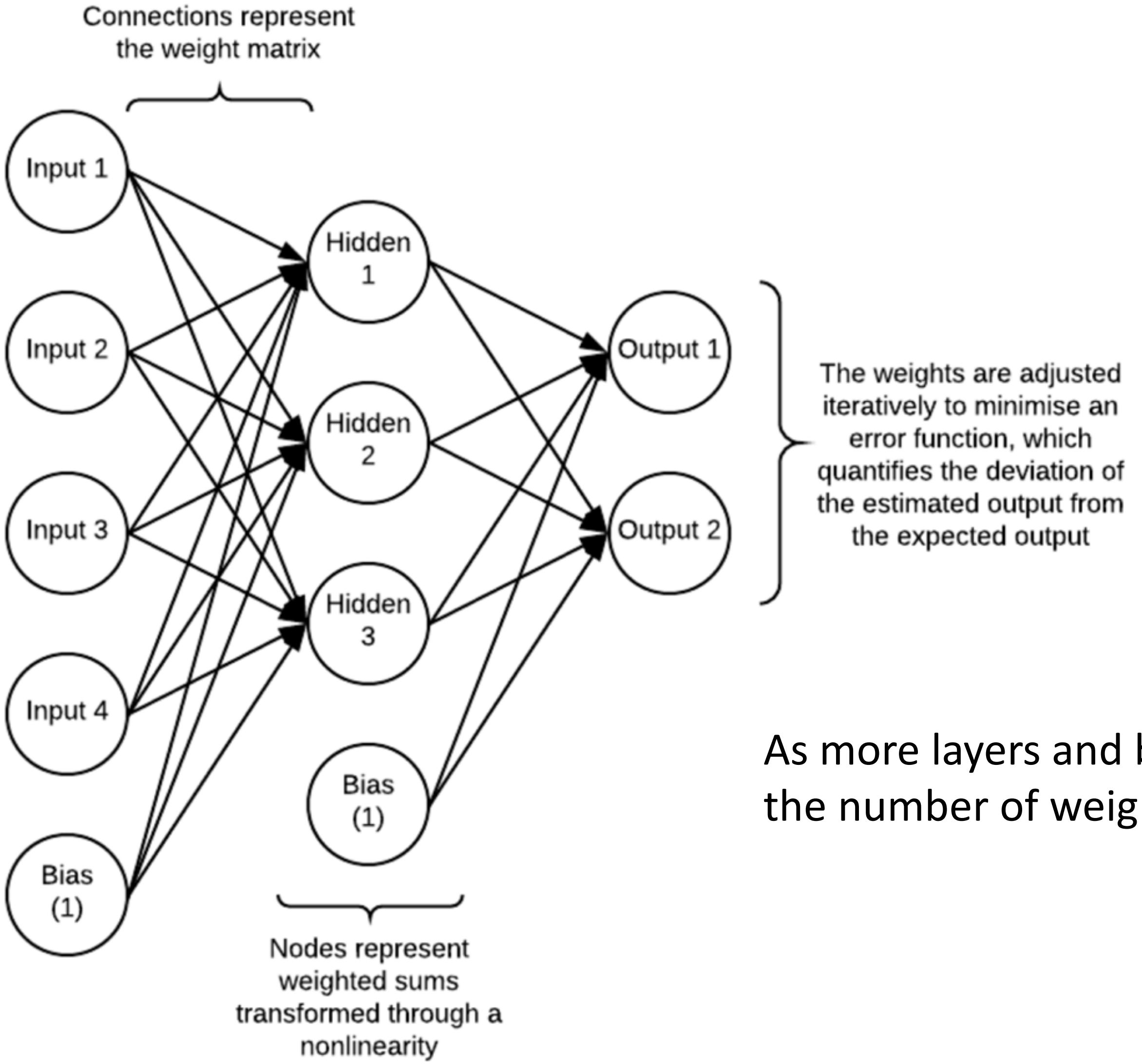
Dense networks are problematic for images



As more layers and bigger images are analysed, the number of weights increases rapidly.

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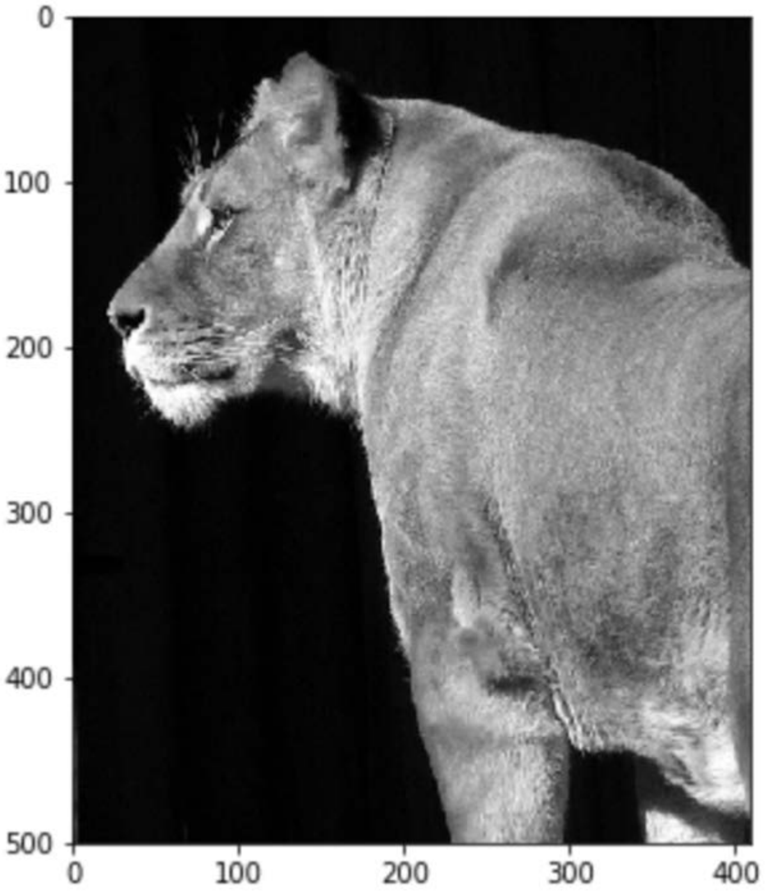
The fundamentals

The convolution operation



0	-1	4	2	0	-2
3	-3	-3	4	4	1
2	-1	0	1	-2	3
-2	3	4	3	-1	1
0	2	1	0	-4	2
-4	3	1	1	-2	0

0	0	0
-1	2	-1
0	0	0

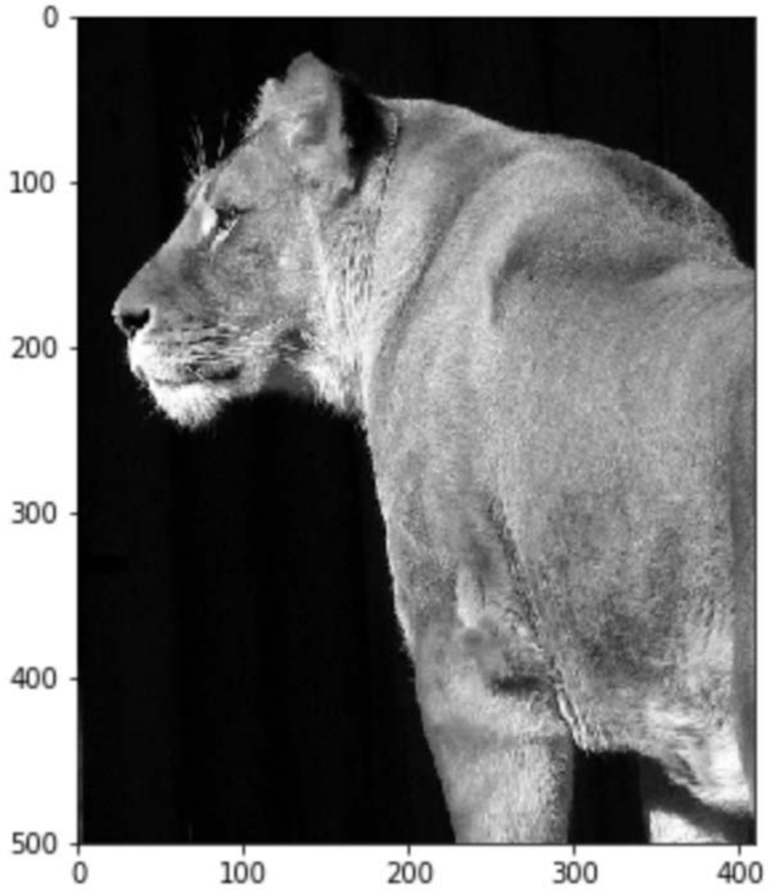
$$(0 \times 0) + (-1 \times 0) + (4 \times 0) + (3 \times -1) + (-3 \times 2) + (-3 \times -1) + (2 \times 0) + (-1 \times 0) + (0 \times 0) = \mathbf{-6}$$

-6	-7	7	3
-4	0	4	-8
4	2	3	-6
3	0	3	-10

Convolutions apply a small set of weights to the entire image as a weighted sum. Traditionally, convolutions were hand-crafted for embossing or edge detection; neural networks learn these parameters automatically.

The fundamentals

The max pooling operation



0	**-1**	4	2	0	-2
3	**-3**	-3	4	4	1
2	-1	0	1	-2	3
-2	3	4	3	-1	1
0	2	1	0	-4	2
-4	3	1	1	-2	0

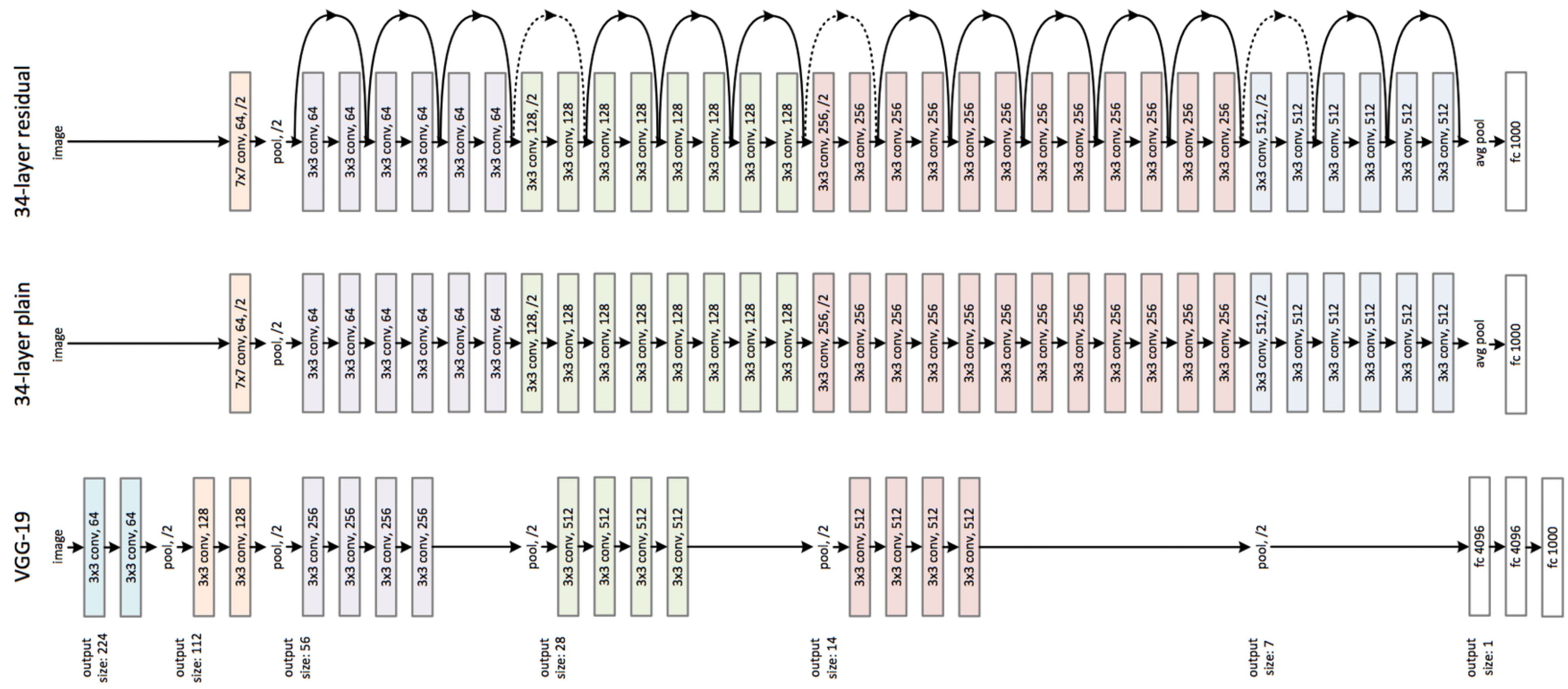
3	4	4
3	4	3
3	1	2

Convolutions apply a small set of weights to the entire image as a weighted sum. Traditionally, convolutions were hand-crafted for embossing or edge detection; neural networks learn these parameters automatically.

The fundamentals

Common CNN architectures

Image: https://arxiv.org/pdf/1512.03385.pdf



Most CNN networks consist of successive convolution and pooling operations, followed by dense layers for classification

Using VGG-19

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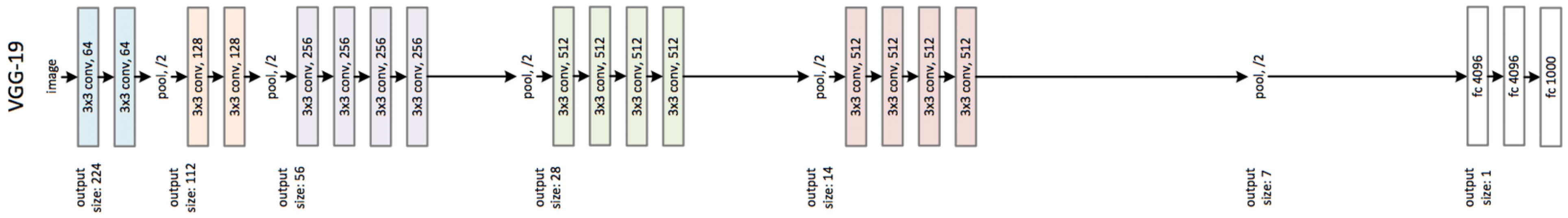
Using VGG-19

Some background



Developed by the Visual Geometry Group, Oxford University in 2015

Achieved about a 71% top-1 accuracy, and about 90% for top-5 accuracy in the ImageNet classification competition (validation set of 150,000 images)

Designed to process images of 224 x 224 pixels, outputs probabilities for 1000 different classes

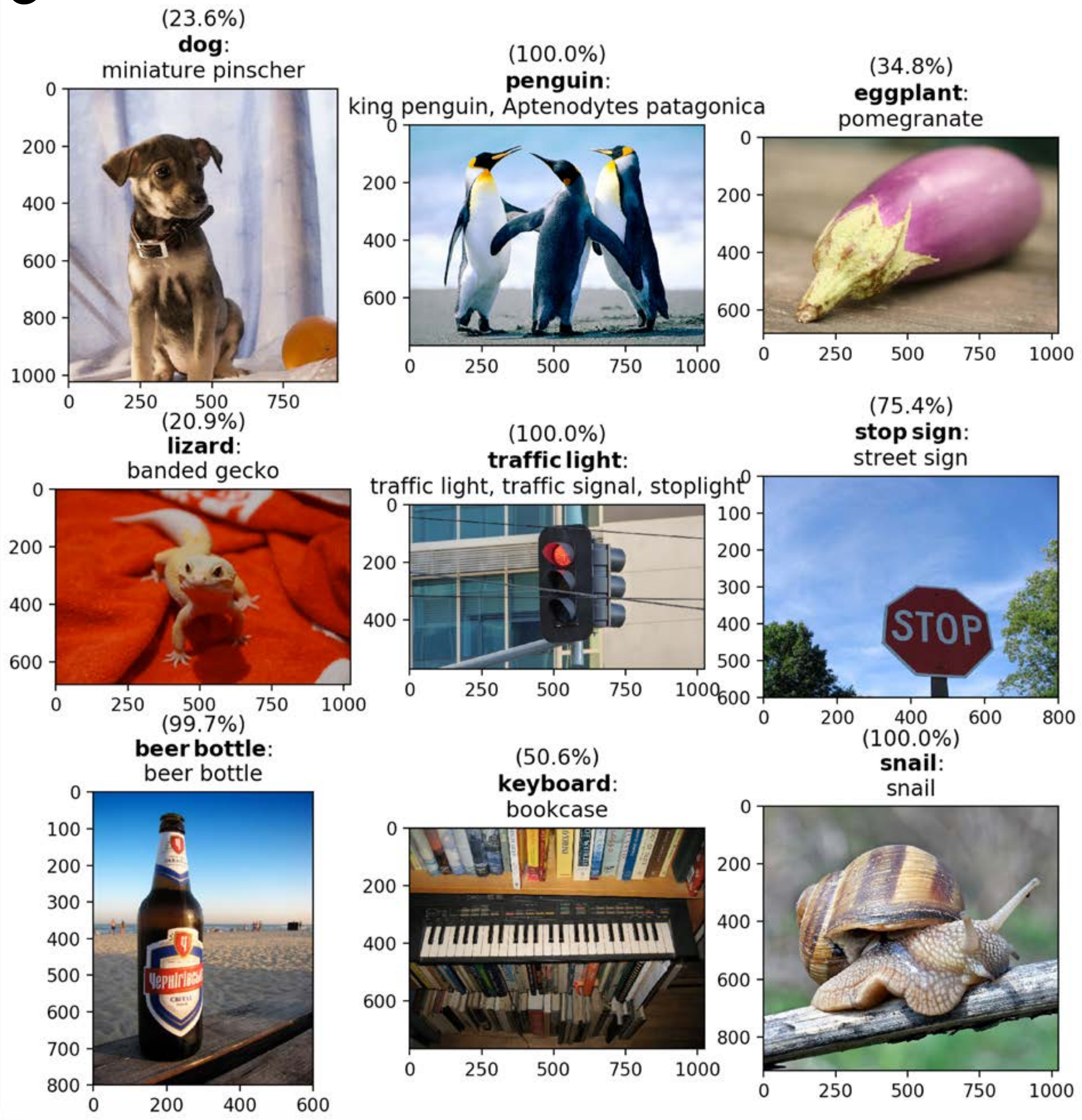
Has about 143,000,000 trainable parameters

Original paper: https://arxiv.org/pdf/1409.1556.pdf

Using VGG-19

Using the network

In **bold** is my annotation; title below is the network prediction from ImageNet classes; percentage probability given in parentheses.



tench, Tinca tinca
goldfish, Carassius
auratus
great white shark, white
shark, man-eater, man-
eating shark,
Carcharodon carcharias
tiger shark, Galeocerdo
cuvieri
hammerhead,
hammerhead shark
electric ray, crampfish,
numbfish, torpedo
stingray
cock
hen
ostrich, Struthio camelus
brambling, Fringilla
montifringilla
goldfinch, Carduelis
carduelis
house finch, linnet,
Carpodacus mexicanus
junco, snowbird
indigo bunting, indigo
finch, indigo bird,
Passerina cyanea
robin, American robin,
Turdus migratorius
bulbul
jay
magpie
chickadee
water ouzel, dipper
kite
bald eagle, American
eagle, Haliaeetus
leucocephalus
vulture
great grey owl, great gray
owl, Strix nebulosa
European fire
salamander, Salamandra
salamandra
common newt, Triturus
vulgaris
eft
spotted salamander,
Ambystoma maculatum
axolotl, mud puppy,
Ambystoma mexicanum
bullfrog, Rana
catesbeiana
tree frog, tree-frog
tailed frog, bell toad,
ribbed toad, tailed toad,
Ascaphus trui
loggerhead, loggerhead
turtle, Caretta caretta
leatherback turtle,
leatherback, leathery
turtle, Dermochelys
coriacea
mud turtle
terrapin
box turtle, box tortoise
banded gecko
common iguana, iguana,
Iguana iguana
American chameleon,
anole, Anolis carolinensis
whiptail, whiptail lizard
agama
frilled lizard,
Chlamydosaurus kingi
alligator lizard
Gila monster, Heloderma
suspectum
green lizard, Lacerta
viridis
African chameleon,
Chamaeleo chamaeleon
Komodo dragon, Komodo
lizard, dragon lizard, giant
lizard, Varanus
komodoensis

African crocodile, Nile
crocodile, Crocodylus
niloticus
American alligator,
Alligator mississipiensis
triceratops
thunder snake, worm
snake, Carphophis
amoenus
ringneck snake, ring-
necked snake, ring snake
hognose snake, puff
adder, sand viper
green snake, grass snake
king snake, kingsnake
garter snake, grass snake
water snake
vine snake
night snake, Hypsiglena
torquata
boa constrictor,
Constrictor constrictor
rock python, rock snake,
Python sebae
Indian cobra, Naja naja
green mamba
sea snake
horned viper, cerastes,
sand viper, horned asp,
Cerastes cornutus
diamondback,
diamondback rattlesnake,
Crotalus adamanteus
sidewinder, horned
rattlesnake, Crotalus
cerastes
trilobite
harvestman, daddy
longlegs, Phalangium
opilio
scorpion
black and gold garden
spider, Argiope aurantia
barn spider, Araneus
cavaticus
garden spider, Aranea
diademata
black widow, Latrodectus
mactans
tarantula
wolf spider, hunting spider
tick
centipede
black grouse
ptarmigan
ruffed grouse, partridge,
Bonasa umbellus
prairie chicken, prairie
grouse, prairie fowl
peacock
quail
partridge
African grey, African gray,
Psittacus erithacus
macaw
sulphur-crested cockatoo,
Kakatoe galerita, Cacatua
galerita
lorikeet
coucal
bee eater
hornbill
hummingbird
jacamar
toucan
drake
red-breasted merganser,
Mergus serrator
goose
black swan, Cygnus
atratus
tusker
echidna, spiny anteater,
anteater
platypus, duckbill,
duckbilled platypus, duck-

billed platypus,
Ornithorhynchus anatinus
wallaby, brush kangaroo
koala, koala bear,
kangaroo bear, native
bear, Phascolarctos
cinereus
wombat
jellyfish
sea anemone, anemone
brain coral
flatworm, platyhelminth
nematode, nematode
worm, roundworm
conch
snail
slug
sea slug, nudibranch
chiton, coat-of-mail shell,
sea cradle,
polyplacophore
chambered nautilus,
pearly nautilus, nautilus
Dungeness crab, Cancer
magister
rock crab, Cancer
irroratus
fiddler crab
king crab, Alaska crab,
Alaskan king crab, Alaska
king crab, Paralithodes
camtschatica
American lobster,
Northern lobster, Maine
lobster, Homarus
americanus
spiny lobster, langouste,
rock lobster, crawfish,
crayfish, sea crawfish
crayfish, crawfish,
crawdad, crawdaddy
hermit crab
isopod
white stork, Ciconia
ciconia
black stork, Ciconia nigra
spoonbill
flamingo
little blue heron, Egretta
caerulea
American egret, great
white heron, Egretta albus
bittern
crane
limpkin, Aramus pictus
European gallinule,
Porphyrio porphyrio
American coot, marsh
hen, mud hen, water hen,
Fulica americana
bustard
ruddy turnstone, Arenaria
interpres
red-backed sandpiper,
dunlin, Erolia alpina
redshank, Tringa totanus
dowitcher
oystercatcher, oyster
catcher
pelican
king penguin,
Aptenodytes patagonica
albatross, mollymawk
grey whale, gray whale,
devilfish, Eschrichtius
gibbosus, Eschrichtius
robustus
killer whale, killer, orca,
grampus, sea wolf,
Orcinus orca
dugong, Dugong dugon
sea lion
Chihuahua
Japanese spaniel
Maltese dog, Maltese
terrier, Maltese

Pekinese, Pekingese,
Peke
Shih-Tzu
Blenheim spaniel
papillon
toy terrier
Rhodesian ridgeback
Afghan hound, Afghan
basset, basset hound
beagle
bloodhound, sleuthhound
bluetick
black-and-tan coonhound
Walker hound, Walker
foxhound
English foxhound
redbone
borzoi, Russian
wolfhound
Irish wolfhound
Italian greyhound
whippet
Ibizan hound, Ibizan
Podenco
Norwegian elkhound,
elkhound
otterhound, otter hound
Saluki, gazelle hound
Scottish deerhound,
deerhound
Weimaraner
Staffordshire bullterrier,
Staffordshire bull terrier
American Staffordshire
terrier, Staffordshire
terrier, American pit bull
terrier, pit bull terrier
Bedlington terrier
Border terrier
Kerry blue terrier
Irish terrier
Norfolk terrier
Norwich terrier
Yorkshire terrier
wire-haired fox terrier
Lakeland terrier
Sealyham terrier,
Sealyham
Airedale, Airedale terrier
cairn, cairn terrier
Australian terrier
Dandie Dinmont, Dandie
Dinmont terrier
Boston bull, Boston terrier
miniature schnauzer
giant schnauzer
standard schnauzer
Scotch terrier, Scottish
terrier, Scottie
Tibetan terrier,
chrysanthemum dog
silky terrier, Sydney silky
soft-coated wheaten
terrier
West Highland white
terrier
Lhasa, Lhasa apso
flat-coated retriever
curly-coated retriever
golden retriever
Labrador retriever
Chesapeake Bay retriever
German short-haired
pointer
vizsla, Hungarian pointer
English setter
Irish setter, red setter
Gordon setter
Brittany spaniel
clumber, clumber spaniel
English springer, English
springer spaniel
Welsh springer spaniel
cocker spaniel, English
cocker spaniel, cocker
Sussex spaniel

Irish water spaniel
kuvasz
schipperke
groenendael
malinois
briard
kelpie
komondor
Old English sheepdog,
bobtail
Shetland sheepdog,
Shetland sheep dog,
Shetland
collie
Border collie
Bouvier des Flandres,
Bouviers des Flandres
Rottweiler
German shepherd,
German shepherd dog,
German police dog,
alsatian
Doberman, Doberman
pinscher
miniature pinscher
Greater Swiss Mountain
dog
Bernese mountain dog
Appenzeller
EntleBucher
boxer
bull mastiff
Tibetan mastiff
French bulldog
Great Dane
Saint Bernard, St Bernard
Eskimo dog, husky
malamute, malemute,
Alaskan malamute
Siberian husky
dalmatian, coach dog,
carriage dog
affenpinscher, monkey
pinscher, monkey dog
basenji
pug, pug-dog
Leonberg
Newfoundland,
Newfoundland dog
Great Pyrenees
Samoyed, Samoyede
Pomeranian
chow, chow chow
keeshond
Brabancon griffon
Pembroke, Pembroke
Welsh corgi
Cardigan, Cardigan
Welsh corgi
toy poodle
miniature poodle
standard poodle
Mexican hairless
timber wolf, grey wolf,
gray wolf, Canis lupus
white wolf, Arctic wolf,
Canis lupus tundrarum
red wolf, maned wolf,
Canis rufus, Canis niger
coyote, prairie wolf, brush
wolf, Canis latrans
dingo, warrigal, warragal,
Canis dingo
dhole, Cuon alpinus
African hunting dog,
hyena dog, Cape hunting
dog, Lycaon pictus
hyena, hyaena
red fox, Vulpes vulpes
kit fox, Vulpes macrotis
Arctic fox, white fox,
Alopex lagopus
grey fox, gray fox,
Urocyon
cinereoargenteus
tabby, tabby cat

tiger cat
Persian cat
Siamese cat, Siamese
Egyptian cat
cougar, puma, catamount,
mountain lion, painter,
panther, Felis concolor
lynx, catamount
leopard, Panthera pardus
snow leopard, ounce,
Panthera uncia
jaguar, panther, Panthera
onca, Felis onca
lion, king of beasts,
Panthera leo
tiger, Panthera tigris
cheetah, chetah,
Acinonyx jubatus
brown bear, bruin, Ursus
arctos
American black bear,
black bear, Ursus
americanus, Euarctos
americanus
ice bear, polar bear,
Ursus Maritimus,
Thalarctos maritimus
sloth bear, Melursus
ursinus, Ursus ursinus
mongoose
meerkat, mierkat
tiger beetle
ladybug, ladybeetle, lady
beetle, ladybird, ladybird
beetle
ground beetle, carabid
beetle
long-horned beetle,
longicorn, longicorn beetle
leaf beetle, chrysomelid
dung beetle
rhinoceros beetle
weevil
fly
bee
ant, emmet, pismire
grasshopper, hopper
cricket
walking stick,
walkingstick, stick insect
cockroach, roach
mantis, mantid
cicada, cicala
leafhopper
lacewing, lacewing fly
dragonfly, darning needle,
devil's darning needle,
sewing needle, snake
feeder, snake doctor,
mosquito hawk, skeeter
hawk
damselfly
admiral
ringlet, ringlet butterfly
monarch, monarch
butterfly, milkweed
butterfly, Danaus
plexippus
cabbage butterfly
sulphur butterfly, sulfur
butterfly
lycaenid, lycaenid
butterfly
starfish, sea star
sea urchin
sea cucumber,
holothurian
wood rabbit, cottontail,
cottontail rabbit
hare
Angora, Angora rabbit
hamster
porcupine, hedgehog
fox squirrel, eastern fox
squirrel, Sciurus niger
marmot

beaver
guinea pig, Cavia cobaya
sorrel
zebra
hog, pig, grunter,
squealer, Sus scrofa
wild boar, boar, Sus
scrofa
warthog
hippopotamus, hippo,
river horse,
Hippopotamus amphibius
ox
water buffalo, water ox,
Asiatic buffalo, Bubalus
bubalis
bison
ram, tup
bighorn, bighorn sheep,
cimarron, Rocky Mountain
bighorn, Rocky Mountain
sheep, Ovis canadensis
ibex, Capra ibex
hartebeest
impala, Aepyceros
melampus
gazelle
Arabian camel,
dromedary, Camelus
dromedarius
llama
weasel
mink
polecat, fitch, foulmart,
foumart, Mustela putorius
black-footed ferret, ferret,
Mustela nigripes
otter
skunk, polecat, wood
pussy
badger
armadillo
three-toed sloth, ai,
Bradypus tridactylus
orangutan, orang,
orangutang, Pongo
pygmaeus
gorilla, Gorilla gorilla
chimpanzee, chimp, Pan
troglodytes
gibbon, Hylobates lar
siamang, Hylobates
syndactylus,
Symphalangus
syndactylus
guenon, guenon monkey
patas, hussar monkey,
Erythrocebus patas
baboon
macaque
langur
colobus, colobus monkey
proboscis monkey,
Nasalis larvatus
marmoset
capuchin, ringtail, Cebus
capucinus
howler monkey, howler
titi, titi monkey
spider monkey, Ateles
geoffroyi
squirrel monkey, Saimiri
sciureus
Madagascar cat, ring-
tailed lemur, Lemur catta
indri, indris, Indri indri,
Indri brevicaudatus
Indian elephant, Elephas
maximus
African elephant,
Loxodonta africana
lesser panda, red panda,
panda, bear cat, cat bear,
Ailurus fulgens
giant panda, panda,
panda bear, coon bear,

Ailuropoda melanoleuca
barracouta, snoek
eel
coho, cohoe, coho
salmon, blue jack, silver
salmon, Oncorhynchus
kisutch
rock beauty, Holocanthus
tricolor
anemone fish
sturgeon
gar, garfish, garpike,
billfish, Lepisosteus
osseus
lionfish
puffer, pufferfish, blowfish,
globefish
abacus
abaya
academic gown,
academic robe, judge's
robe
accordion, piano
accordion, squeeze box
acoustic guitar
aircraft carrier, carrier,
flattop, attack aircraft
carrier
airliner
airship, dirigible
altar
ambulance
amphibian, amphibious
vehicle
analog clock
apiary, bee house
apron
ashcan, trash can,
garbage can, wastebin,
ash bin, ash-bin, ashbin,
dustbin, trash barrel, trash
bin
assault rifle, assault gun
backpack, back pack,
knapsack, packsack,
rucksack, haversack
bakery, bakeshop,
bakehouse
balance beam, beam
balloon
ballpoint, ballpoint pen,
ballpen, Biro
Band Aid
banjo
bannister, banister,
balustrade, balusters,
handrail
barbell
barber chair
barbershop
barn
barometer
barrel, cask
barrow, garden cart, lawn
cart, wheelbarrow
baseball
basketball
bassinet
bassoon
bathing cap, swimming
cap
bath towel
bathtub, bathing tub, bath,
tub
beach wagon, station
wagon, wagon, estate car,
beach waggon, station
waggon, waggon
beacon, lighthouse,
beacon light, pharos
beaker
bearskin, busby, shako
beer bottle
beer glass
bell cote, bell cot
bib

bicycle-built-for-two,
tandem bicycle, tandem
bikini, two-piece
binder, ring-binder
binoculars, field glasses,
opera glasses
birdhouse
boathouse
bobsled, bobsleigh, bob
bolo tie, bolo, bola tie,
bola
bonnet, poke bonnet
bookcase
bookshop, bookstore,
bookstall
bottlecap
bow
bow tie, bow-tie, bowtie
brass, memorial tablet,
plaque
brassiere, bra, bandeau
breakwater, groin, groyne,
mole, bulwark, seawall,
jetty
breastplate, aegis, egis
broom
bucket, pail
buckle
bulletproof vest
bullet train, bullet
butcher shop, meat
market
cab, hack, taxi, taxicab
caldron, cauldron
candle, taper, wax light
cannon
canoe
can opener, tin opener
cardigan
car mirror
carousel, carrousel,
merry-go-round,
roundabout, whirligig
carpenter's kit, tool kit
carton
car wheel
cash machine, cash
dispenser, automated
teller machine, automatic
teller machine, automated
teller, automatic teller,
ATM
cassette
cassette player
castle
catamaran
CD player
cello, violoncello
cellular telephone, cellular
phone, cellphone, cell,
mobile phone
chain
chainlink fence
chain mail, ring mail, mail,
chain armor, chain
armour, ring armor, ring
armour
chain saw, chainsaw
chest
chiffonier, commode
chime, bell, gong
china cabinet, china
closet
Christmas stocking
church, church building
cinema, movie theater,
movie theatre, movie
house, picture palace
cleaver, meat cleaver,
chopper
cliff dwelling
cloak
clog, geta, patten, sabot
cocktail shaker
coffee mug
coffeepot

coil, spiral, volute, whorl,
helix
combination lock
computer keyboard,
keypad
confectionery,
confectionary, candy store
container ship,
containership, container
vessel
convertible
corkscrew, bottle screw
cornet, horn, trumpet,
trump
cowboy boot
cowboy hat, ten-gallon hat
cradle
crane
crash helmet
crate
crib, cot
Crock Pot
croquet ball
crutch
cuirass
dam, dike, dyke
desk
desktop computer
dial telephone, dial phone
diaper, nappy, napkin
digital clock
digital watch
dining table, board
dishrag, dishcloth
dishwasher, dish washer,
dishwashing machine
disk brake, disc brake
dock, dockage, docking
facility
dogsled, dog sled, dog
sleigh
dome
doormat, welcome mat
drilling platform, offshore
rig
drum, membranophone,
tympan
drumstick
dumbbell
Dutch oven
electric fan, blower
electric guitar
electric locomotive
entertainment center
envelope
espresso maker
face powder
feather boa, boa
file, file cabinet, filing
cabinet
fireboat
fire engine, fire truck
fire screen, fireguard
flagpole, flagstaff
flute, transverse flute
folding chair
football helmet
forklift
fountain
fountain pen
four-poster
freight car
French horn, horn
frying pan, frypan, skillet
fur coat
garbage truck, dustcart
gasmask, respirator, gas
helmet
gas pump, gasoline
pump, petrol pump, island
dispenser
goblet
go-kart
golf ball
golfcart, golf cart
gondola

gong, tam-tam
gown
grand piano, grand
greenhouse, nursery,
glasshouse
grille, radiator grille
grocery store, grocery,
food market, market
guillotine
hair slide
hair spray
half track
hammer
hamper
hand blower, blow dryer,
blow drier, hair dryer, hair
drier
hand-held computer,
hand-held microcomputer
handkerchief, hankie,
hanky, hankey
hard disc, hard disk, fixed
disk
harmonica, mouth organ,
harp, mouth harp
harp
harvester, reaper
hatchet
holster
home theater, home
theatre
honeycomb
hook, claw
hoopskirt, crinoline
horizontal bar, high bar
horse cart, horse-cart
hourglass
iPod
iron, smoothing iron
jack-o'-lantern
jean, blue jean, denim
jeep, landrover
jersey, T-shirt, tee shirt
jigsaw puzzle
jinrikisha, ricksha,
rickshaw
joystick
kimono
knee pad
knot
lab coat, laboratory coat
ladle
lampshade, lamp shade
laptop, laptop computer
lawn mower, mower
lens cap, lens cover
letter opener, paper knife,
paperknife
library
lifeboat
lighter, light, igniter, ignitor
limousine, limo
liner, ocean liner
lipstick, lip rouge
Loafer
lotion
loudspeaker, speaker,
speaker unit, loudspeaker
system, speaker system
loupe, jeweler's loupe
lumbermill, sawmill
magnetic compass
mailbag, postbag
mailbox, letter box
maillot
maillot, tank suit
manhole cover
maraca
marimba, xylophone
mask
matchstick
maypole
maze, labyrinth
measuring cup
medicine chest, medicine
cabinet

megalith, megalithic
structure
microphone, mike
microwave, microwave
oven
military uniform
milk can
minibus
miniskirt, mini
minivan
missile
mitten
mixing bowl
mobile home,
manufactured home
Model T
modem
monastery
monitor
moped
mortar
mortarboard
mosque
mosquito net
motor scooter, scooter
mountain bike, all-terrain
bike, off-roader
mountain tent
mouse, computer mouse
mousetrap
moving van
muzzle
nail
neck brace
necklace
nipple
notebook, notebook
computer
obelisk
oboe, hautboy, hautbois
ocarina, sweet potato
odometer, hodometer,
mileometer, milometer
oil filter
organ, pipe organ
oscilloscope, scope,
cathode-ray oscilloscope,
CRO
overskirt
oxcart
oxygen mask
packet
paddle, boat paddle
paddlewheel, paddle
wheel
padlock
paintbrush
pajama, pyjama, pj's,
jammies
palace
panpipe, pandean pipe,
syrinx
paper towel
parachute, chute
parallel bars, bars
park bench
parking meter
passenger car, coach,
carriage
patio, terrace
pay-phone, pay-station
pedestal, plinth, footstall
pencil box, pencil case
pencil sharpener
perfume, essence
Petri dish
photocopier
pick, plectrum, plectron
pickelhaube
picket fence, paling
pickup, pickup truck
pier
piggy bank, penny bank
pill bottle
pillow
ping-pong ball

pinwheel
pirate, pirate ship
pitcher, ewer
plane, carpenter's plane,
woodworking plane
planetarium
plastic bag
plate rack
plow, plough
plunger, plumber's helper
Polaroid camera, Polaroid
Land camera
pole
police van, police wagon,
paddy wagon, patrol
wagon, wagon, black
Maria
poncho
pool table, billiard table,
snooker table
pop bottle, soda bottle
pot, flowerpot
potter's wheel
power drill
prayer rug, prayer mat
printer
prison, prison house
projectile, missile
projector
puck, hockey puck
punching bag, punch bag,
punching ball, punchball
purse
quill, quill pen
quilt, comforter, comfort,
puff
racer, race car, racing car
racket, racquet
radiator
radio, wireless
radio telescope, radio
reflector
rain barrel
recreational vehicle, RV,
R.V.
reel
reflex camera
refrigerator, icebox
remote control, remote
restaurant, eating house,
eating place, eatery
revolver, six-gun, six-
shooter
rifle
rocking chair, rocker
rotisserie
rubber eraser, rubber,
pencil eraser
rugby ball
rule, ruler
running shoe
safe
safety pin
saltshaker, salt shaker
sandal
sarong
sax, saxophone
scabbard
scale, weighing machine
school bus
schooner
scoreboard
screen, CRT screen
screw
screwdriver
seat belt, seatbelt
sewing machine
shield, buckler
shoe shop, shoe-shop,
shoe store
shoji
shopping basket
shopping cart
shovel
shower cap
shower curtain

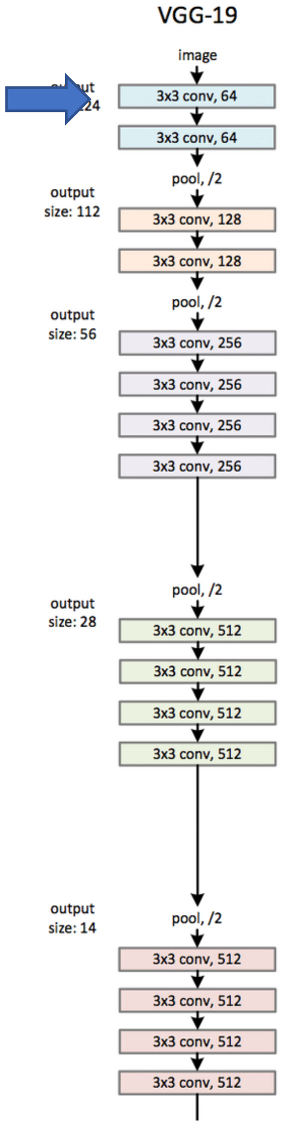
ski
ski mask
sleeping bag
slide rule, slipstick
sliding door
slot, one-armed bandit
snorkel
snowmobile
snowplow, snowplough
soap dispenser
soccer ball
sock
solar dish, solar collector,
solar furnace
sombrero
soup bowl
space bar
space heater
space shuttle
spatula
speedboat
spider web, spider's web
spindle
sports car, sport car
spotlight, spot
stage
steam locomotive
steel arch bridge
steel drum
stethoscope
stole
stone wall
stopwatch, stop watch
stove
strainer
streetcar, tram, tramcar,
trolley, trolley car
stretcher
studio couch, day bed
stupa, tope
submarine, pigboat, sub,
U-boat
suit, suit of clothes
sundial
sunglass
sunglasses, dark glasses,
shades
sunscreen, sunblock, sun
blocker
suspension bridge
swab, swob, mop
sweatshirt
swimming trunks, bathing
trunks
swing
switch, electric switch,
electrical switch
syringe
table lamp
tank, army tank, armored
combat vehicle, armoured
combat vehicle
tape player
teapot
teddy, teddy bear
television, television
system
tennis ball
thatch, thatched roof
theater curtain, theatre
curtain
thimble
thresher, thrasher,
threshing machine
throne
tile roof
toaster
tobacco shop, tobacconist
shop, tobacconist
toilet seat
torch
totem pole
tow truck, tow car,
wrecker
toyshop
tractor

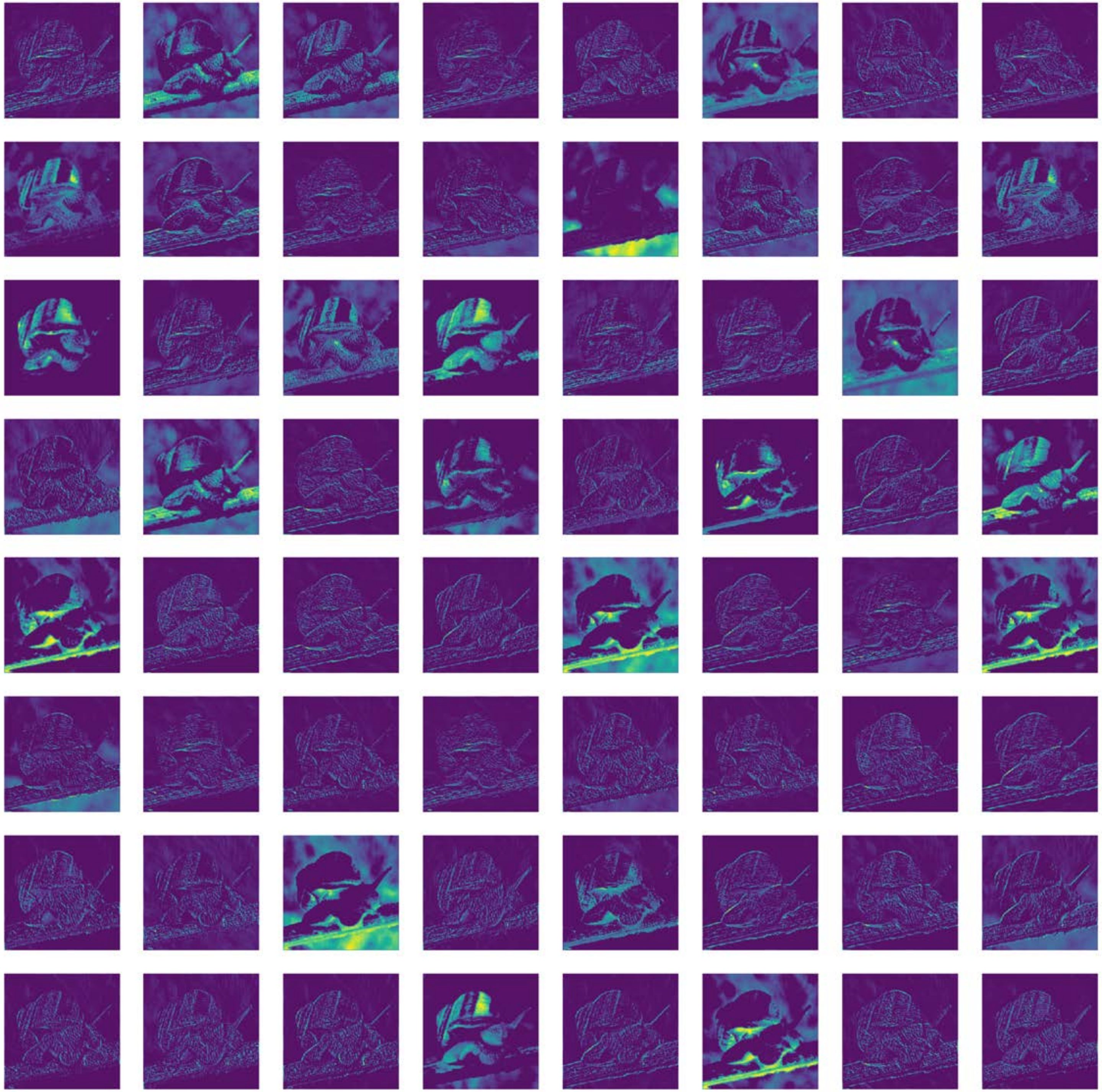
trailer truck, tractor trailer,
trucking rig, rig,
articulated lorry, semi
tray
trench coat
tricycle, trike, velocipede
trimaran
tripod
triumphal arch
trolleybus, trolley coach,
trackless trolley
trombone
tub, vat
turnstile
typewriter keyboard
umbrella
unicycle, monocycle
upright, upright piano
vacuum, vacuum cleaner
vase
vault
velvet
vending machine
vestment
viaduct
violin, fiddle
volleyball
waffle iron
wall clock
wallet, billfold, notecase,
pocketbook
wardrobe, closet, press
warplane, military plane
washbasin, handbasin,
washbowl, lavabo, wash-
hand basin
washer, automatic
washer, washing machine
water bottle
water jug
water tower
whiskey jug
whistle
wig
window screen
window shade
Windsor tie
wine bottle
wing
wok
wooden spoon
wool, woolen, woollen
worm fence, snake fence,
snake-rail fence, Virginia
fence
wreck
yawl
yurt
web site, website, internet
site, site
comic book
crossword puzzle,
crossword
street sign
traffic light, traffic signal,
stoplight
book jacket, dust cover,
dust jacket, dust wrapper
menu
plate
guacamole
consomme
hot pot, hotpot
trifle
ice cream, icecream
ice lolly, lolly, lollipop,
popsicle
French loaf
bagel, beigel
pretzel
cheeseburger
hotdog, hot dog, red hot
mashed potato
head cabbage
broccoli
cauliflower

zucchini, courgette
spaghetti squash
acorn squash
butternut squash
cucumber, cuke
artichoke, globe artichoke
bell pepper
cardoon
mushroom
Granny Smith
strawberry
orange
lemon
fig
pineapple, ananas
banana
jackfruit, jak, jack
custard apple
pomegranate
hay
carbonara
chocolate sauce,
chocolate syrup
dough
meat loaf, meatloaf
pizza, pizza pie
potpie
burrito
red wine
espresso
cup
eggnog
alp
bubble
cliff, drop, drop-off
coral reef
geyser
lakeside, lakeshore
promontory, headland,
head, foreland
sandbar, sand bar
seashore, coast,
seacoast, sea-coast
valley, vale
volcano
ballplayer, baseball player
groom, bridegroom
scuba diver
rapeseed
daisy
yellow lady's slipper,
yellow lady-slipper,
Cypripedium calceolus,
Cypripedium parviflorum
corn
acorn
hip, rose hip, rosehip
buckeye, horse chestnut,
conker
coral fungus
agaric
gyromitra
stinkhorn, carrion fungus
earthstar
hen-of-the-woods, hen of
the woods, Polyporus
frondosus, Grifola
frondosa
bolete
ear, spike, capitulum
toilet tissue, toilet paper,
bathroom tissue

Using VGG-19

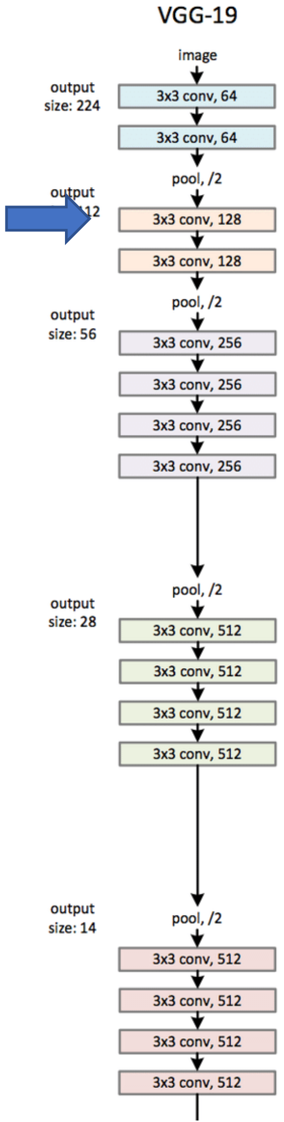
What does the network see?

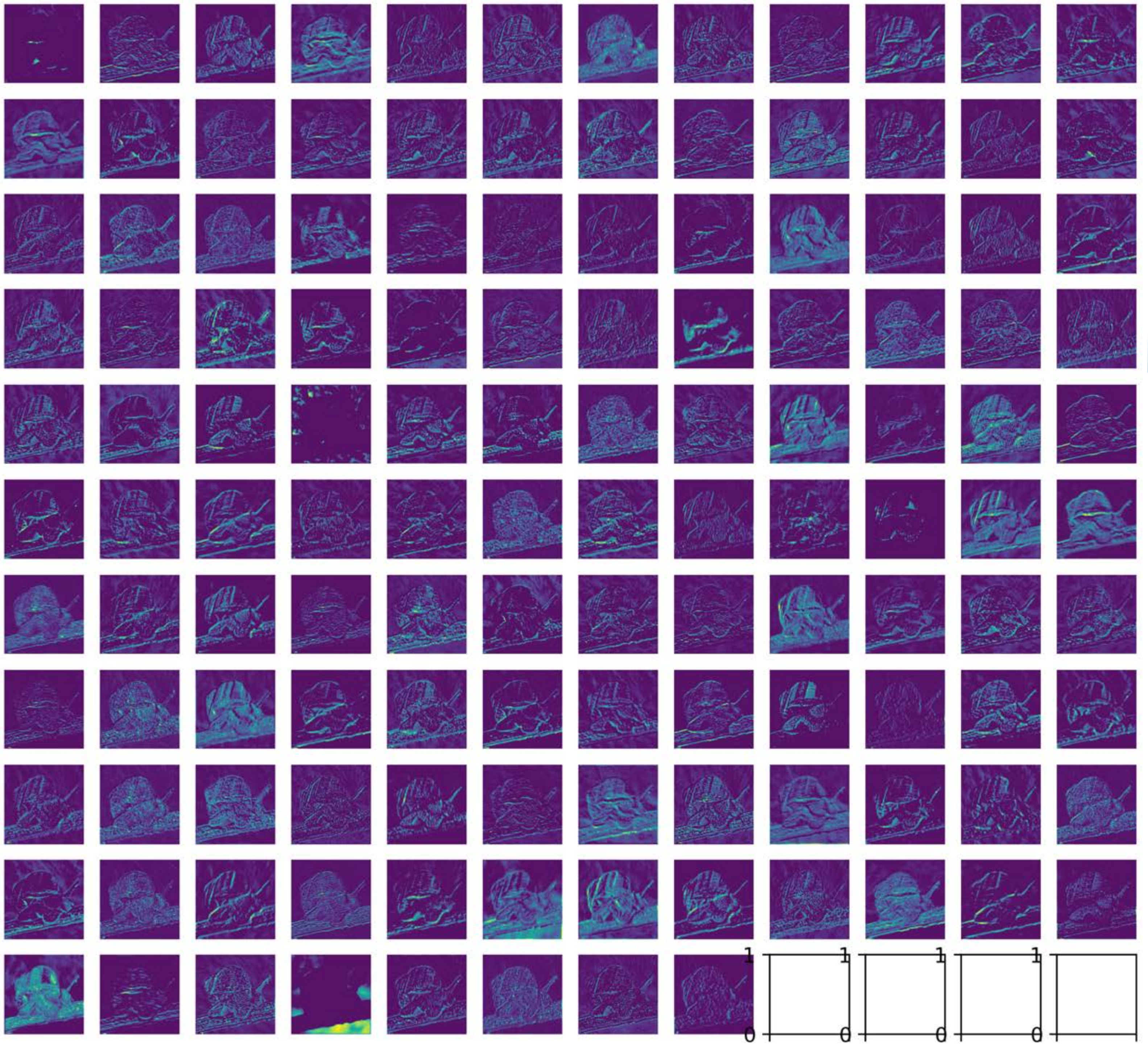




Using VGG-19

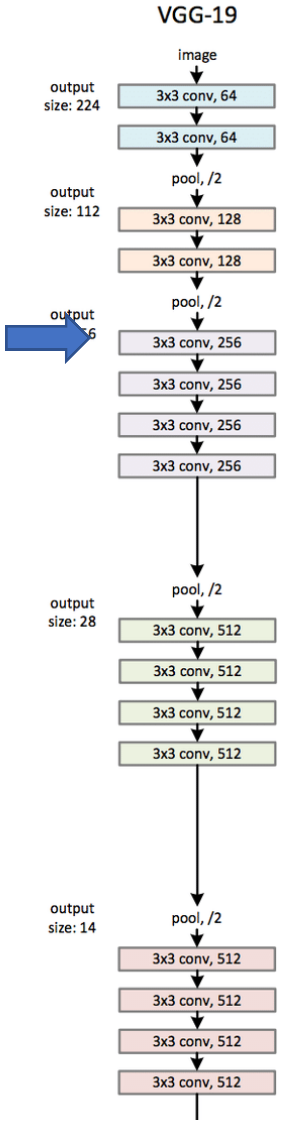
What does the network see?

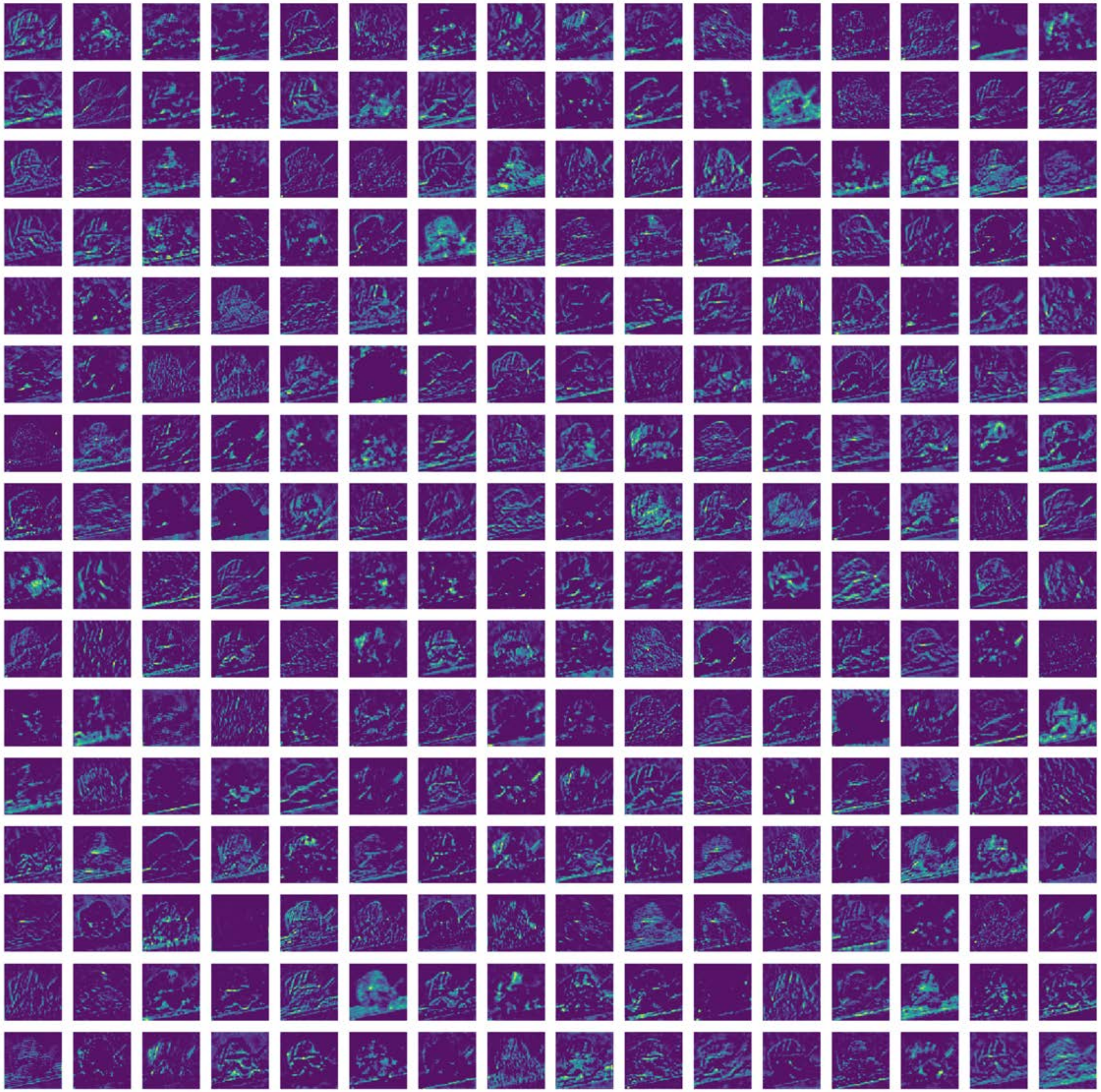




Using VGG-19

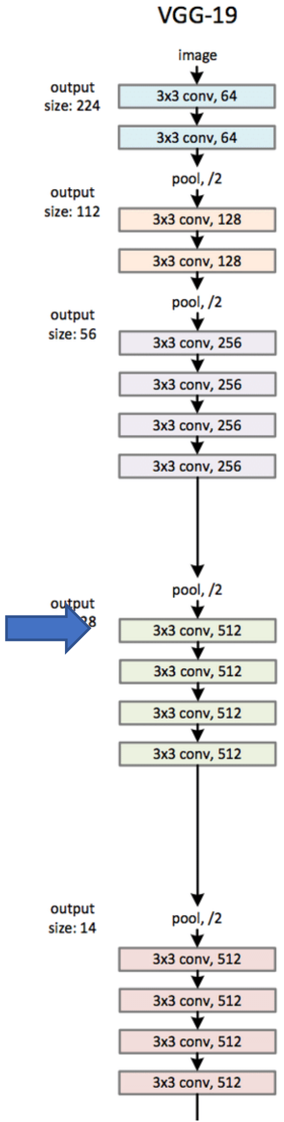
What does the network see?

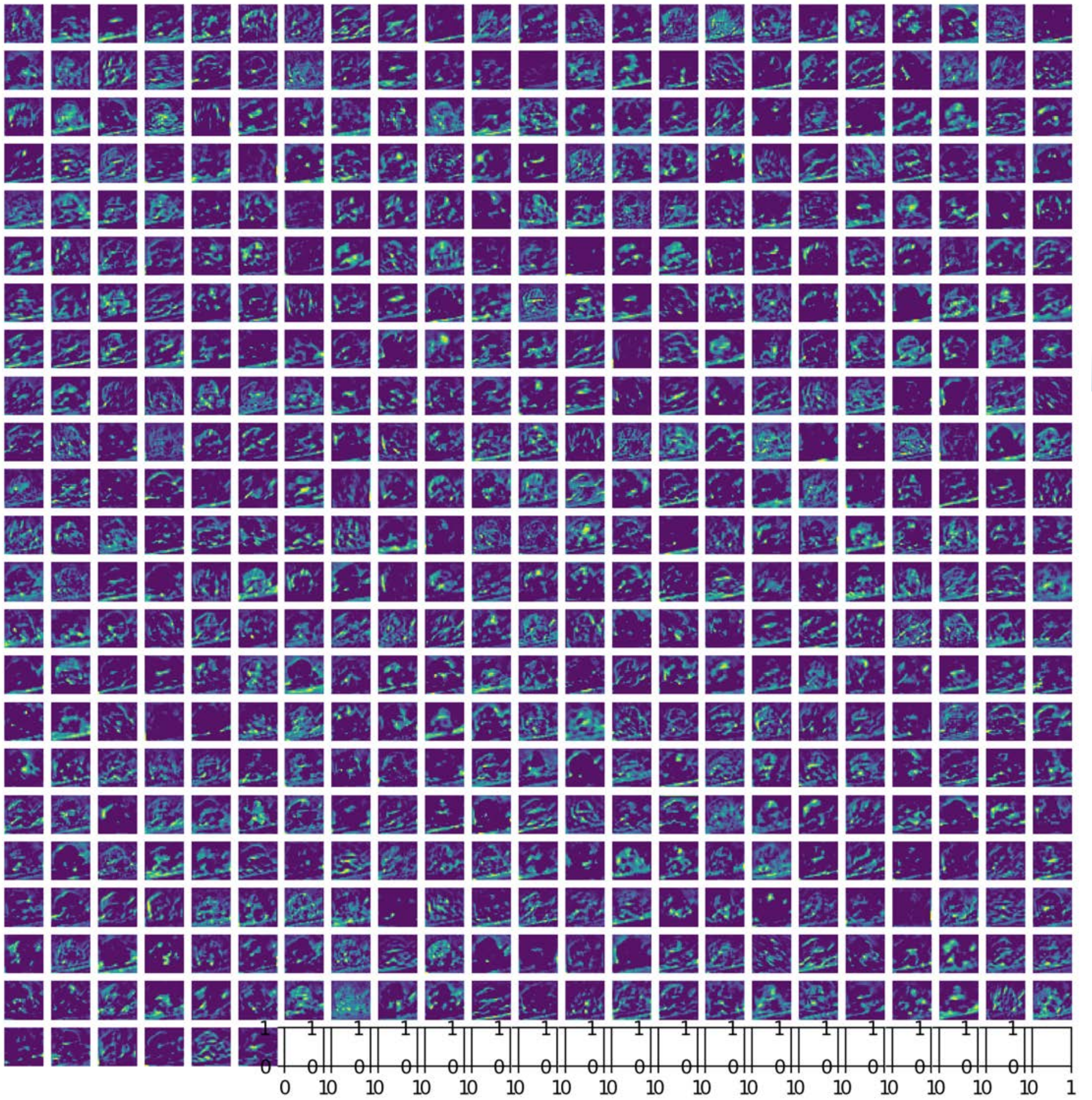




Using VGG-19

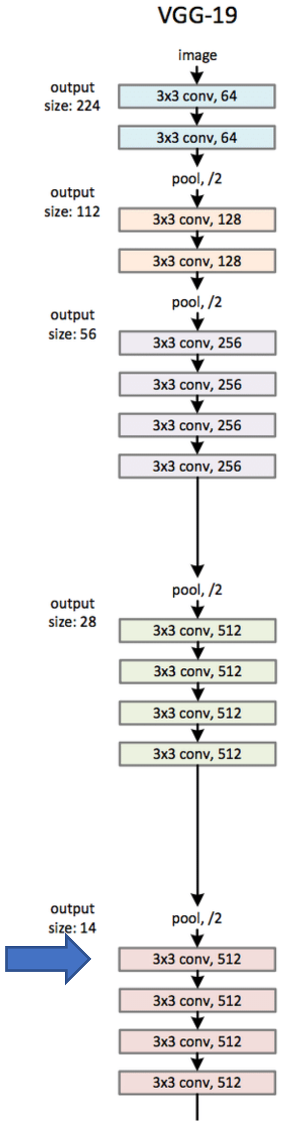
What does the network see?

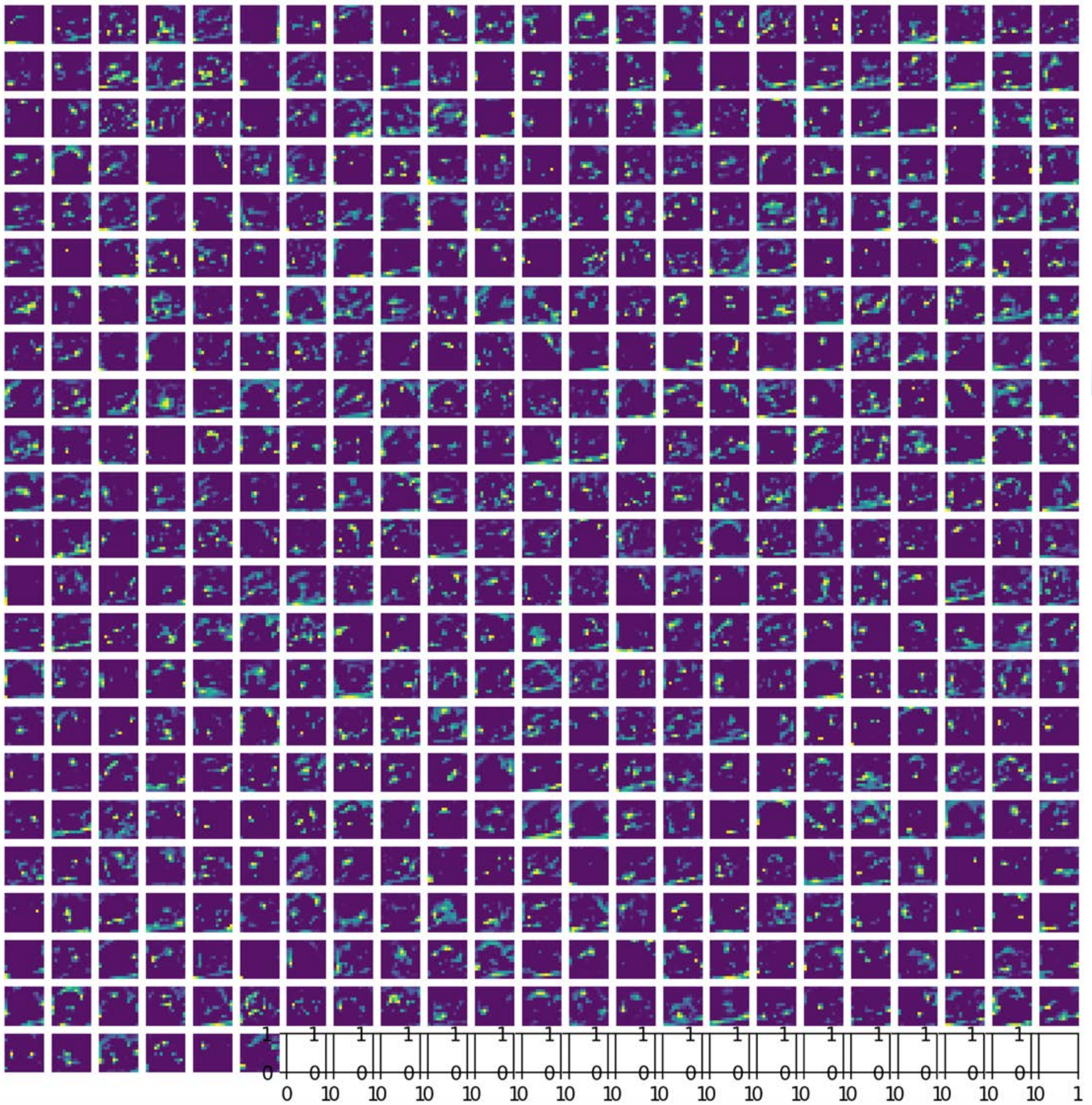




Using VGG-19

What does the network see?





Using VGG-19

What does the network see?

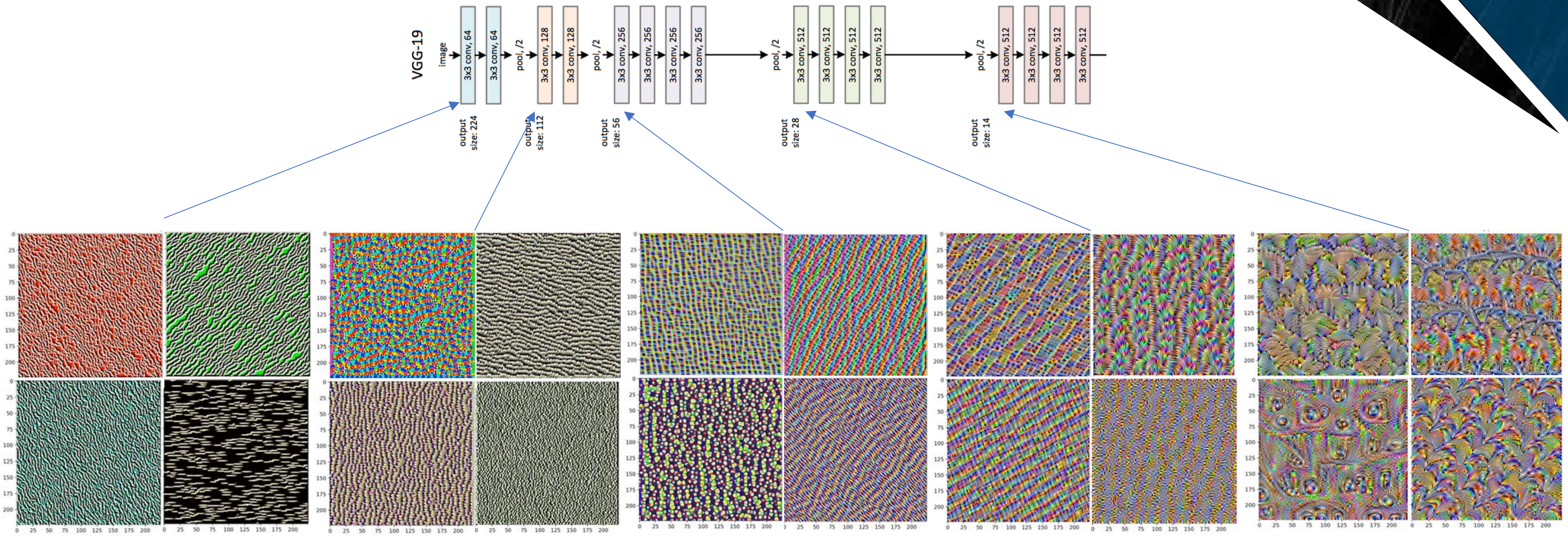
Rather than activate filters using an image, we can generate an image designed to activate specific filters.

https://github.com/jasonrig/transfer-learning-demos

```
python3 -m TransferLearningDemo.demos.vgg_19_activate_filters
```

VGG-19

What does the network see?



Filters closer to the input capture **lower-level features**

Filters closer to the output capture **high-level features**

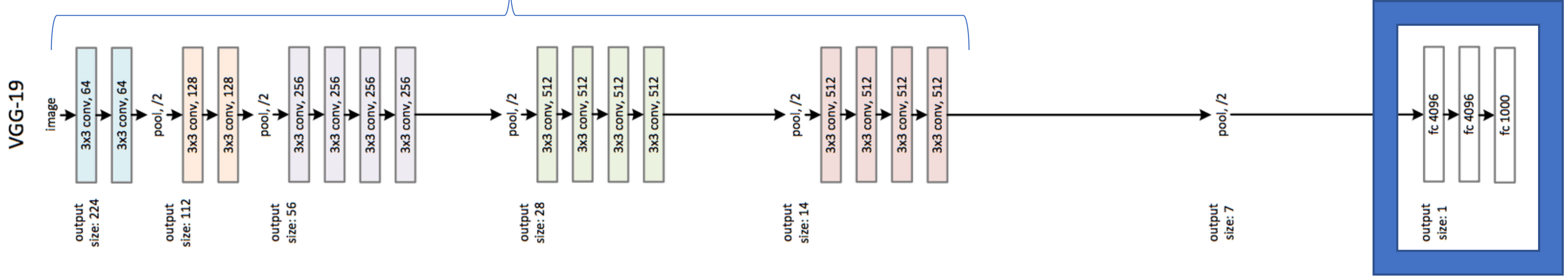
Repurposing VGG-19

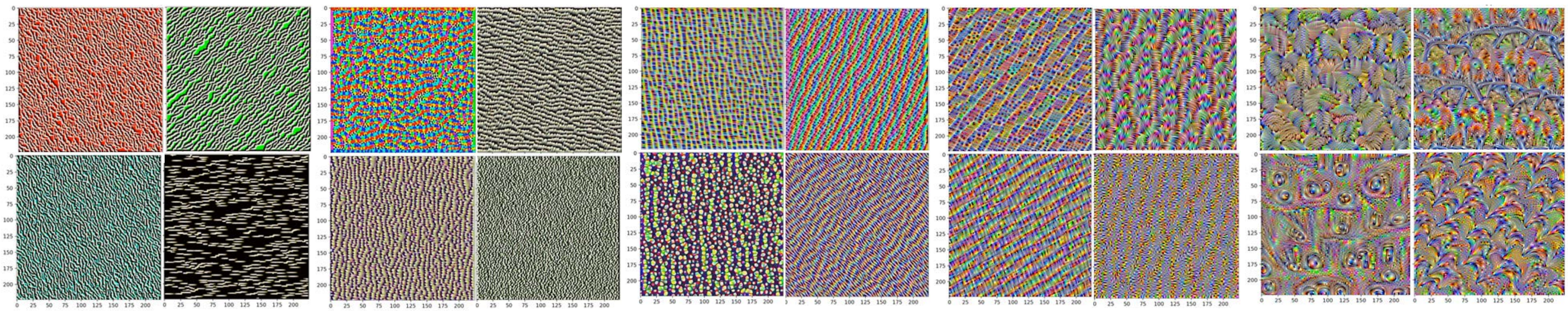
Repurposing VGG-19

Parameter reuse

These features generally don't change much

These layers are strongly linked with the network task





Repurposing VGG-19

Parameter reuse

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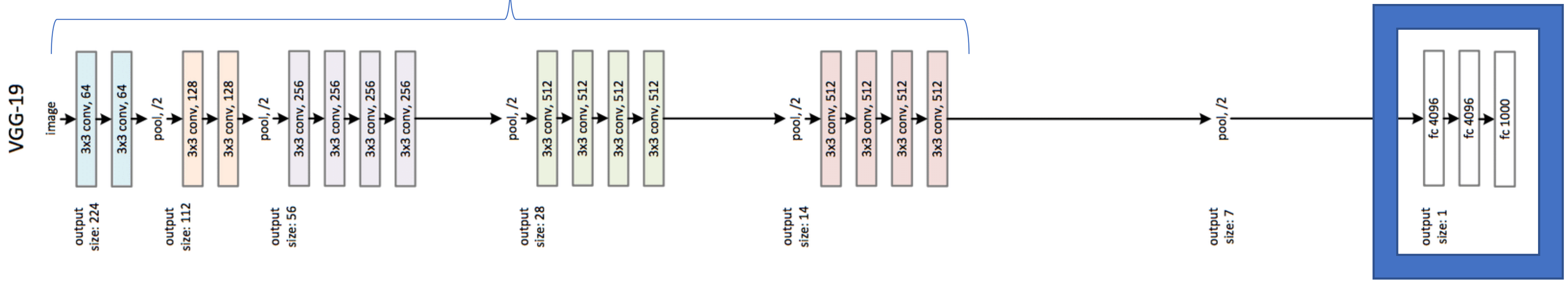

Motivation:

Pretrained networks have learnt parameters from a vast number of training exampled (ImageNet +14 mil images)

Some domains have very limited data

Low-level features in CNNs are almost universal; always hard edges or simple textures

Repurposing VGG-19

Retinal haemorrhage detection – STARE dataset

Dataset description:

400 retinal photographs
44 features annotates per image

Each feature can have more than one classification, *e.g.* microaneurisms can be:

- Unknown
- Absent
- Few anywhere
- Many anywhere

VGG-19 has been retrained as a binary classifier for retinal haemorrhages with approximately 75-80% accuracy

Training took approximately 20 minutes on a single GPU

http://cecas.clemson.edu/~ahoover/stare/

Repurposing VGG-19

Retinal haemorrhage detection – Example results on unseen images

Testing the VGG-19 haemorrhage detector:

```
[{'probabilities':
array([9.9999166e-01,
8.3547111e-06], dtype=float32),
'predictions': 0}]
```

http://webvision.med.utah.edu/book/part-i-foundations/simple-anatomy-of-the-retina/

```
[{'probabilities':
array([0.00233166, 0.9976683 ],
dtype=float32), 'predictions':
1}]
```

https://clinicalgate.com/nonproliferative-diabetic-retinopathy-and-diabetic-macular-edema/

https://github.com/jasonrig/transfer-learning-demos

```
python3 -m TransferLearningDemo.demos.vgg_19_retrain_fc train

python3 -m TransferLearningDemo.demos.vgg_19_retrain_fc evaluate

python3 -m TransferLearningDemo.demos.vgg_19_retrain_fc predict <image_name>
```

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Repurposing VGG-19

Retinal haemorrhage detection – Training methodology

STARE images were partitioned into:

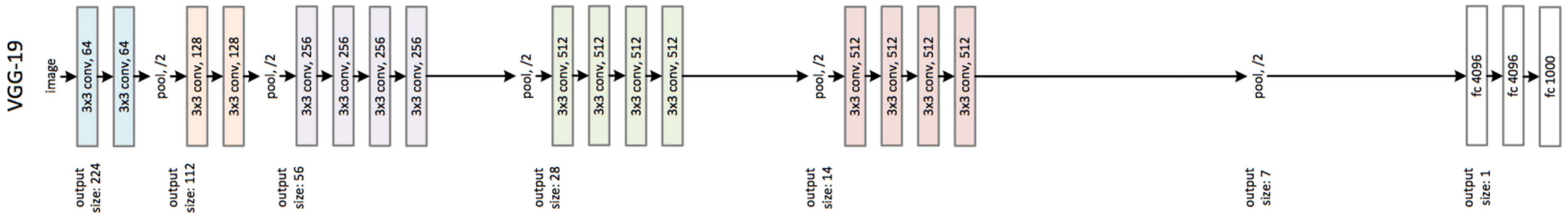
- Haemorrhagic [0, 1]
- Non-haemorrhagic [1, 0]

All *conv* layers were frozen; their parameters remained unchanged during training

All *fc* layers were allowed to train

The final *fc* layer with 1000 outputs was replaced with a new one with 2 outputs, reflecting the new labels and initialised to random weights

75 images were selected randomly for testing and not included during training



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Repurposing VGG-19

Retinal haemorrhage detection – Training methodology

Data augmentation:

Necessary because there are only 325 training examples

Each time an image was presented to the model for training, it was:

- Randomly flipped left-right
- Randomly flipped top-bottom
- Randomly cropped (cropped patches varied from 224x224 – no cropping – to 200x200)
- Resized to 224x224

Data augmentation allows us to anticipate and produce variations that might be seen outside of our training set without obtaining new data

Reinterpreting VGG-19

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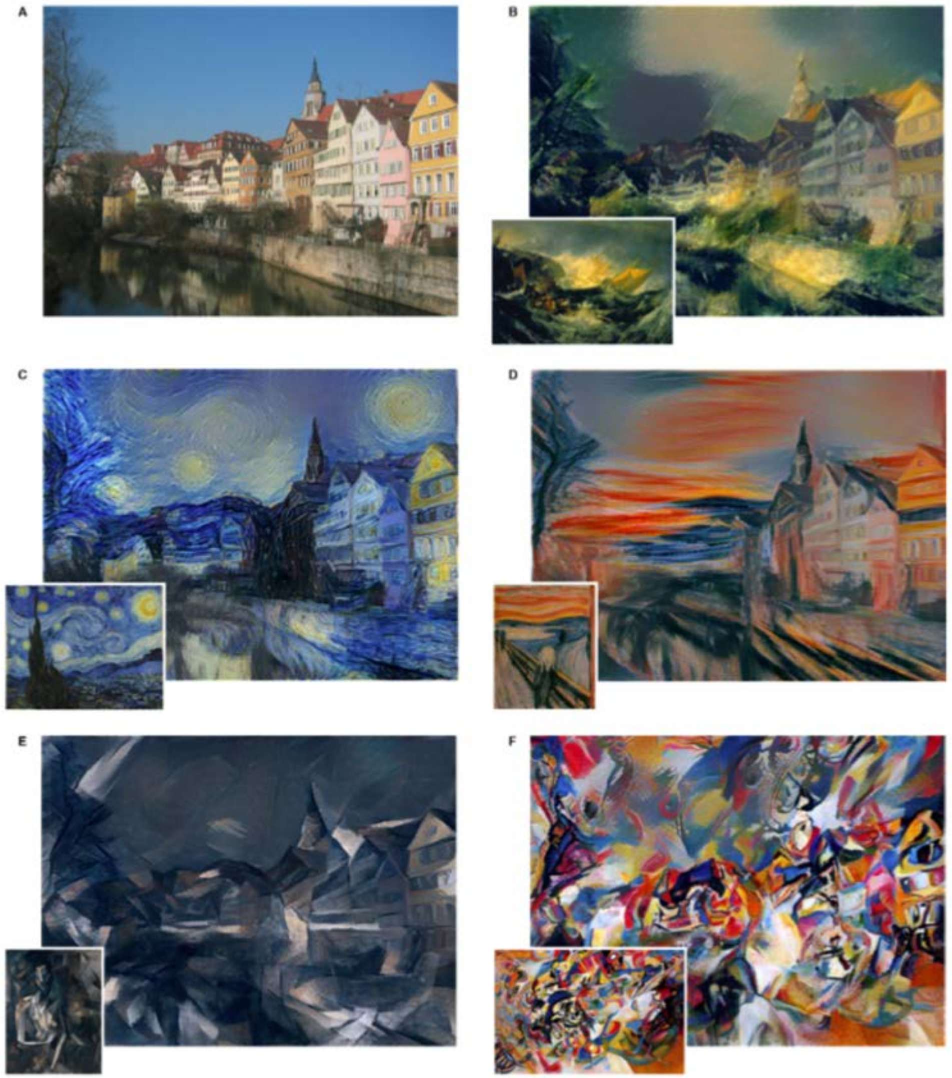
Reinterpreting VGG-19

Neural style transfer

The activations generated by pretrained CNN models can be used to generate new images in the style of other images

This requires us to optimise for:

- Image content; and,
- Image style



https://arxiv.org/pdf/1508.06576.pdf

Reinterpreting VGG-19

Neural style transfer – defining style

Style is defined using the Gram matrix (similar to the covariance matrix) between the activation maps of each filter in each layer:

$$G_A = A \cdot A^T$$

Where A is a 2D matrix containing an unrolled vector of each activation for each filter in the given network layer

Intuitively, *it captures the distribution of activations, which reflect now likely certain structures of the image occur together*

To optimise for style, we essentially minimise the squared difference between G of the generated image and the style image for selected network layers:

$$J_S = \gamma \sum_{i=1}^{n_c} \sum_{j=1}^{n_c} \left(G_{ij}^{\text{style}} - G_{ij}^{\text{generated}} \right)^2$$

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Reinterpreting VGG-19

Neural style transfer – defining content

Content is defined as the difference between network activations of the content image and the generated image.

$$J_c = \gamma \sum \left(A^{\text{content}} - A^{\text{generated}}\right)^2$$

The total loss is therefore:

$$J = \alpha J_S + (1 - \alpha) J_C$$

https://github.com/jasonrig/transfer-learning-demos

```
python3 -m TransferLearningDemo.demos.vgg_19_style_transfer
```

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The code

Code used to produce all figures available on GitHub

https://github.com/jasonrig/transfer-learning-demos

Pip installable! GPU not required (except for VGG-19 retraining)

```
pip install -U git+https://github.com/jasonrig/transfer-learning-demos
```

Pretrained model data from:

https://github.com/tensorflow/models/tree/master/research/slim