

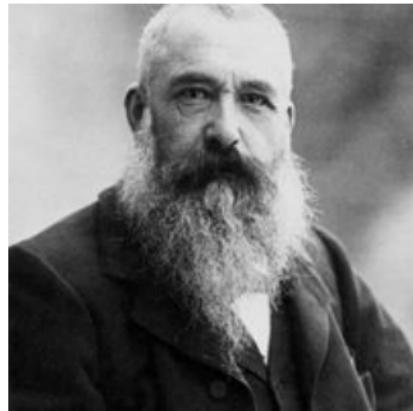
# The Power of Transfer Learning in Artist Identification

Xingyu Zhou

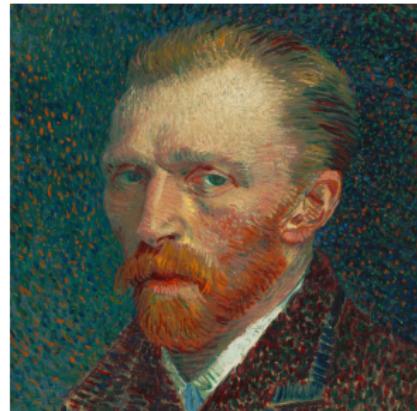
The Ohio State University

April 30, 2018

# Warm Up



Claude Monet



Vincent Van Gogh

# Try it yourself



# Try it yourself



Claude Monet



Vincent Van Gogh

# Try it yourself



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Claude Monet



Vincent Van Gogh

Can we solve it with machine learning?

Can we solve it with machine learning?

Let's try it

Data set

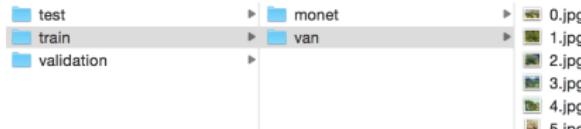
# WIKIART

VISUAL ART ENCYCLOPEDIA

## Data set



- ▶ We collect **300** images for *each* artist.
- ▶ We split into 240 for training, 30 for validation and 30 for testing.
- ▶ Folder structure:



# Platform



# Platform



- ▶ We use Keras with tensorflow backend to support neural networks.
- ▶ We use *Google Colaboratory* as our computing engine.
  - ▶ Free Tesla K80 GPU!
  - ▶ It is similar to Jupyter notebook:

A screenshot of the Google Colaboratory interface. At the top, there's a dark header bar with the 'CO' logo, the file name 'project\_VGG\_van.ipynb', and a star icon. Below the header is a menu bar with File, Edit, View, Insert, Runtime, Tools, and Help. Underneath the menu is a toolbar with CODE, TEXT, and CELL buttons. The main area shows a code cell with a play button and the text '11s'. Below the cell is a 'databricks' button. The code cell contains the following Python code:

```
[ ] from google.colab import files  
files.upload()
```

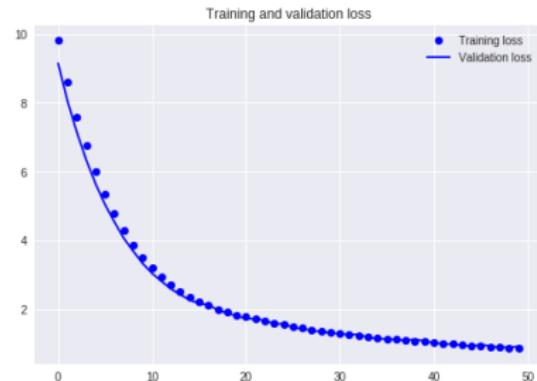
# Baseline CNN

model.summary()

| Layer (type)                   | Output Shape         | Param # |
|--------------------------------|----------------------|---------|
| conv2d_1 (Conv2D)              | (None, 222, 222, 32) | 896     |
| max_pooling2d_1 (MaxPooling2D) | (None, 111, 111, 32) | 0       |
| conv2d_2 (Conv2D)              | (None, 109, 109, 64) | 18496   |
| max_pooling2d_2 (MaxPooling2D) | (None, 54, 54, 64)   | 0       |
| conv2d_3 (Conv2D)              | (None, 52, 52, 128)  | 73856   |
| max_pooling2d_3 (MaxPooling2D) | (None, 26, 26, 128)  | 0       |
| conv2d_4 (Conv2D)              | (None, 24, 24, 128)  | 147584  |
| max_pooling2d_4 (MaxPooling2D) | (None, 12, 12, 128)  | 0       |
| flatten_1 (Flatten)            | (None, 18432)        | 0       |
| dropout_1 (Dropout)            | (None, 18432)        | 0       |
| dense_1 (Dense)                | (None, 512)          | 9437696 |
| dense_2 (Dense)                | (None, 1)            | 513     |

Total params: 9,679,041  
Trainable params: 9,679,041  
Non-trainable params: 0

# Baseline CNN



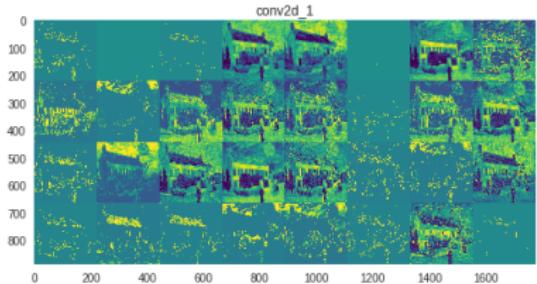
# Baseline CNN



Test Accuracy: 83.3% 😐

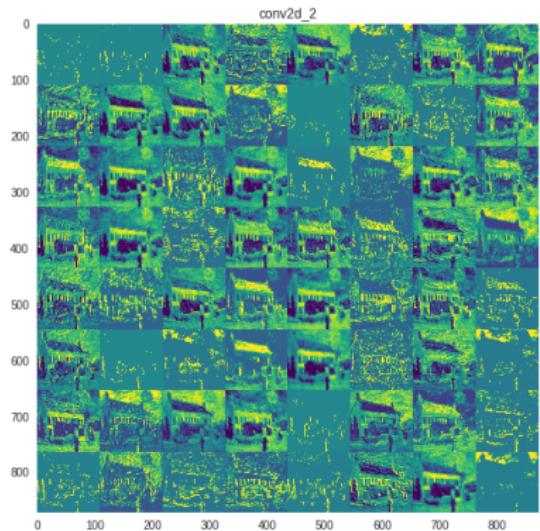
Found 60 images belonging to 2 classes.  
test acc: 0.8333333233992258

# Activations Visualization

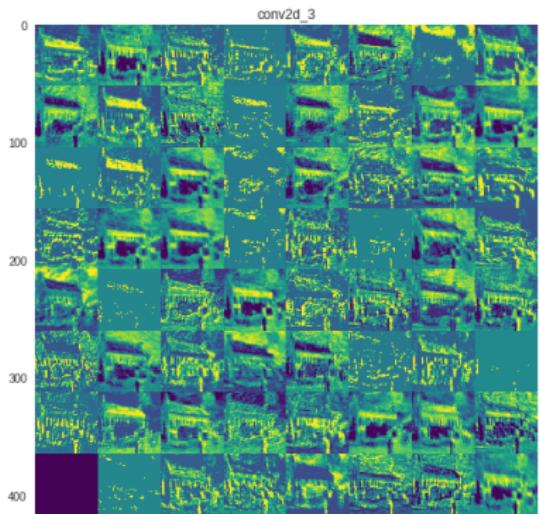


First layer: it keeps almost all of the information in the initial image.

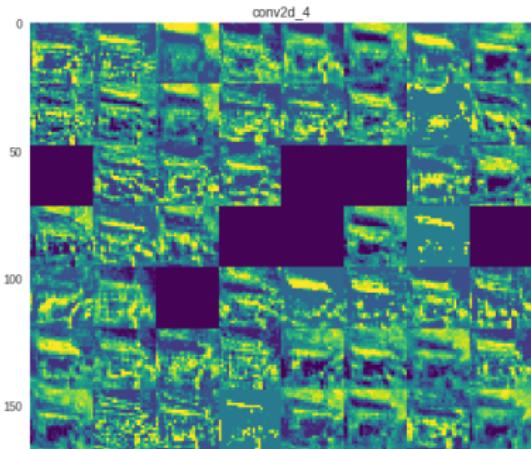
# Activations Visualization



# Activations Visualization



# Activations Visualization



Higher layers:

- ▶ activations become *abstract*, less information about the visual contents.
- ▶ the sparsity of the activations increases.

Well, the result is okay, but definitely not **perfect**, is it?

Well, the result is okay, but definitely not perfect, is it?

I agree, let's improve it!

# Transfer Learning

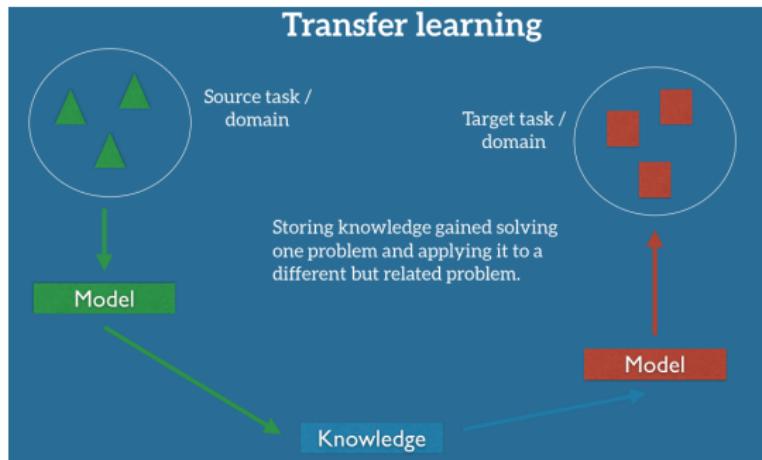


Figure: Transfer learning setup<sup>1</sup>

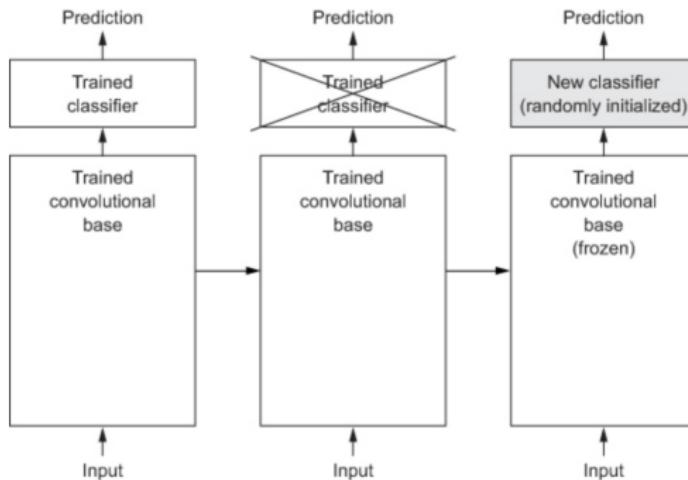
## Source:

- ▶ Task: ImageNet
- ▶ Model: VGG16

## Target:

- ▶ Task: Artist identification
- ▶ Model: Softmax classifier

# Transfer learning



In our case:

- ▶ Trained convolutional base: VGG16
- ▶ New classifier: Softmax.

# Transfer learning with VGG16

- ▶ Load pre-trained VGG16 model as base.

```
[ ] from keras.applications import VGG16  
  
conv_base = VGG16(weights='imagenet',  
                   include_top=False,  
                   input_shape=(224, 224, 3))
```

- ▶ Extract features

```
[ ] train_features = np.reshape(train_features, (480, 7 * 7 * 512))  
validation_features = np.reshape(validation_features, (60, 7 * 7 * 512))  
test_features = np.reshape(test_features, (60, 7 * 7 * 512))  
  
[ ] np.shape(train_features)  
[] (480, 25088)
```

- ▶ Add densely connected classifier

```
❶ from keras import models  
from keras import layers  
from keras import optimizers  
from keras import regularizers  
  
model = models.Sequential()  
model.add(layers.Dense(256, kernel_regularizer=regularizers.l2(5e-5),  
                      activation='relu', input_dim=7 * 7 * 512))  
model.add(layers.Dropout(0.5))  
model.add(layers.Dense(1, activation='sigmoid'))
```

## Before we start...

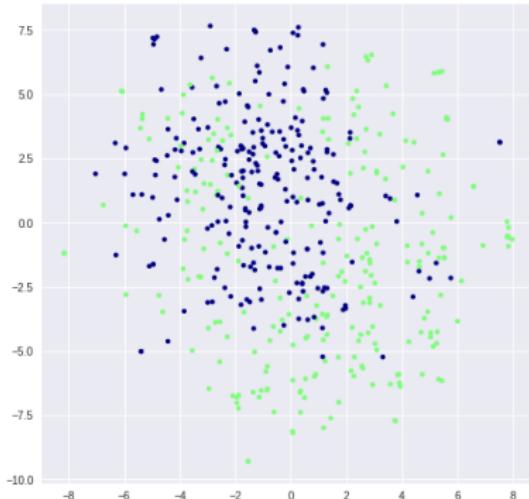


Figure: Bottleneck features visualization, created by *tsne*

# Now, let's train it...



# Now, let's train it...



Test Accuracy: 94.6% 😊

Nice result, but, shall we be satisfied with it?

Nice result, but, shall we be satisfied with it?

No, let's further improve it!

# Fine tuning

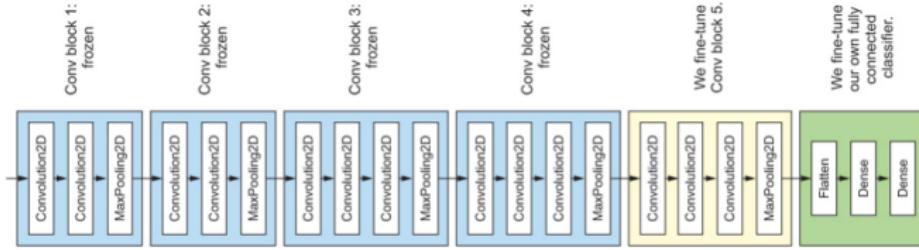


Figure: Frozen certain layers and fine tuning certain blocks only.

# Show me the result...



# Show me the result...



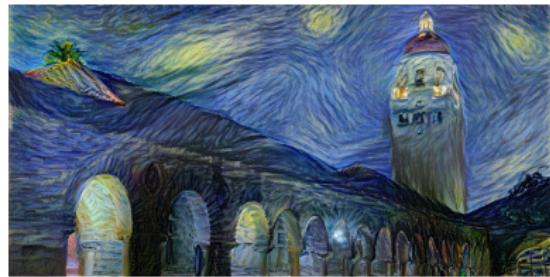
Test Accuracy: 98.3% (make mistake on just **one** image) 😊

```
test_generator = test_datagen.flow_from_directory(  
    test_dir,  
    target_size=(224, 224),  
    batch_size=10,  
    class_mode='binary')  
test_loss, test_acc = model.evaluate_generator(test_generator, steps = 6)  
test_acc  
  
Found 60 images belonging to 2 classes.  
0.9833333293596903
```

The missing one...



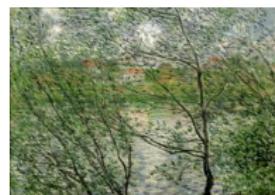
# Does it really learn?



## Some technicals

- ▶ Use data processing and augmentation.
- ▶ Batch size is 10.
- ▶ Training for 80 epochs.
- ▶ Optimizer is RMSprop with learning rate  $2e^{-5}$ .
- ▶ Activation is ReLu.
- ▶ L2 regularization of  $1e^{-5}$ .
- ▶ Dropout with probability 0.5.

Really nice, but, wait a minute...can you distinguish which **column** is  
Monet's works?



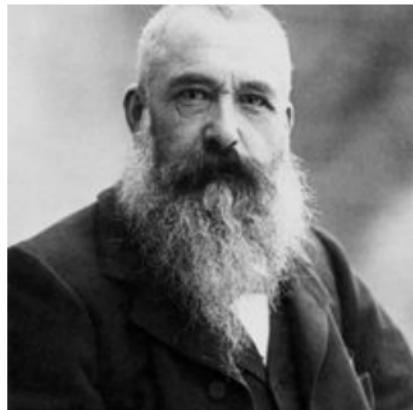
Really nice, but, wait a minute...can you distinguish which **column** is  
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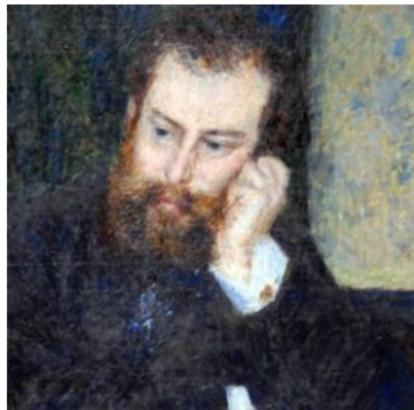
Claude Monet

Alfred Sisley

# A harder problem...

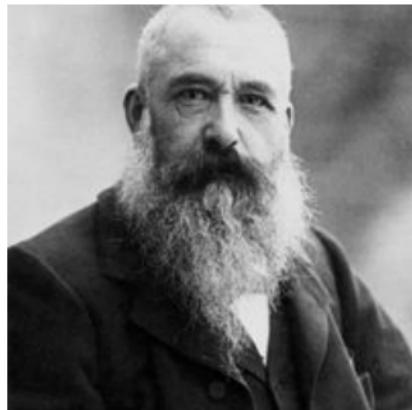


Claude Monet

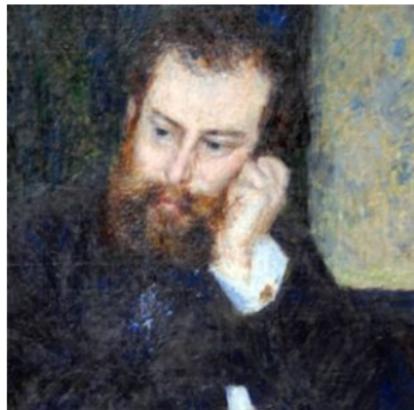


Alfred Sisley

## A harder problem...



Claude Monet



Alfred Sisley

- ▶ Exactly the same period.
- ▶ Nearly the same style.
- ▶ Almost the same scenarios.

Is it possible?

# Show me the result...



# Show me the result...



Test Accuracy: 86.6% 😐

Future direction:

- ▶ Try model ensemble.
- ▶ Try batch normalization.
- ▶ Try dynamical rate adjustment.
- ▶ Try other pre-trained models (tried ResNet, not successful.)

## Take-away

- ▶ Transfer learning is powerful.
- ▶ VGG16 is very easy to train (maybe your first choice).
- ▶ Go try the Google colab (too good to be true).
- ▶ Keras maybe your first choice, easy and effective.

Learn more about the details and code:

[xingyuzhou.org/blog](http://xingyuzhou.org/blog)