Model Optimization 101

Sayak Paul (@RisingSayak)

$whoami

- I call `model.fit()` @ [PyImageSearch]
- Netflix Nerd 👀
- My coordinates are here - https://sayak.dev/

Acknowledgement

- ML-GDEs
- Khanh LeViet from Google

Ideal audience

- ML Developers having worked on image models (in Keras).
- Engineers looking for ways to optimize models for deployment purposes.

What are we up to today?

- What is model optimization?
- Why should we care about it?
- Different areas for a model to optimize
- Mapping areas to optimization techniques
  - Quantization
  - Pruning
- Considerations
- Further directions and QA

About the conventions used

- tf - tensorflow
- tfmot & MOT - tensorflow_model_optimization_toolkit
- TF Lite - TensorFlow Lite

What is model optimization?

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- Reducing the power usage to run a model

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    - Latency during serving is not suitable for critical applications.

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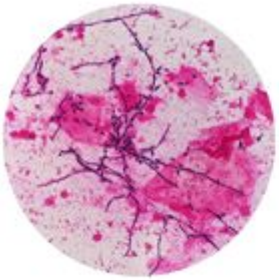
- Consider deploying your models to Raspberry Pis, Mobile Phones, Microcontrollers...
- Moreover, heavier models tend to have ***latency***.
- Heavier models can affect the infrastructure costs significantly.
- What if cloud-based model hosting is not an option (cost, network connectivity, privacy concerns, etc.)?

Different areas for a model to optimize



Different areas for a model to optimize

- Reduced numerical precision?
  - A model's parameters and the activations are generally represented in `float32`.

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- Are all the operations of a model's graph needed during inference?
- Do all the parameters of a model contribute to its performance?
- Back and forth between GPU and non-GPU kernels (explained here wonderfully).

Mapping areas to optimization techniques

- Reduced numerical precision? - **Quantization**
- Are all the operations of a model's graph needed during inference? - **Layer fusion, constant folding**
- Do all the parameters of a model contribute to its performance? - **Pruning**

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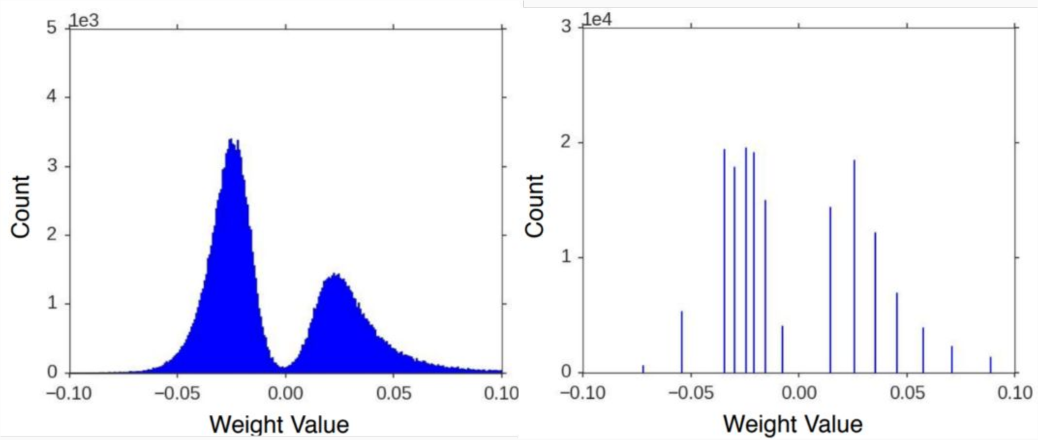
Quantization in deep learning

- Works by reducing the precision of the numbers used to represent a model's parameters and sometimes activations too (`float32` mostly).
- This results in smaller model sizes and faster computations.



[Source]

Quantization mostly come in two flavors

- Post-training quantization
- Quantization-aware training

Post-training quantization

- Happens ***after*** a model is trained.

```python
# Data
x = [-1, 0, 1, 2, 3, 4]
y = [-3, -1, 1, 3, 5, 7]
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model.compile(optimizer='sgd', loss='mean_squared_error')
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converter = tf.lite.TFLiteConverter.from_keras_model(model)

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- **tf.lite.Optimize.DEFAULT**
- tf.lite.Optimize.OPTIMIZE_FOR_SIZE
- tf.lite.Optimize.OPTIMIZE_FOR_LATENCY

```
# Serialize the TF Lite model
f = open("model.tflite", "wb")
f.write(tflite_model)
f.close
```

Post-training quantization

Different forms of post-training quantization available in TF Lite:

Technique	Benefits	Hardware
Dynamic range quantization	4x smaller, 2-3x speedup, accuracy	CPU
Full integer quantization	4x smaller, 3x+ speedup	CPU, Edge TPU, etc.
Float16 quantization	2x smaller, potential GPU acceleration	CPU/GPU

Check out here: [Post-training quantization]

Notebook demo: https://bit.ly/edge-tpu

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- What if we could somehow inform the model about this while training it?
- Enter quantization-aware training!

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Source

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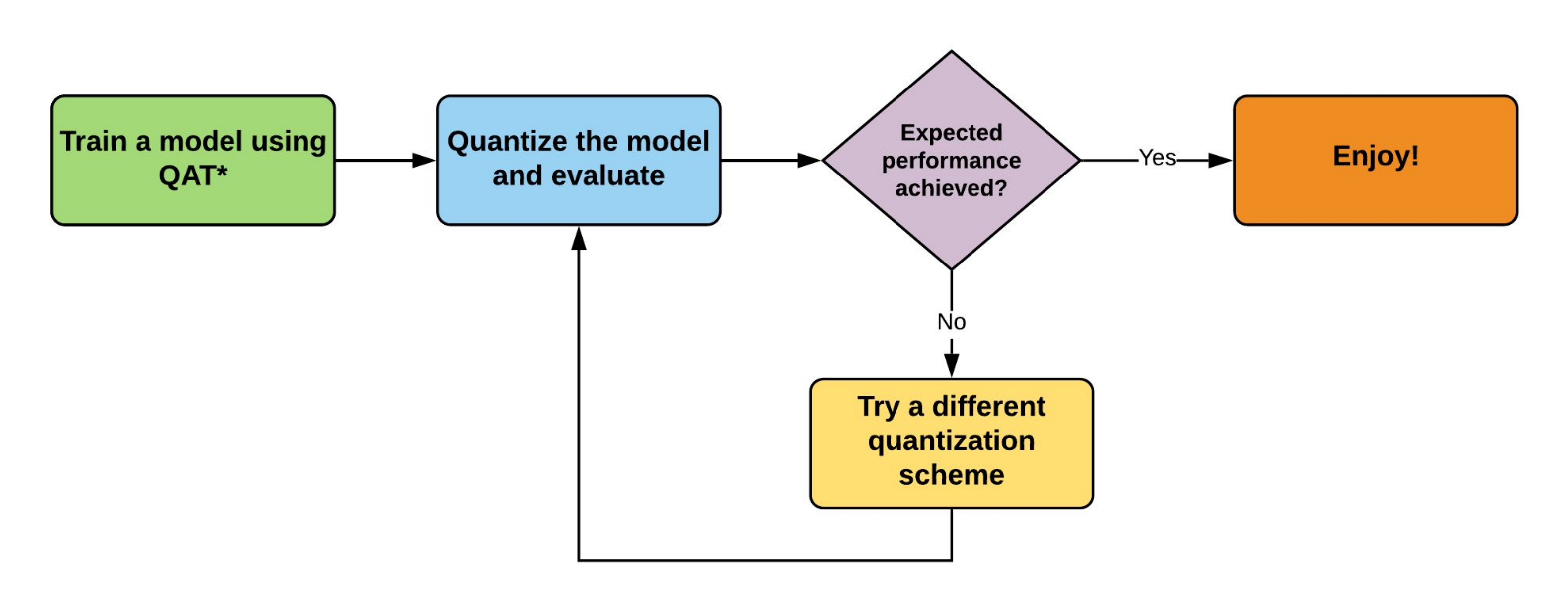
# Continue with training as usual.
quantized_model.compile(...)
quantized_model.fit(...)
```

Source

Notebook demo:
https://bit.ly/tale-quantization

So, the recipe so far



* one can train parts of a model using QAT as well (see here)

Quantization best practices in TF Lite and MOT

- Performance best practices
- Quantization aware training comprehensive guide

Do all the parameters of a model contribute to its performance?

Switching gears to model's parameters

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- Zeroing those parameters out is referred to as *Pruning*.
- Can take place *while* and *after* training.

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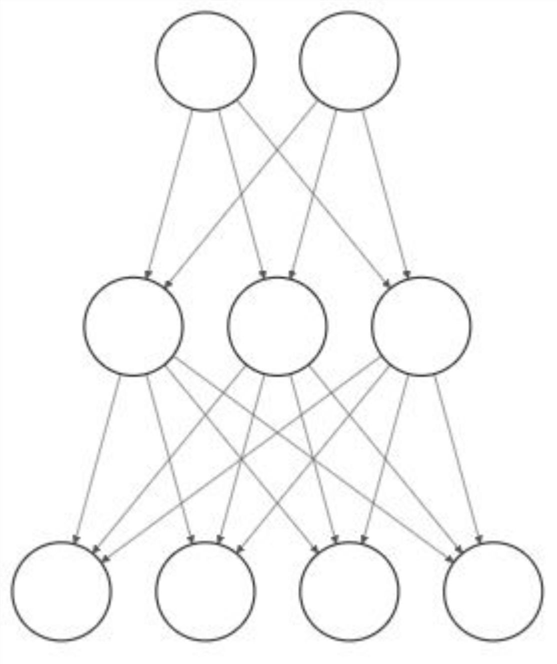

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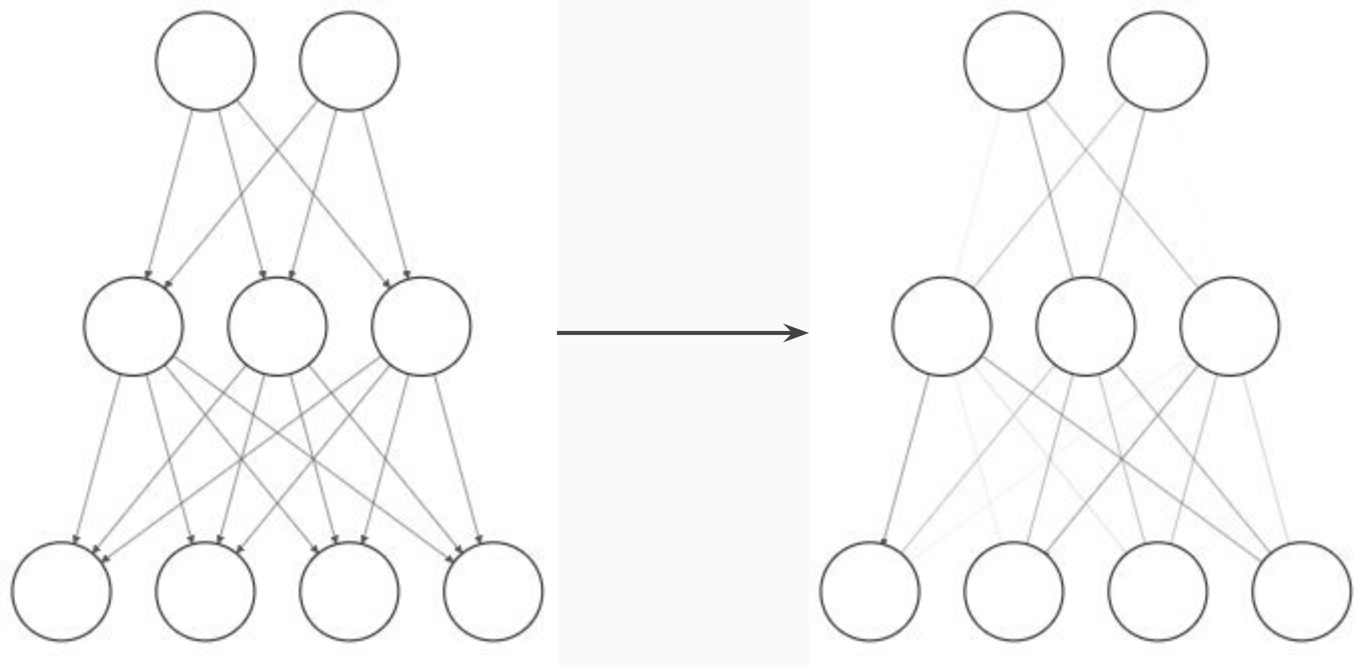

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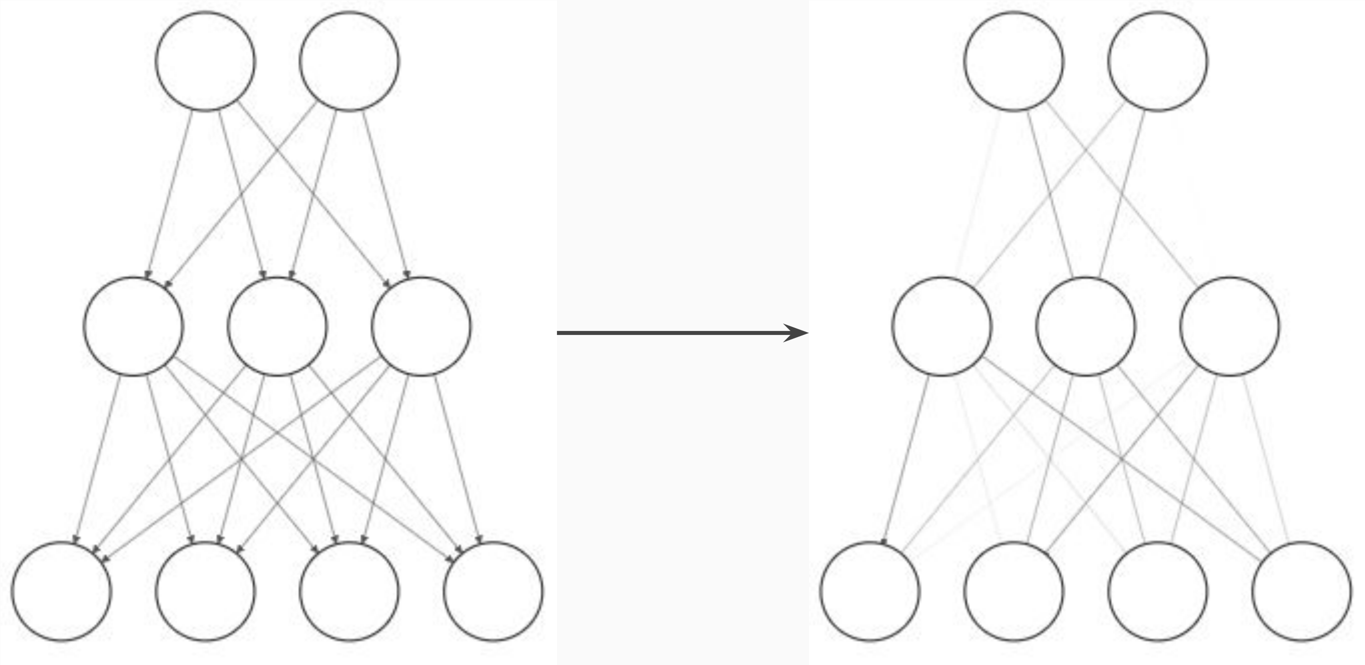
# Prune, compile, and re-train.
model_for_pruning = prune_low_magnitude(model, **pruning_params)
model_for_pruning.compile(...)
model_for_pruning.fit(...)
```

Get on-boarded: Pruning in Keras example

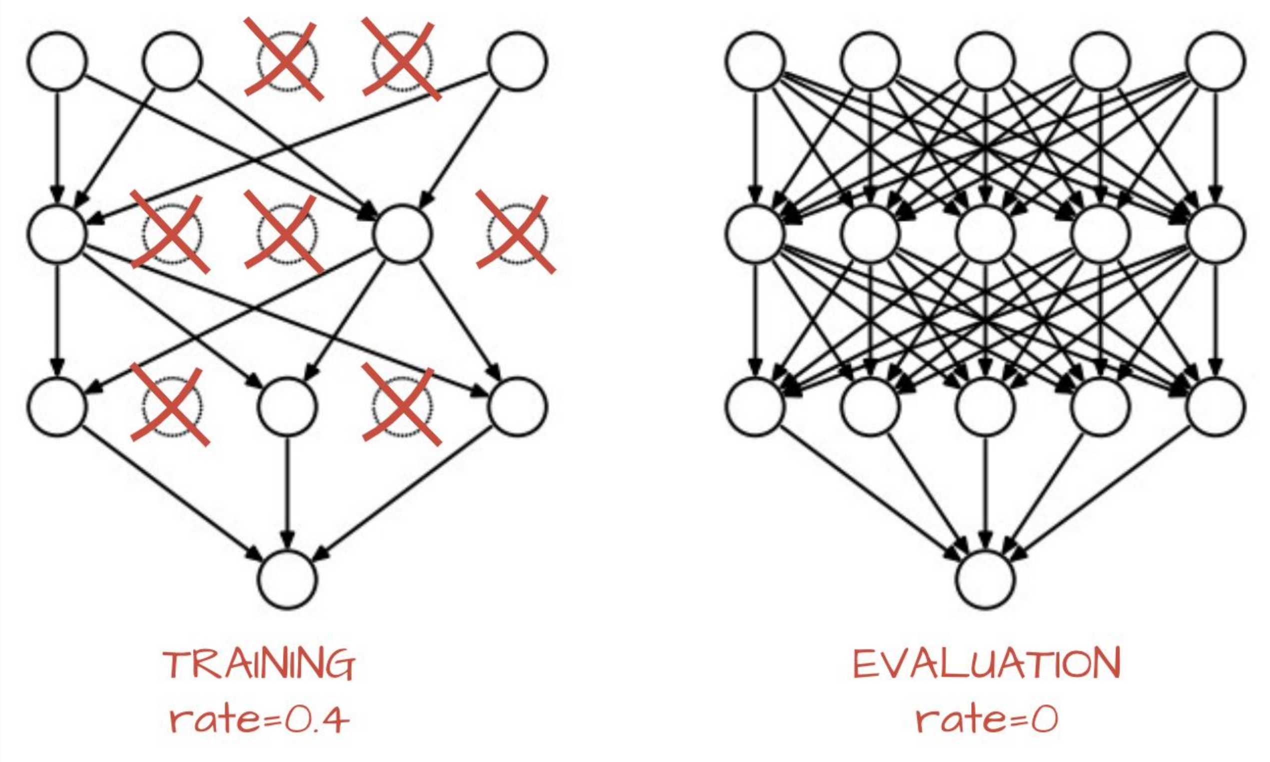
You might be wondering …

This thingy ...




Isn't this Dropout?
imgflip.com

Well...



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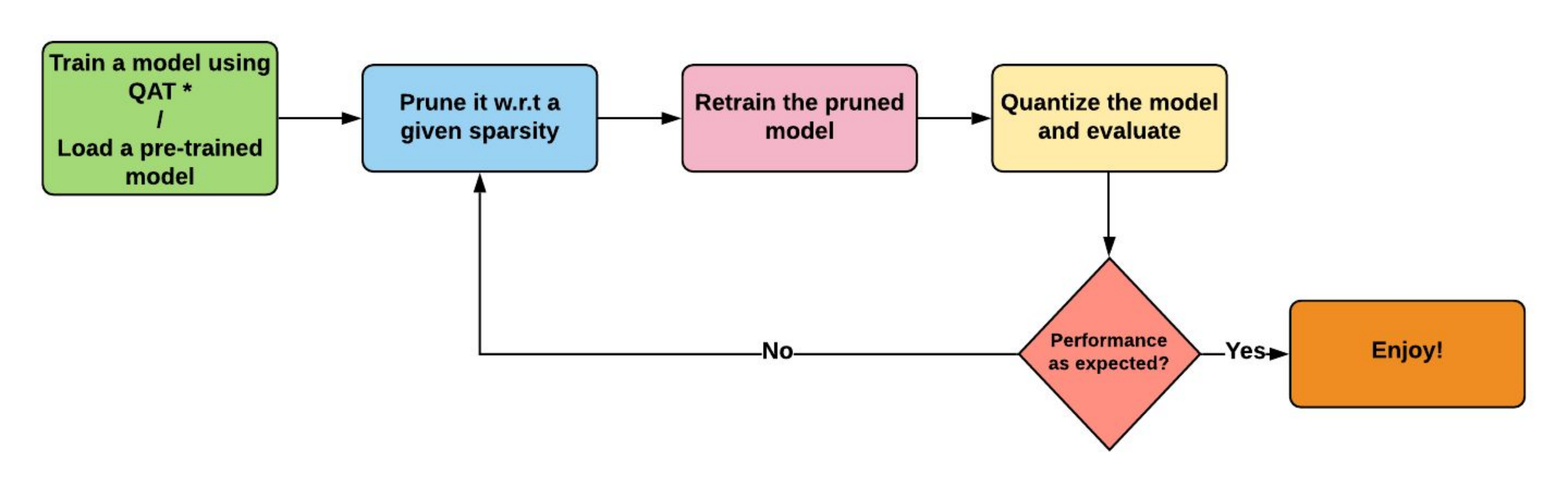
For the interested ones: [The Lottery Ticket Hypothesis with Jonathan Frankle]

Pruning best practices in MOT

- [Pruning comprehensive guide]

Here's another recipe



* one can train models using pruning callbacks (see [here]())
one can prune parts of a model (see [here]())

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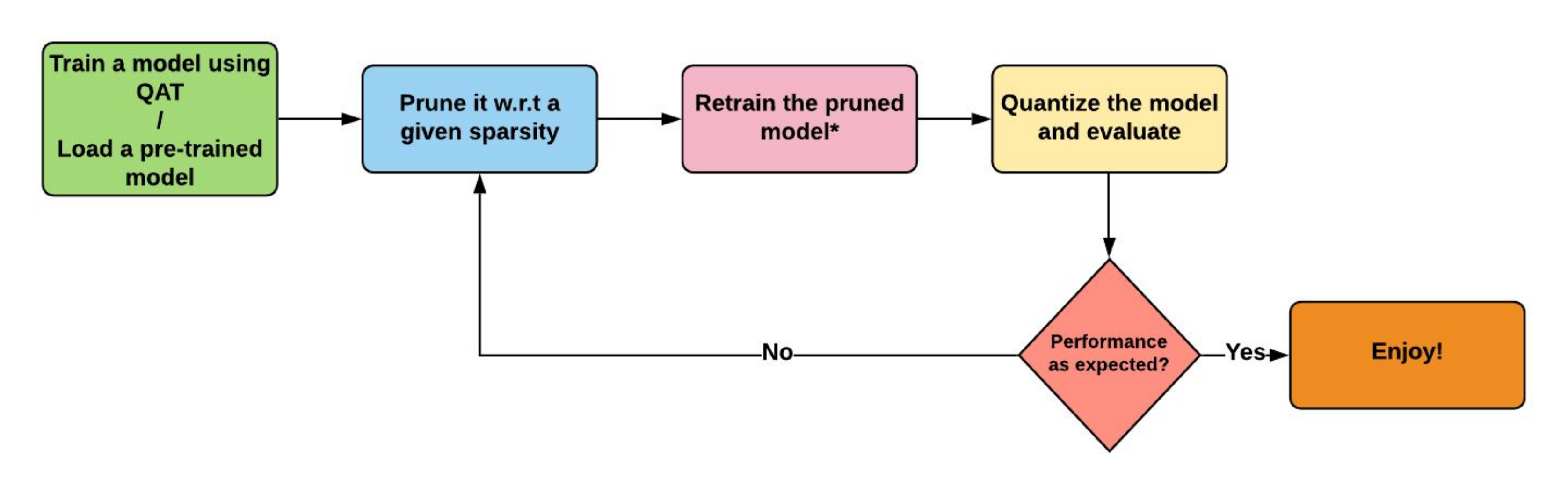

* to recover any lost accuracy

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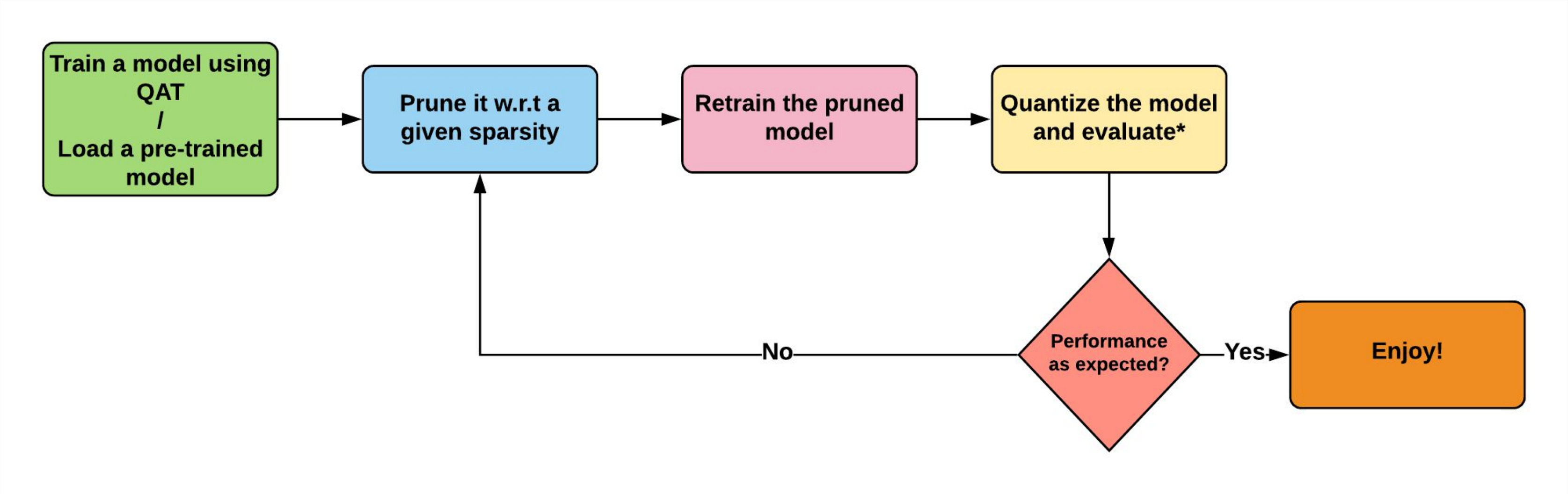

* inference will be faster for pruned models with TF Lite in future
(see here)


MAKE YOUR OWN OPTIMIZATION
RECIPES AND EXPERIMENT!
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Resources

- TensorFlow Lite guide
- TensorFlow Model Optimization
- Device-based Models with TensorFlow Lite
- Introduction to TensorFlow Lite
- Awesome TF Lite
- TinyML

Join tflite@tensorflow.org and participate in the discussions!

Some further things to explore

- Movement Pruning*
- Lottery Ticket Hypothesis
- Weight Rewinding (generalization of Lottery Ticket Hypothesis)
- Knowledge Distillation
- Early Exit
- Deep Compression
- Low Rank Approximation

* particularly useful for models in Transfer Learning regime

Deck available here: https://bit.ly/mo-101

Let's get connected on Twitter! I am [@RisingSayak](https://twitter.com/RisingSayak).