Transfer Learning with Convolutional Neural Networks

Off the shelf top notch performances



Eric Feuilleaubois

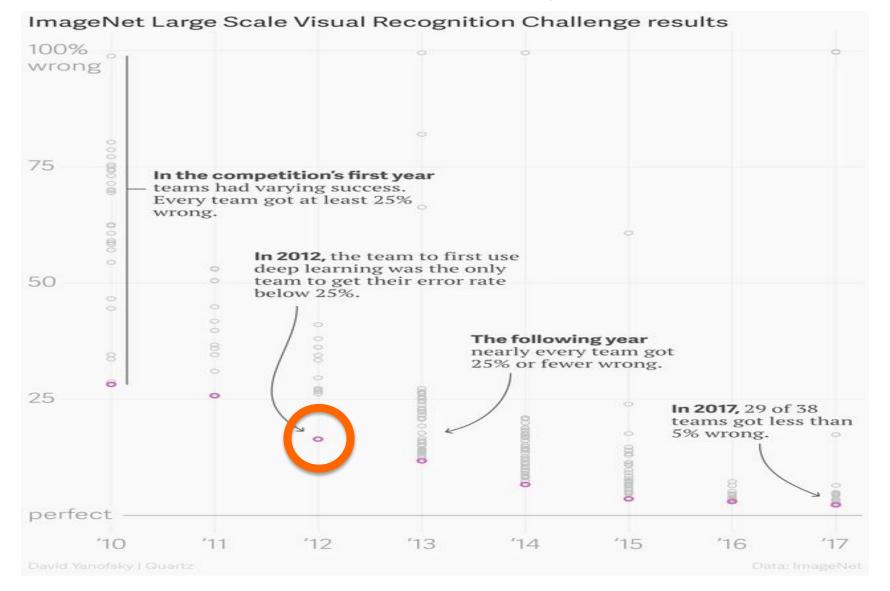
Ph.D in Artificial Neural Networks

Deep Learner / Machine Learner

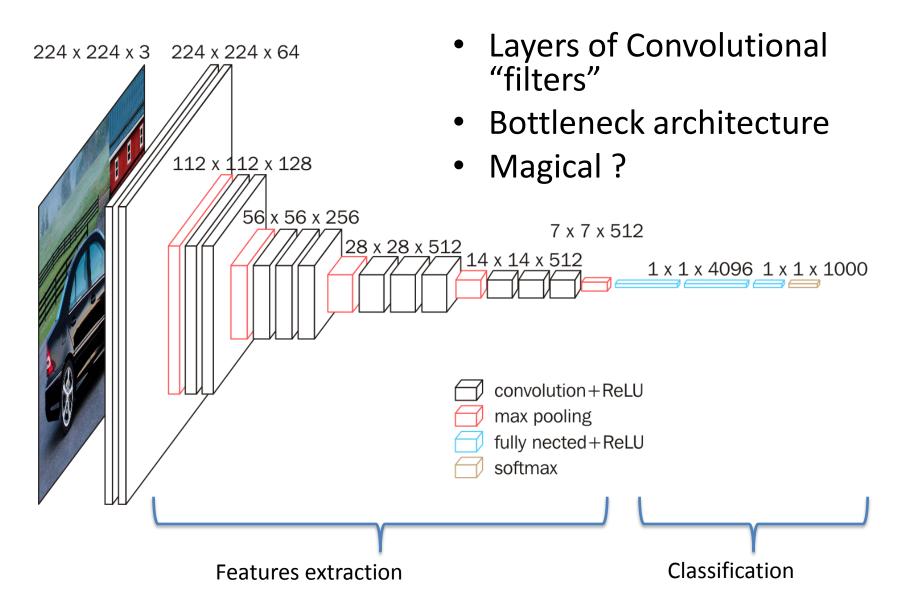
Curator of **Deep_In_Depth** - news feed on Deep Learning, Machine Learning and Data Science

Writer for Medium - Towards data science

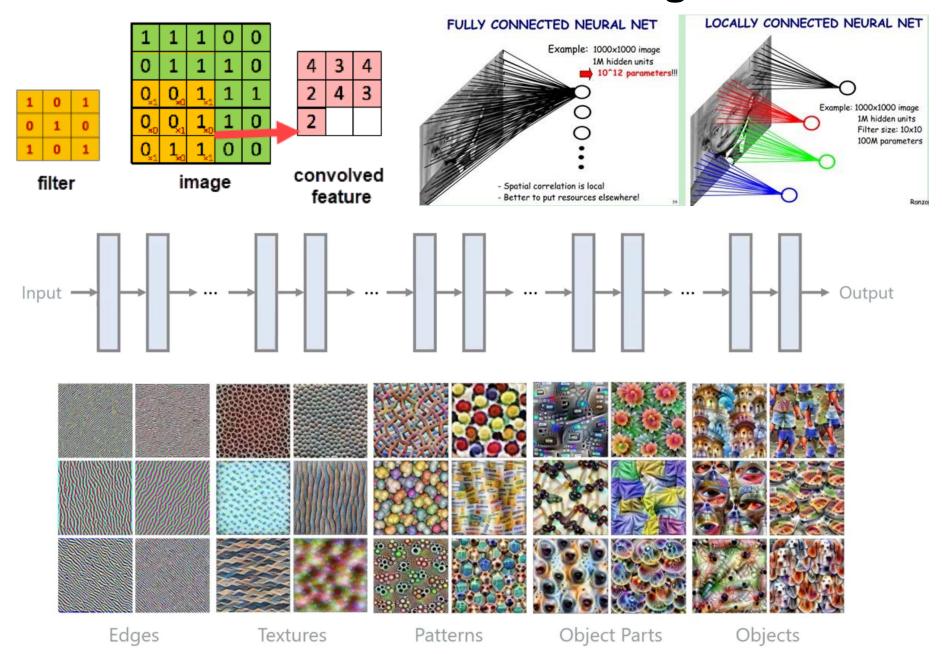
Convolutional Neural Networks A breakthough



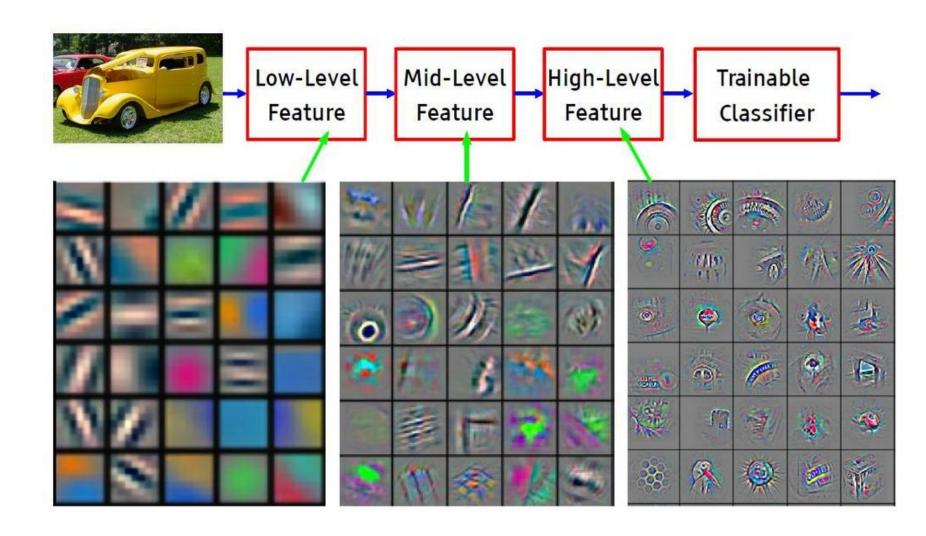
Convolutional Neural Networks VGG-16 example



CNNs – Inner working



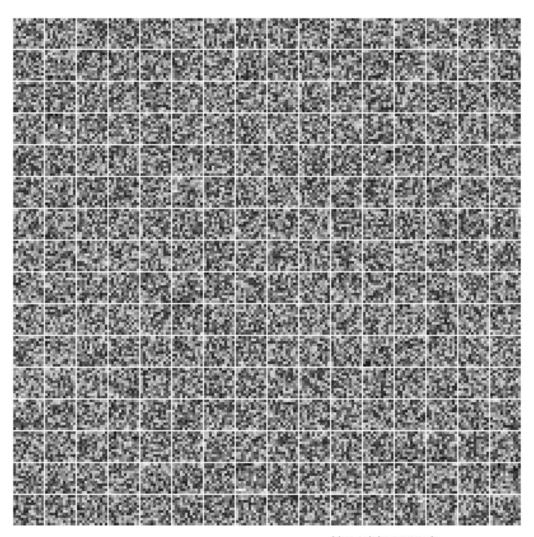
CNNs – Feature Extraction



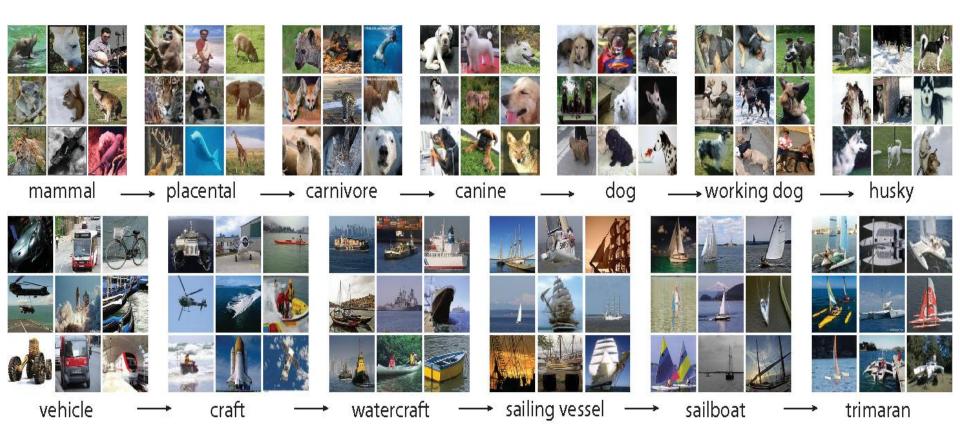
Training CNNs

- Big Dataset of 100 thousands images usually millions
- Labelled data → Takes time to build
- Try out many different Network architecture
- Hyperparameter value :
 - training method, rate
 - Weights initial values
- No feature engineering

Training CNNs – Live view



ImageNet Database



ImageNet Dataset

- 1,000 image categories
- Training 1,2 Million images
- Validation & test 150,000 images

```
n07714571 - head cabbage
n07714990 - broccoli
n07715103 - cauliflower
n07716358 - zucchini, courgette
n07718472 - cucumber, cuke
n07718747 - artichoke, globe artichoke
n07720875 - bell pepper
n07730033 - cardoon
n07734744 - mushroom
n07742313 - Granny Smith
n07745940 - strawberry
n07747607 - orange
n07749582 - lemon
n07753113 - fig
n07753275 - pineapple, ananas
n07753592 - banana
```

n07768694 - pomegranate

Veg Dataset - 4124 records

Pumpkin







Watermelon







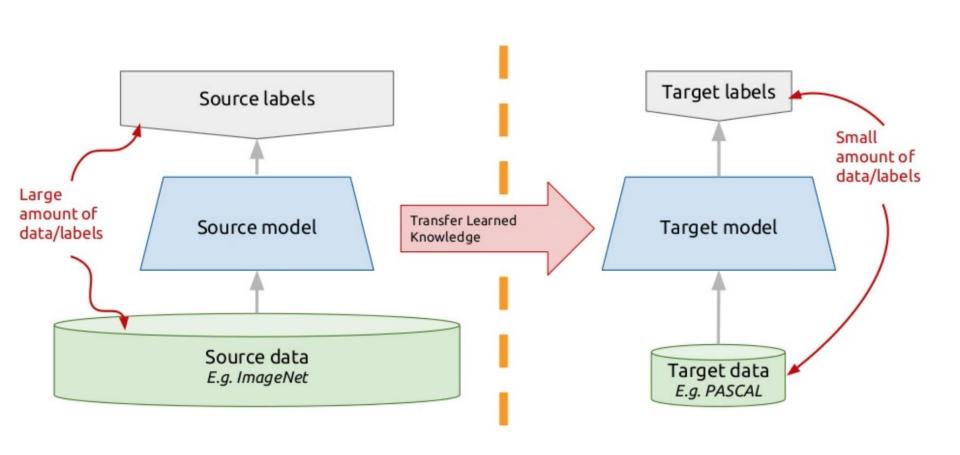








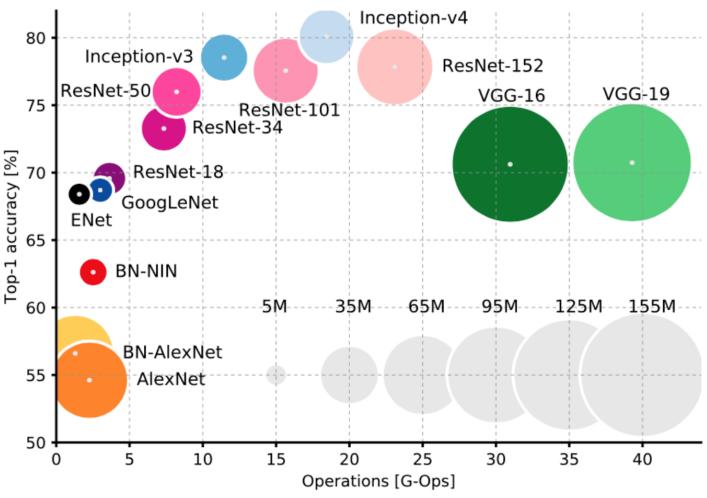
Principle of Transfert Learning



Aim: Predict classes (labels) that have not been seen by the source (pre-trained) model

Motivations for CNN TL

- Availability of Open CNN Models with Top class performance

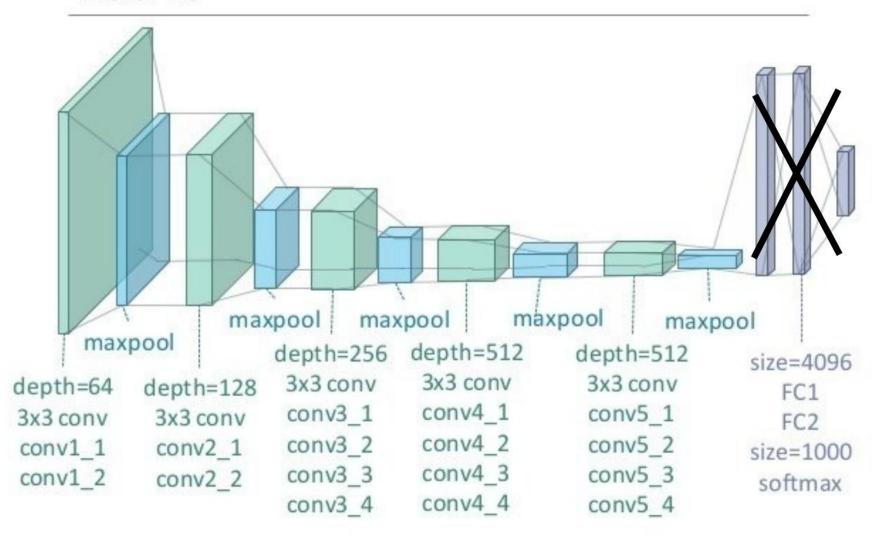


From: AN ANALYSIS OF DEEP NEURAL NETWORK MODELS FOR PRACTICAL APPLICATIONS Alfredo Canziani & Eugenio Culurciello & Adam Paszke

CNN Transfert Learning

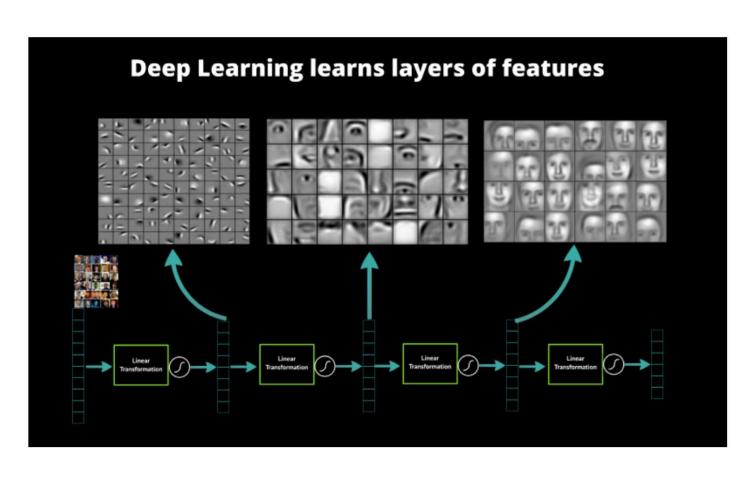
Trained with ImageNet

VGG 19



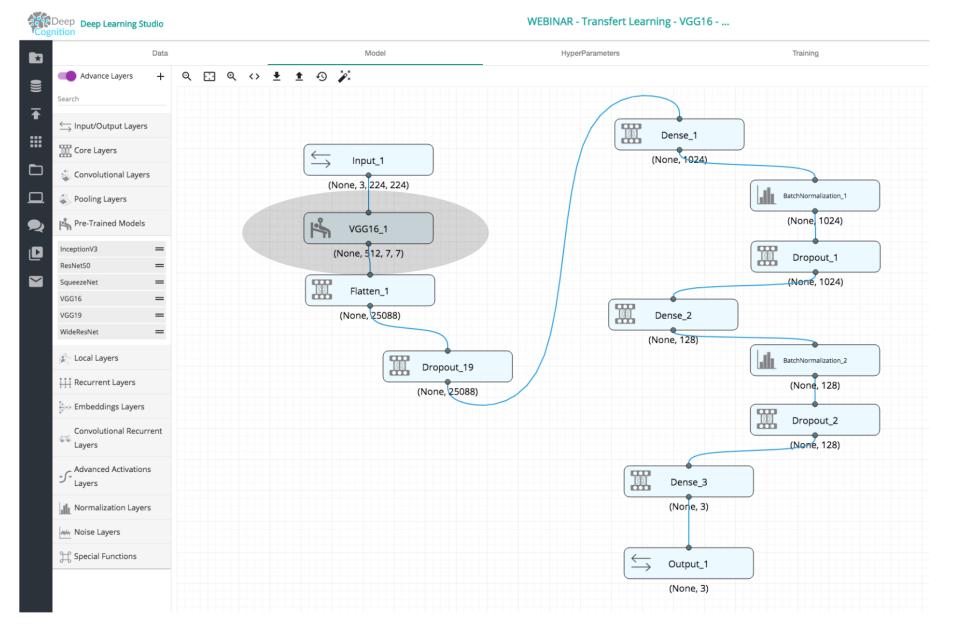
Proof by Features

- CNNs detect
 visual features
 (patterns) in
 images
 - First layerslearn "basic"features
 - Last layers learn"advanced" features
 - Top layersclassify



Basic features are very similar from one CNN model to another --> No need to re-learn them, best to re-use them

DL model with pre-trained VGG16



Training results

Dataset	Train Acc. (%)	Validation Acc. (%)
300 - 7%	95	88
600 - 14%	96	89
900 - 21%	97	90
3917 - 95%	97	91
300 - with Data Aug.	98	88
600- with Data Aug.	98	90
900- with Data Aug.	98	90

Wrong results



WaterMelon

Training Dataset

300 - 600 - 900



Pumpkin

300 - 600 - 900



WaterMelon

300 - 600

Result for "difficult" images



Pumpkin

300 - 600 - 900



Tomato

300 - 600 - 900



WaterMelon

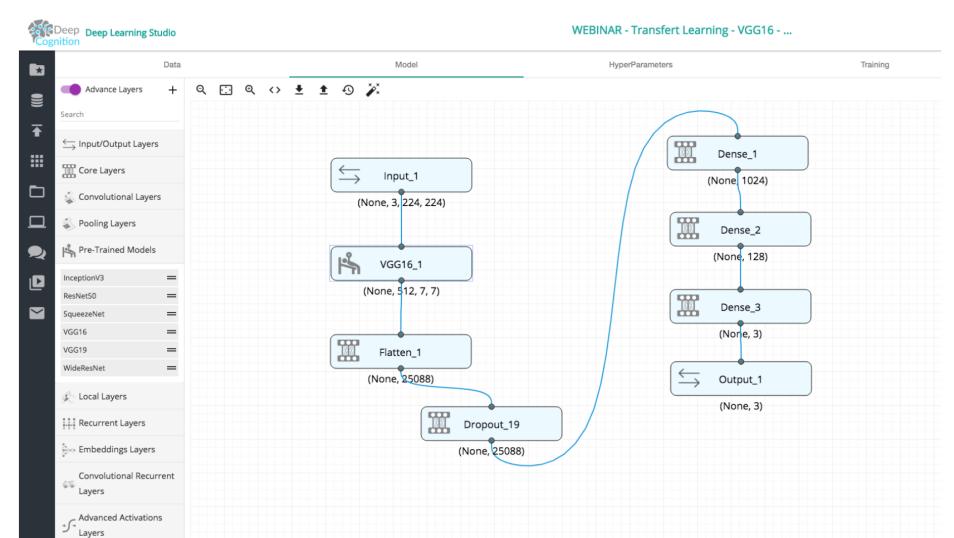
300 - 600 - 900

Fine-tuning TL models

Two approaches:

- 1) Fine tune the **convolutional** part of the CNN
 - Retrained the last convolutional layer (Deep Learning Studio provide easy way to do it)
 - Freezing and training specific layers
- 2) Fine tune the classification part of the CNN
 - Classification architecture optimisation
 - number of neuron in the classification layers
 - Hyper-parameter optimization

Simpler DL model with pre-trained VGG16



Normalization Layers

W Noise Layers

Special Functions

Training results

Dataset	Train Acc. (%)	Validation Acc. (%)
300 - Simpler	99	88
300 - 512 - 64	99	86
300 - MSimpler-no BN	98	84
300 - Simpler VGG 10% trainable	99	89
3917 - 95% - Simpler	98	93.5
95% - MSimpler-no BN	40	35
95% - MSimpler- BN	97	92

Benefits of CNN Transfert Learning

- Dataset does not need to be huge
- Save time and effort
 - no CNN architecture search
 - training phase faster
 - less computing power needed
- Produce very good models that can then be fine tune
- Can be applied to very diverse classification problem
- Less likely to overtrain

And drawbacks:

- need a fair amount of memory on GPU
- not fully tunable with Keras

Alternatives

- CNN architecture & hyperparameter "automatic" tuning
 - AutoML (Architecture) driven by "AI"
 - IBM Watson Suite (Hyperpameters)
 - Microsoft Custom Vision Services

- Drawbacks
 - Limited exploration of the space of possibilities
 - Black box inside a "black API"