MOBILE DEEP BUT SMALL

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WiFi : SG-Guest

Problems with Installation? ASK!



PLAN OF ACTION

TODAY

- Mobile : General & Specific
- Personal Project work



PLAN OF ACTION

27-NOV

- Reinforcement Learning(?)
- Finalize Projects

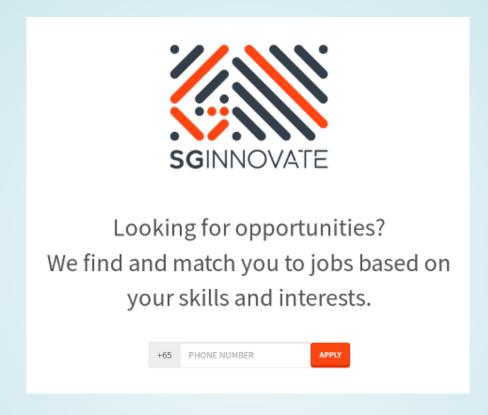


PERSONAL PROJECTS

- Form to fill in
- Plan to finish: 27-Nov (last session)
- WSG DEADLINE: 30-Nov, including write-ups:
 - "Punchy Headline"
 - Minimum : README.md on GitHub page
 - Hosted slides / demo
 - Lightning Talk



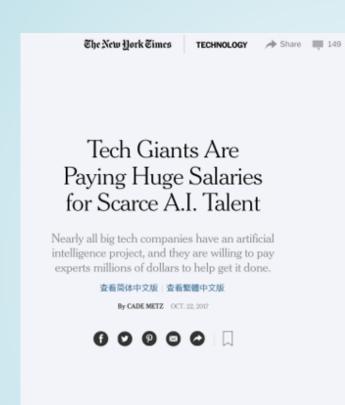
SGINNOVATE



http://bit.ly/2ialg60 nicolette@sginnovate.com



NEW YORK TIMES





Article Link



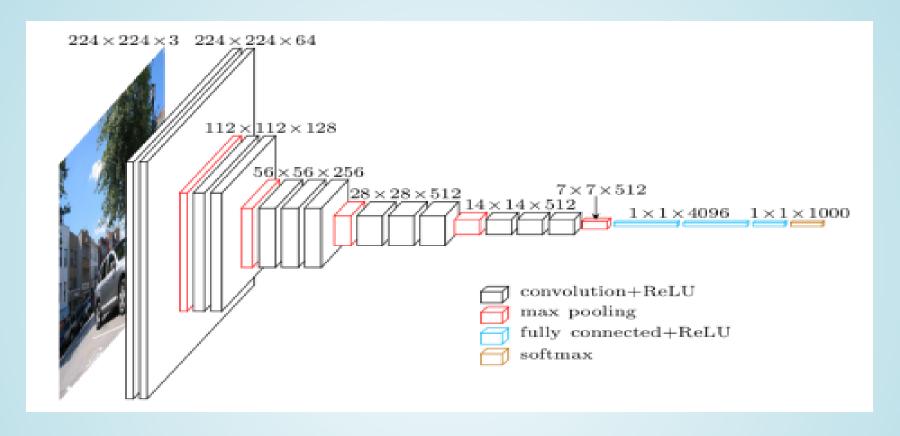
IMAGE COMPETITION

- ImageNet aka ILSVRC
- over 15 million labeled high-resolution images...
 - ... in over 22,000 categories





NETWORKS HAVE EVOLVED



VGG 16 (2014)



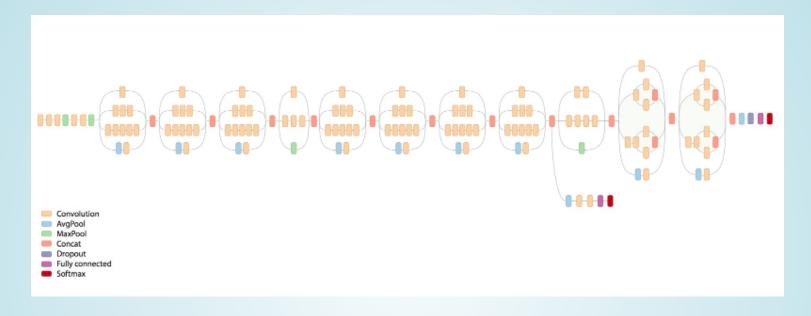
GETTING DEEPER ...

```
Convolution Pooling Softmax Other
```

GoogLeNet (2014)



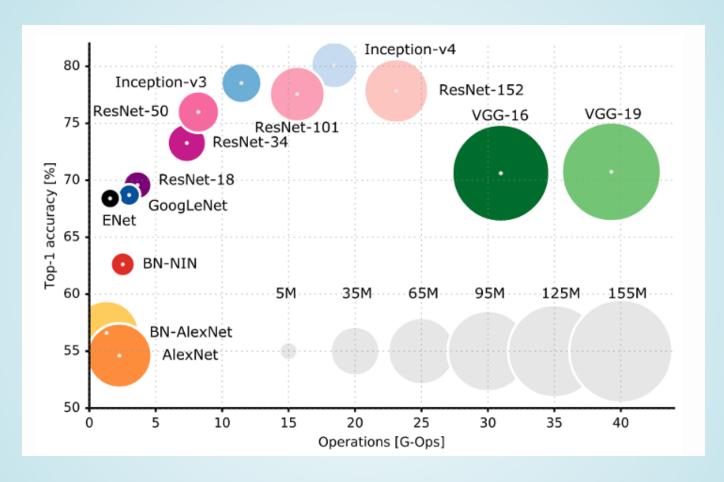
... EVEN MORE COMPLEX



Google Inception-v3 (2015)



MODEL SIZE / PERFORMANCE



github.com/mdda/deep-learning-workshop/ notebooks/2-CNN/4-ImageNet/0-modelzoo-tfkeras.ipynb

BUT WHAT ABOUT MOBILE?

- Better performance ⇒ larger network
- But mobile needs us to :
 - Compress
 - Downgrade
 - Restructure



ENERGY USAGE

Table 1: Energy table for 45nm CMOS process [20]. DRAM access uses three orders of magnitude more energy than simple arithmetic and 128x more than SRAM.

Operation	Energy [pJ]	Relative Cost
32 bit int ADD	0.1	1
32 bit float ADD	0.9	9
32 bit Register File	1	10
32 bit int MULT	3.1	31
32 bit float MULT	3.7	37
32 bit 32KB SRAM	5	50
32 bit DRAM	640	6400

EIE: Efficient Inference Engine on Compressed Deep Neural Network (ISCA'16)



COMPRESS / DOWNGRADE

- Sparsity
- High precisions are not required
- Quantisation
- Compressibility



SPARSITY

- Weights near zero → Zero
- Clamp these weights during training



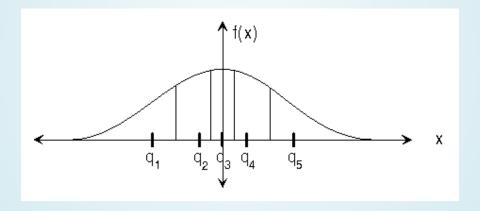
LOW-PRECISION TRAINING

- Quantise weights in forward pass
- Use 'full resolution' derivative to do backprop
- 6-bits per parameter seems to work



QUANTISATION

- Bucket weights into a few levels
- Store bucket positions and bucket indexes
- eg: 4 buckets (2 bits per weight index)

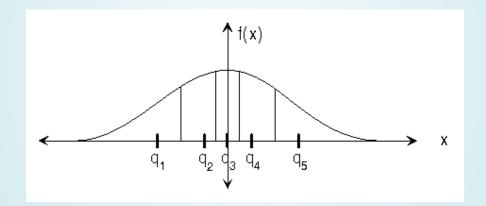


Quantisation in TensorFlow



COMPRESSIBILITY

- Bucket weights into a few levels
- Store bucket positions and bucket indexes
- But make bucket positions ZIPable





RESTRUCTURE 5X5

- Normal CNN '5x5' layer operation :
 - Has (5x5+1) parameters (per input channel)
- Convert to 2 stacked 3x3 layers :
 - Has 2x(3x3+1) parameters (per input channel)
- Parameter count : $26x50=1300 \rightarrow 20x50=1000$



RESTRUCTURE 3X3

- Normal '3x3' CNN layer operation :
 - For each output channel:
 - Run separate '3x3' kernels over all input channels
 - Allows anywhere-to-anywhere interactions
- Parameter count: (3x3+1)x50 = 500



SEPARABLE CONVOLUTIONS

- Separable CNN layer operation :
 - For each output channel:
 - Run one '3x3' kernel over all input channels
 - Do a weight sum (a '1x1' convolution) over results
 - Separate texture vs layer operations
- Parameter count: (3x3+1)x1 + 1x1x(50+1) = 61



+VARIATIONS

- Need to be careful that factorisation doesn't destroy performance
- Lots of scope for experimentation :
 - Xception
 - Depthwise Separable Convolutions for Neural Machine Translation



PRACTICALITIES

- Understand tradeoffs
- Use pre-defined models
- Hardware should start to arrive soon

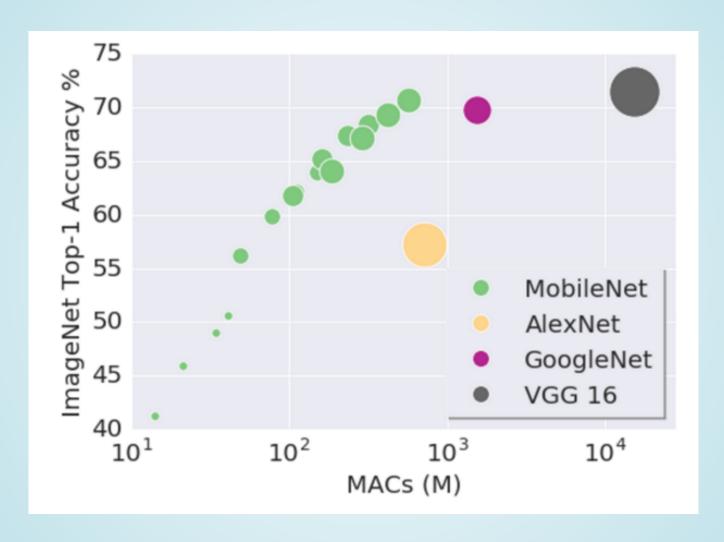


SQUEEZENET

- SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size
- 1x1 and 3x3 layers
- No fully-connected layer



MOBILENETS ~ TF



github.com/tensorflow/research/slim/ RED DRAGON AI nets/mobilenet_v1.md

MOBILENETS ~ KERAS

github.com/keras/applications/ mobilenet.py

```
from keras.applications.mobilenet import MobileNet
from keras.applications.mobilenet preprocess_input, decode_predictions
img = keras_preprocessing_image.load_img(img_path)
#...
x = preprocess_input(img)
model = MobileNet(weights='imagenet')
preds = model.predict(x)

predictions = decode_predictions(preds, top=1)
```

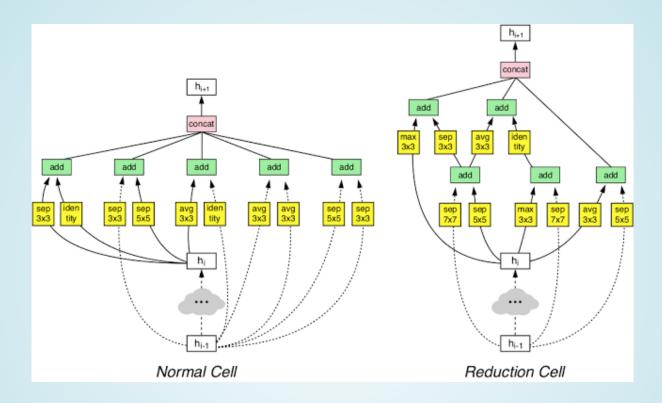


AUTOML

- Recent idea: Search for architecture
 - Optimise for desired performance trade-off
 - Makes use of many GPUs/TPUs
 - Google Blog post
- NB: Not so flexible for 'mash-ups'



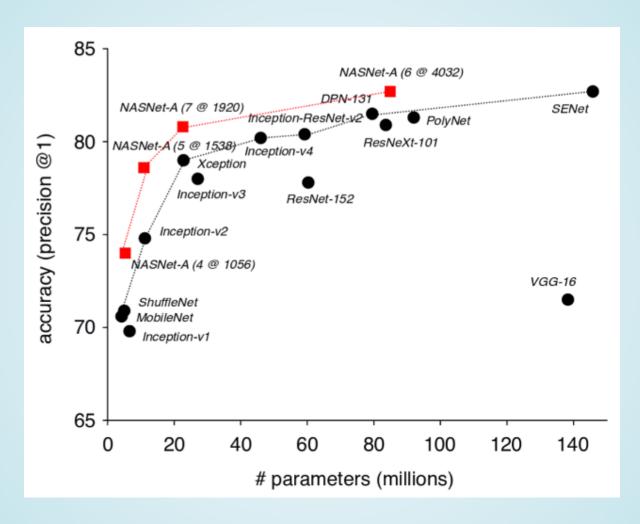
NASNET DESIGN



Learning Transferable Architectures for Scalable Image Recognition (Nov-2017)



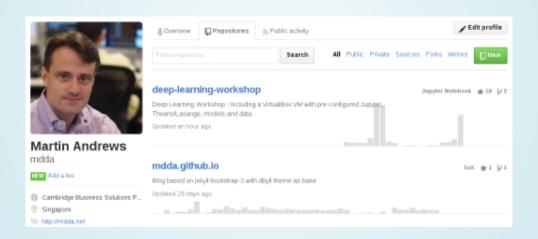
NASNET ~ TF



github.com/tensorflow/research/ slim/nets/nasnet

WRAP-UP

- Explore structure vs accuracy tradeoffs
- Even tiny models work 'well enough'
- Lots more behind all this



* Please add a star... *



- QUESTIONS -

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