Model Optimizations: Pruning

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- **Deploying models on edge devices** with restrictions on processing, memory and/or power-consumption
- **Reducing payload size** for over-the-air model updates
- Enabling execution on hardware restricted-to or optimized-for fixed-point operations
- Optimizing models for special purpose hardware accelerators.

The MLOps **Personas**

ML Engineer

ML Researcher

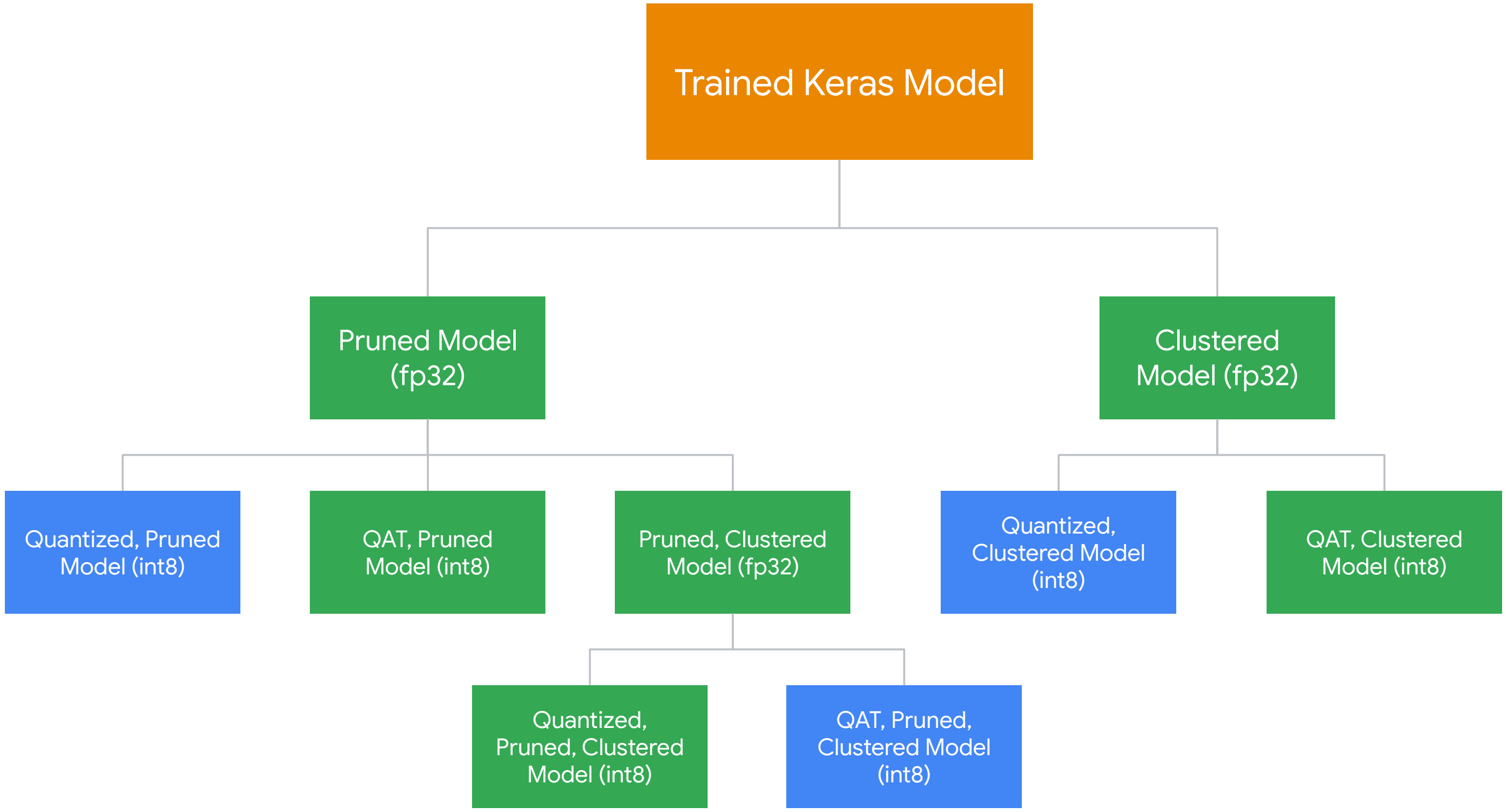
Data Scientist

Data Engineer

Software Engineer

DevOps

Business Analyst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Pruned Model (fp32)
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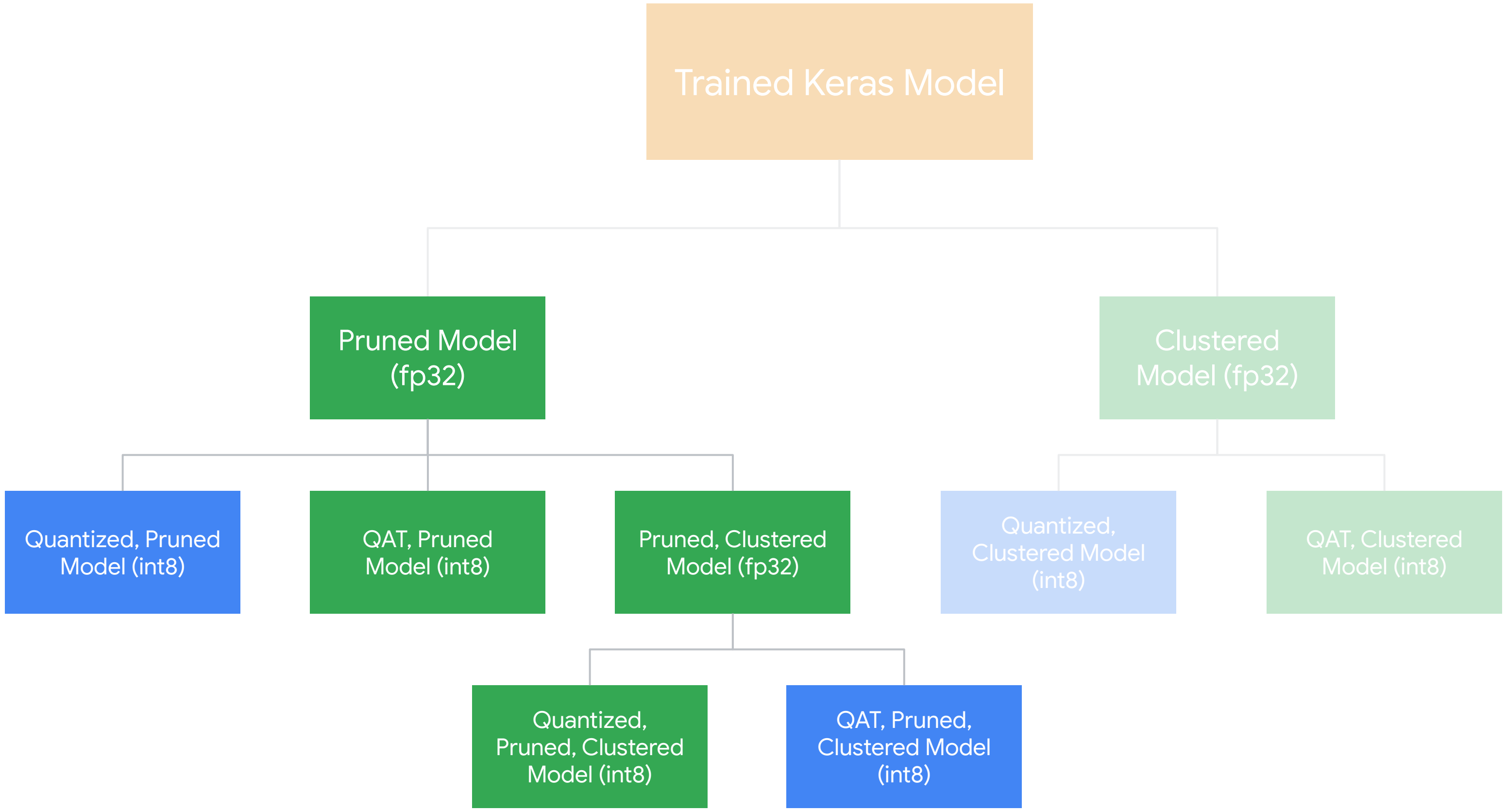
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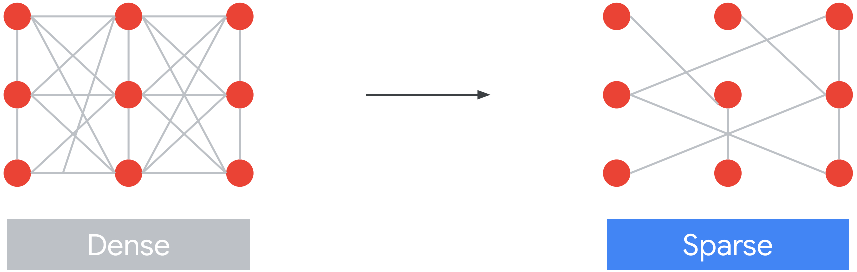
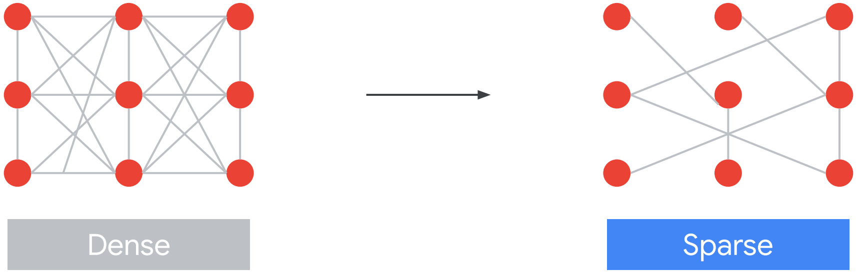

Dense
Sparse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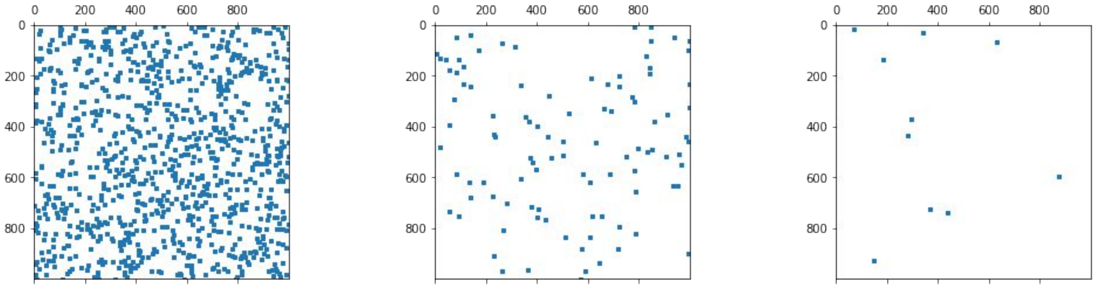
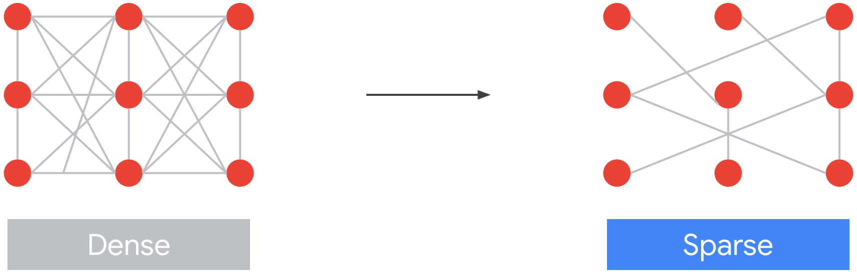
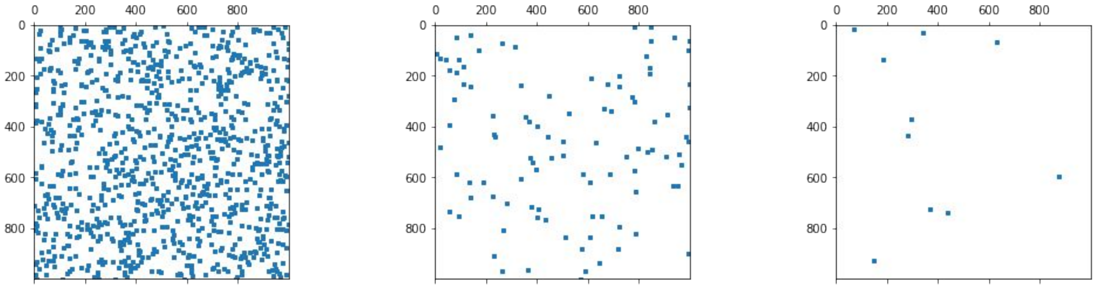
Sparse


0
200
400
600
800

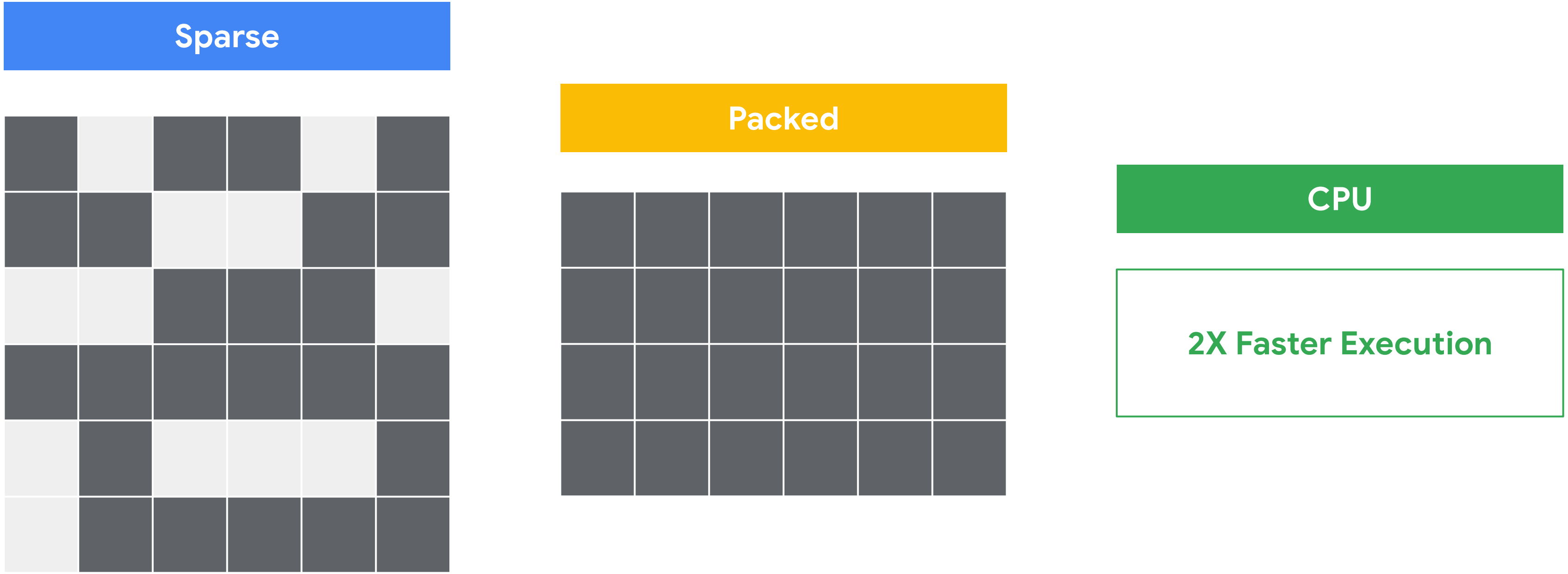




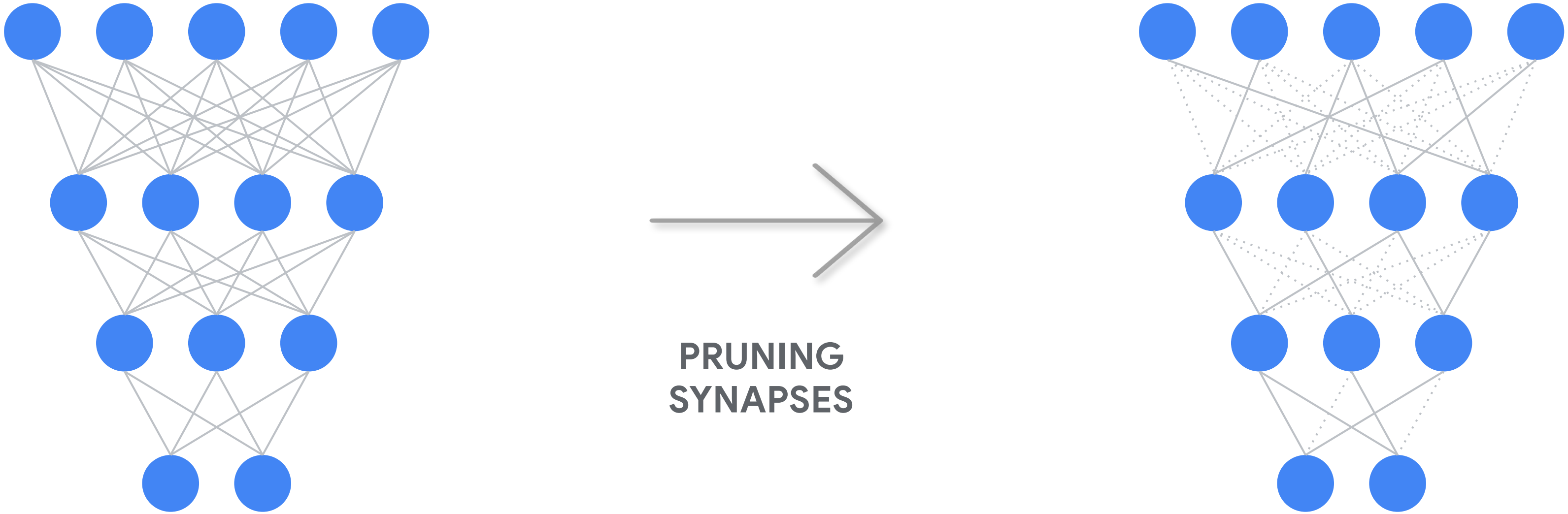
3	4	8
7	6	3
5	5	1

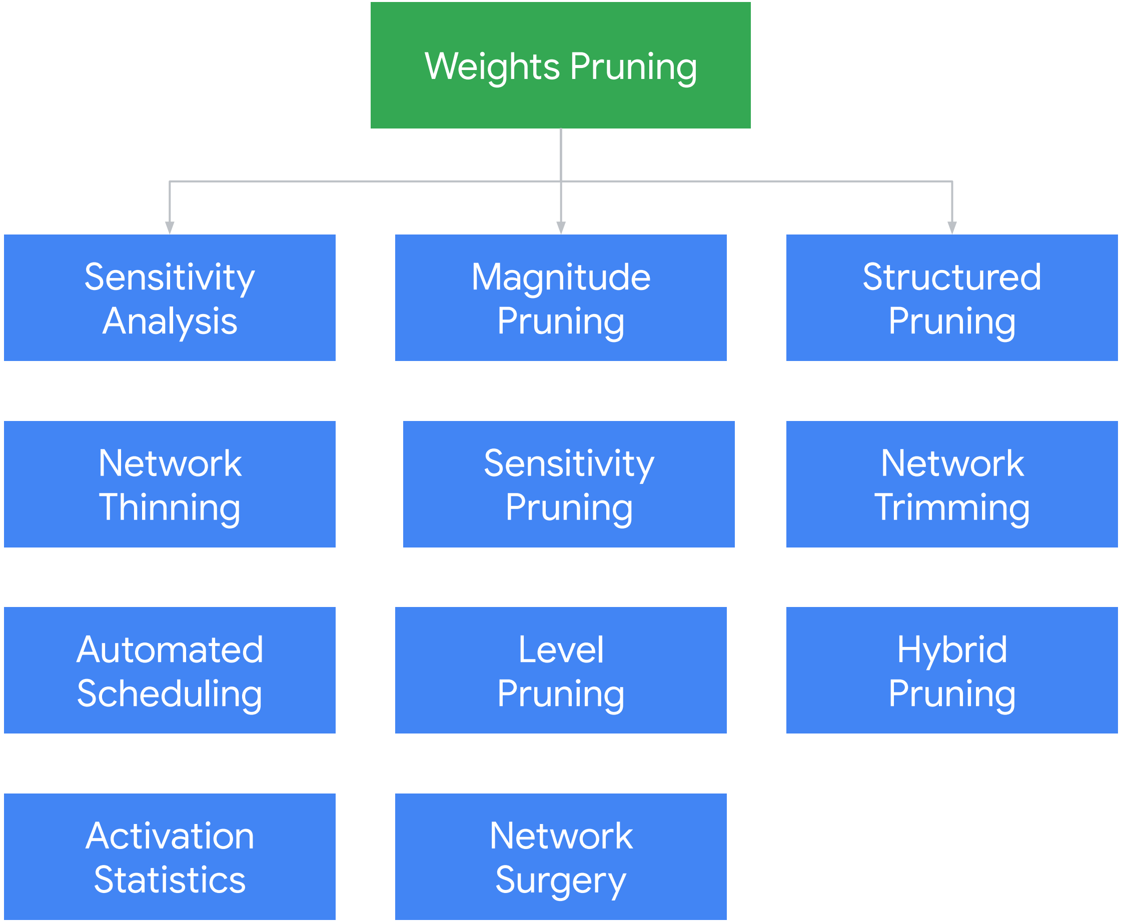
0	4	8
7	6	3
0	5	0

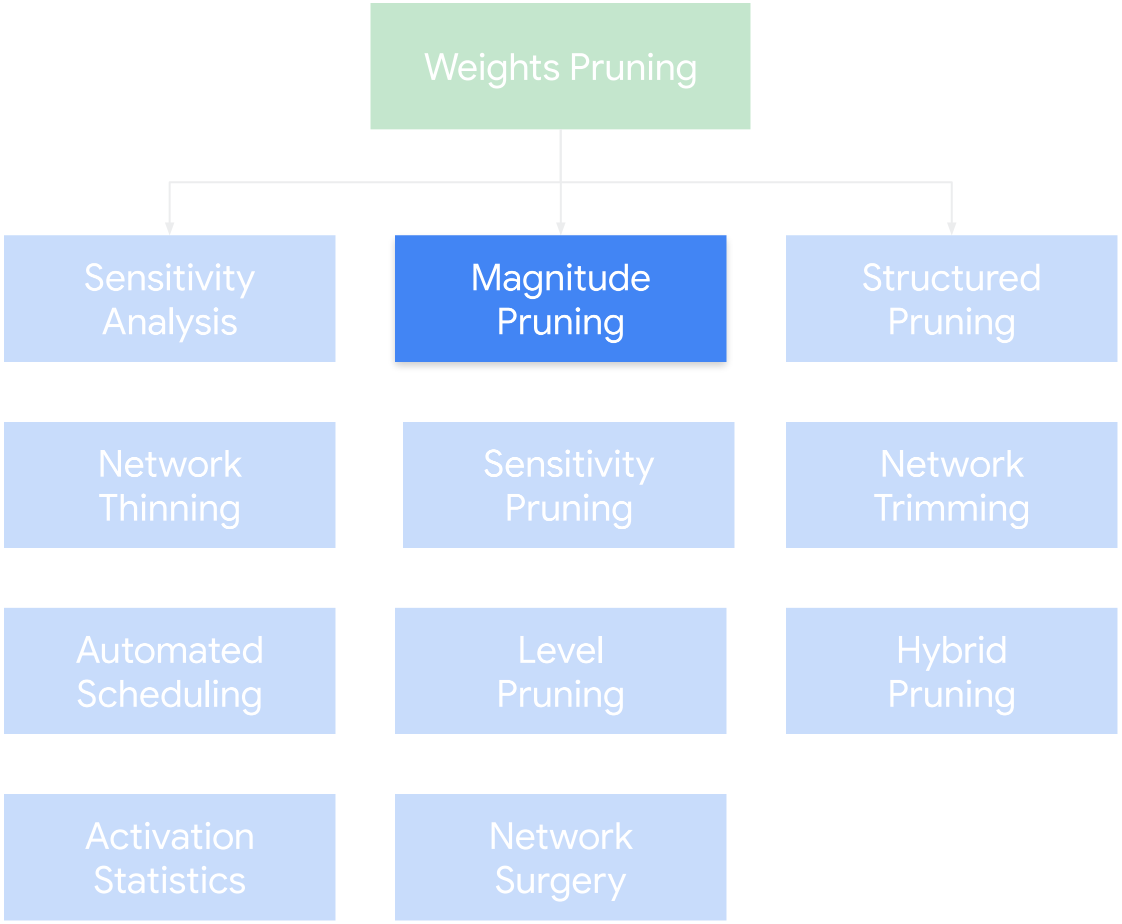
0	4	0
7	0	3
0	5	0


Sparse
Packed
CPU
2X Faster Execution

Pruning




Weights Pruning
Sensitivity Analysis
Magnitude Pruning
Structured Pruning
Network Thinning
Sensitivity Pruning
Network Trimming
Automated Scheduling
Level Pruning
Hybrid Pruning
Activation Statistics
Network Surgery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Magnitude Pruning

- Sparse models are **easier to compress**

$$thresh(w_i) = \begin{cases} w_i : & if\ |w_i| > \lambda \\ 0 : & if\ |w_i| \leq \lambda \end{cases}$$

Magnitude Pruning

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- We can **skip the zeroes during inference for latency** improvements

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Magnitude Pruning

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- We can **skip the zeroes during inference for latency** improvements
- Up to **6x improvement**

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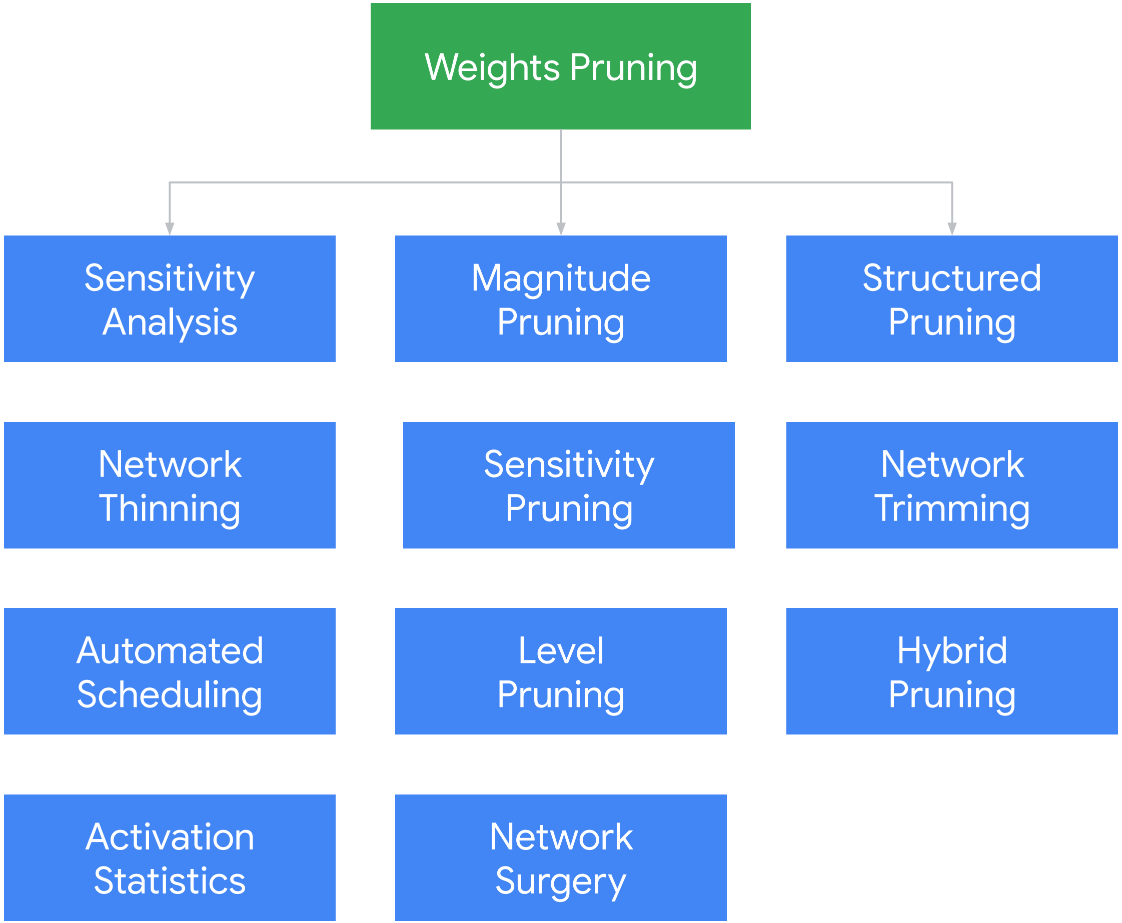
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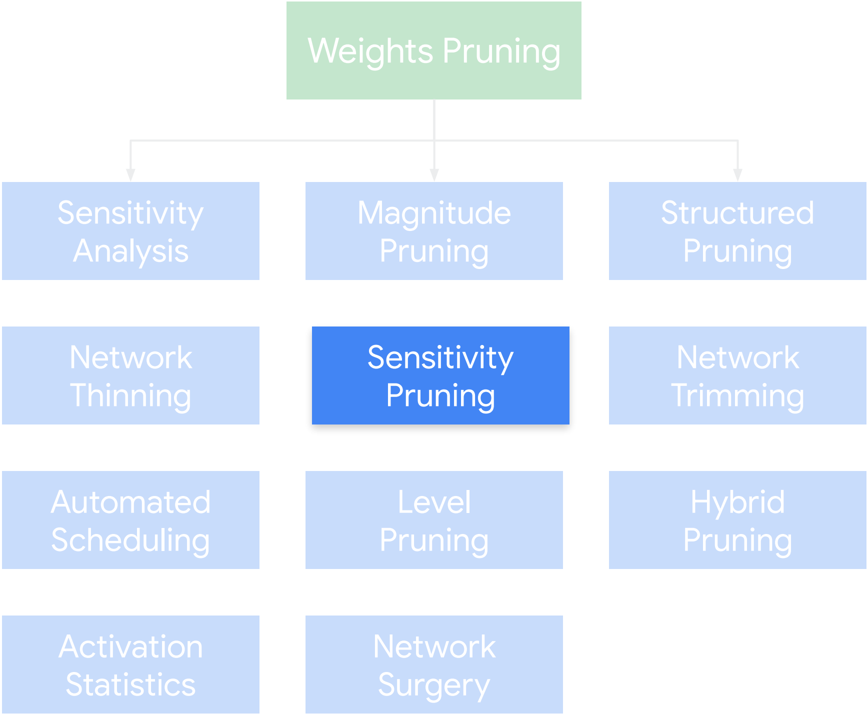

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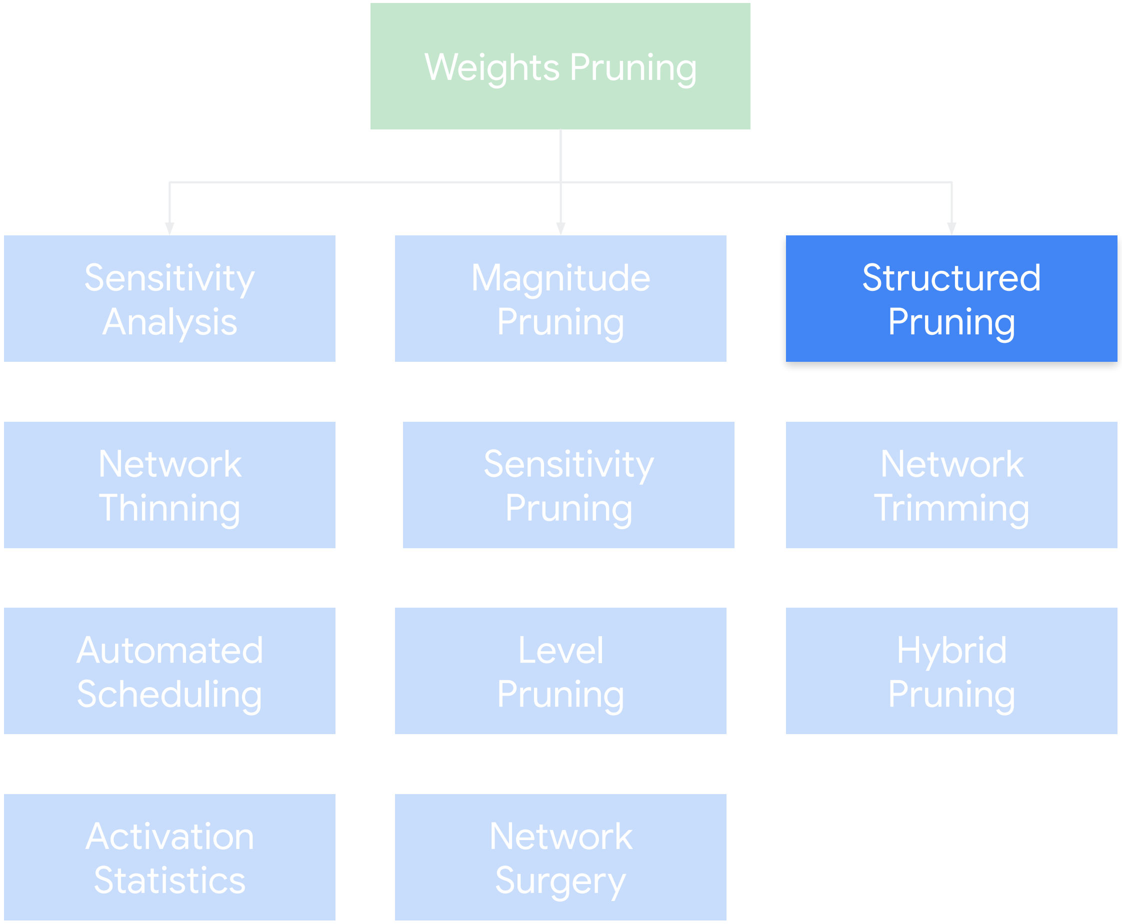
$\lambda = s * \sigma_l$ *where* σ_l *is the std of layer* l *as measured on the dense model*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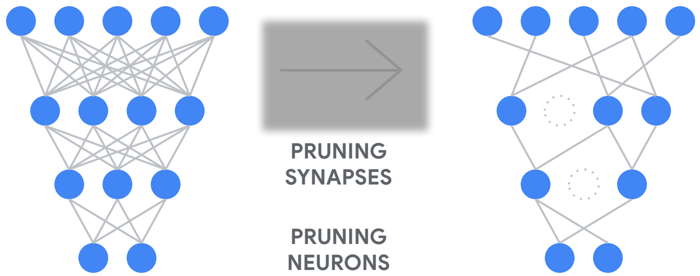
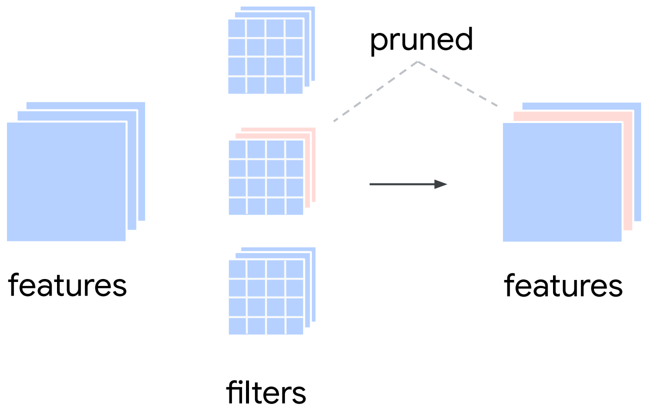
Unstructured Pruning



Structured Pruning



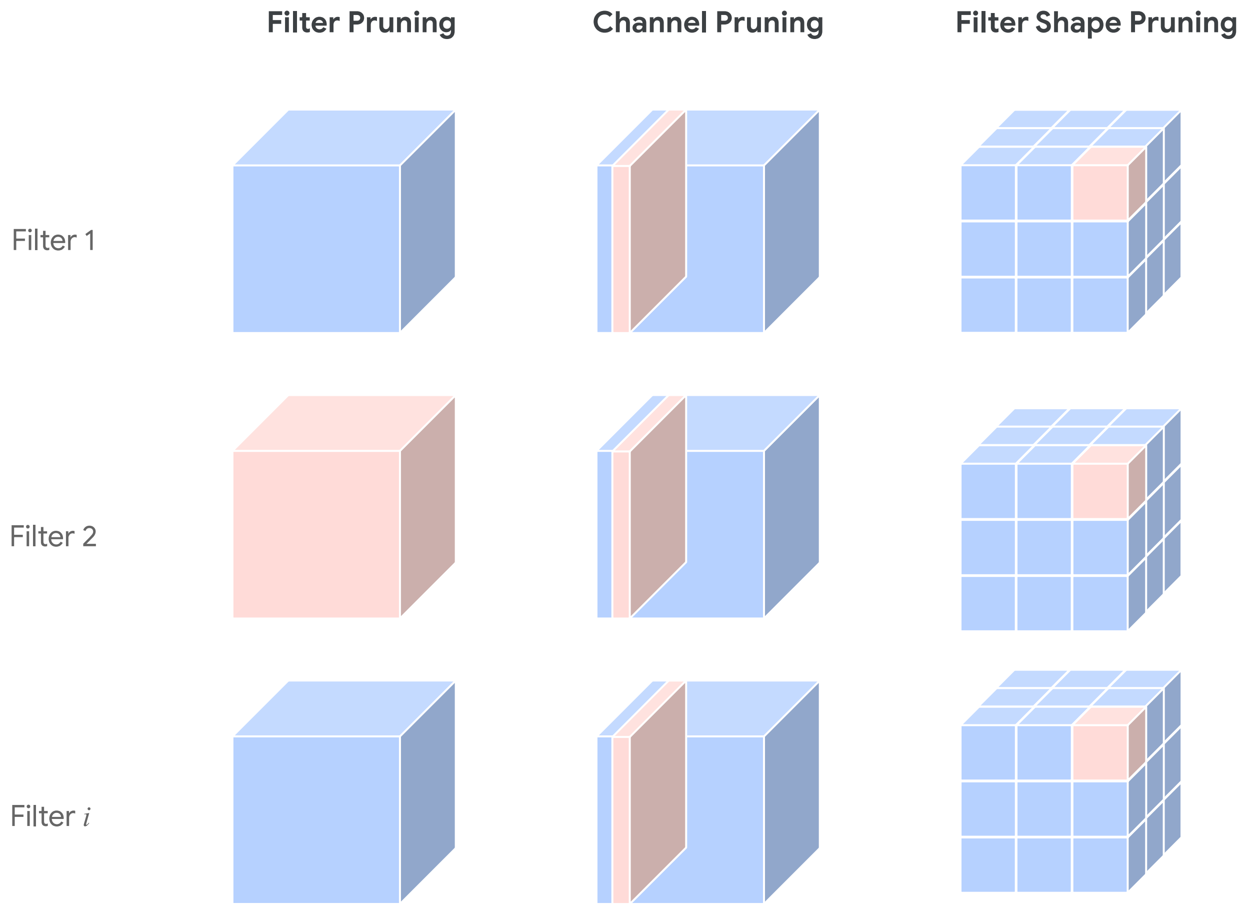

Filter Pruning
Channel Pruning
Filter Shape Pruning
Filter 1
Filter 2
Filter i

Image Classification

Model	Non-sparse Top-1 Accuracy	Sparse Accuracy	Sparsity
InceptionV3	78.1%	78.0%	50%
		76.1%	75%
		74.6%	87.5%
MobilenetV1 224	71.04%	70.84%	50%

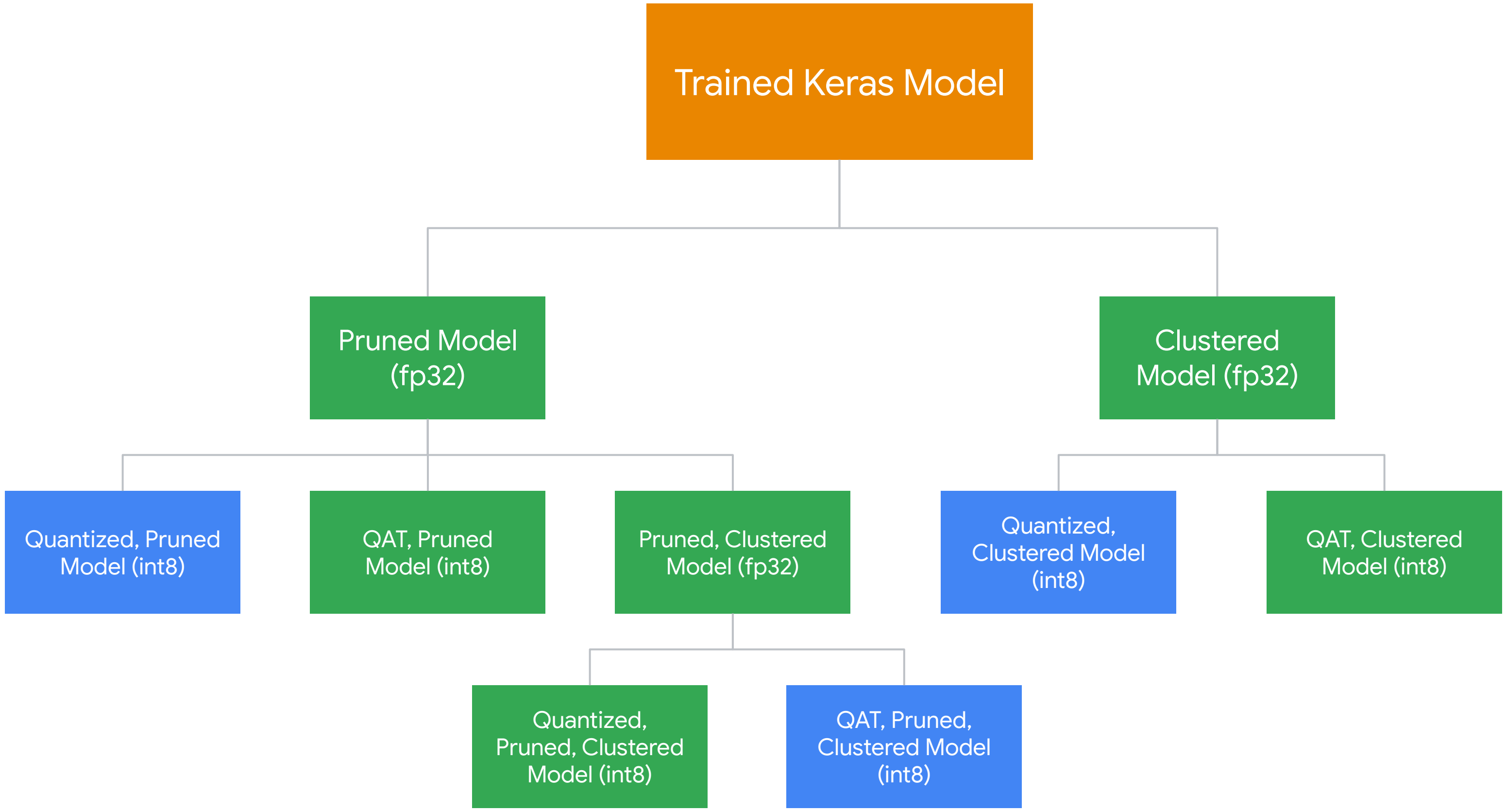
The models were tested on Imagenet.

Language Translation

Model	Non-sparse BLEU	Sparse BLEU	Sparsity
GNMT EN-DE	26.77	26.86	80%
		26.52	85%
		26.19	90%
GNMT DE-EN	29.47	29.50	80%
		29.24	85%
		28.81	90%

Keyword Spotting

Model	Non-sparse Accuracy	Structured Sparse Accuracy (2 by 4 pattern)	Random Sparse Accuracy (target sparsity 50%)
DS-CNN-L	95.23	94.33	94.84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