ML Modeling Pipelines in Production

Part 2: Model Resource Management Techniques

Ramin Toosi

High-dimensional data

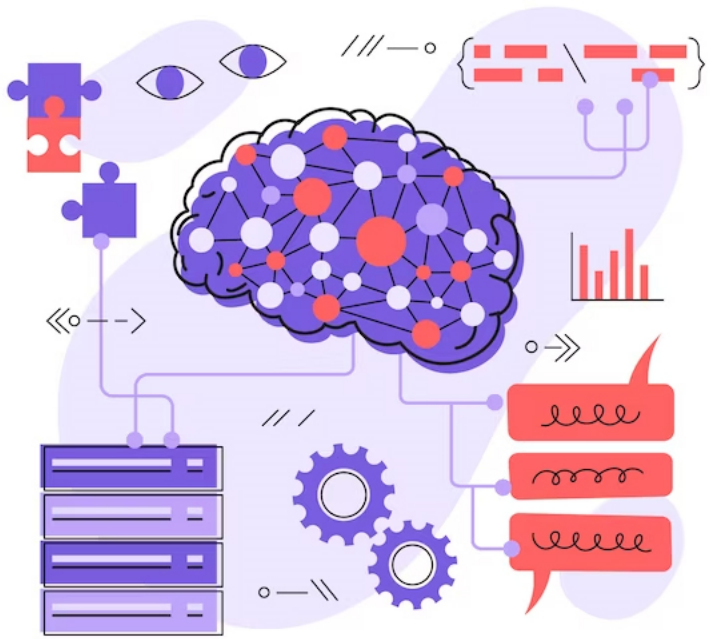
- **Before, when it was all about data mining**
  - Domain experts selected features
  - Designed feature transforms
  - Small number of more relevant features were enough
- **Now, data science is about integrating everything**
  - Data generation and storage is less of a problem
  - Squeeze out the best from data
  - More high-dimensional data having more features

A note about neural networks

- Yes, neural networks will perform a kind of automatic feature selection
- However, that's not as efficient as a well-designed dataset and model
  - Much of the model can be largely "shut off" to ignore unwanted features
  - Even unused parts of the consume space and compute resources
  - Unwanted features can still introduce unwanted noise
  - Each feature requires infrastructure to collect, store, and manage

Why is high-dimensional data a problem?

- More dimensions → more features
- Risk of overfitting our models
- Distances grow more and more alike
- No clear distinction between clustered objects
- Concentration phenomenon for Euclidean distance



Curse of dimensionality

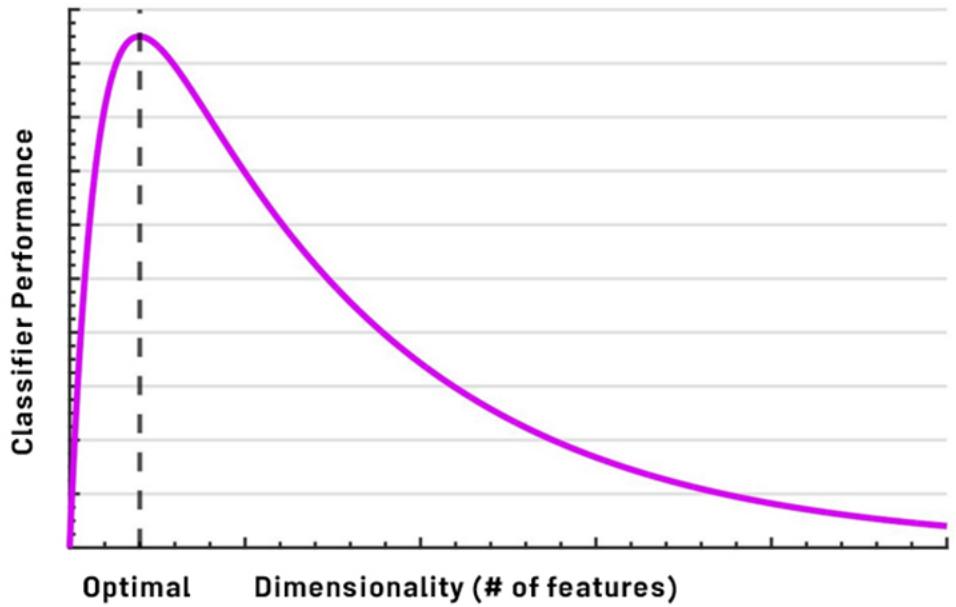
- "As we add more dimensions we also increase the processing power we need to train the model and make predictions, as well as the amount of training data required"

Badreesh Shetty

Why are more features bad?

- Redundant / irrelevant features
- More noise added than signal
- Hard to interpret and visualize
- Hard to store and process data

The performance of algorithms ~ the number of dimensions



Adding dimensions increases feature space volume

1-D

1	2	3	4	5

2-D

(1, 1)	(1, 2)	(1, 3)	(1, 4)	(1, 5)
(2, 1)	(2, 2)	(2, 3)	(2, 4)	(2, 5)
(3, 1)	(3, 2)	(3, 3)	(3, 4)	(3, 5)
(4, 1)	(4, 2)	(4, 3)	(4, 4)	(4, 5)
(5, 1)	(5, 2)	(5, 3)	(5, 4)	(5, 5)

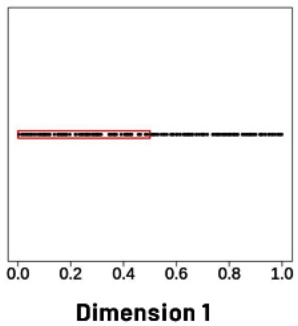
... ...

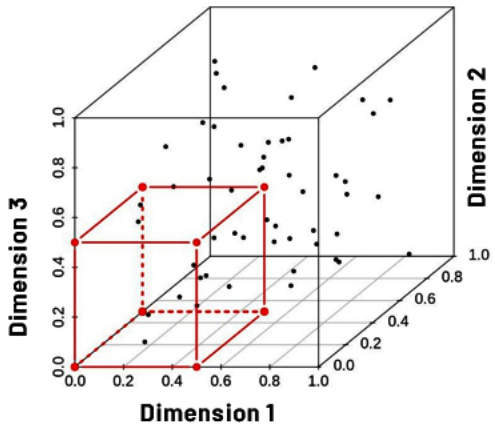
Curse of dimensionality in the distance function

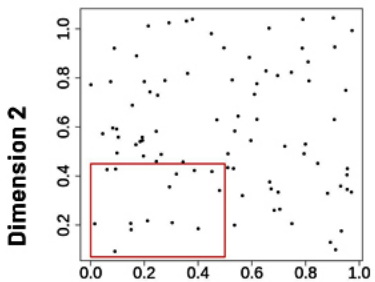
- New dimensions add non-negative terms to the sum
- Distance increases with the number of dimensions
- **For a given number of examples**, the feature space becomes increasingly sparse

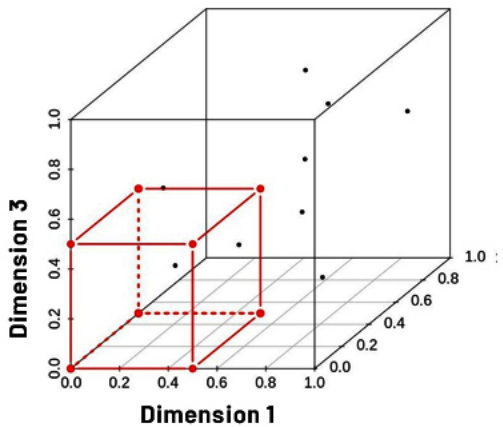
Euclidean distance $d_{ij} = \sqrt{\sum_{k=1}^{n}(x_{ik} - x_{jk})^2}$

Increasing sparsity with higher dimensions



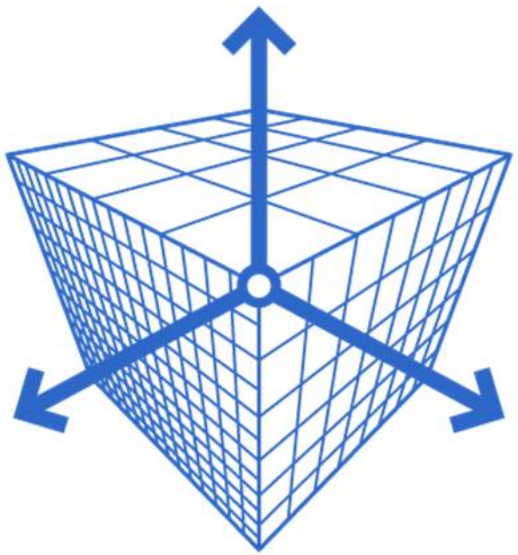






How dimensionality impacts in other ways

- Runtime and system memory requirements
- Solutions take longer to reach global optima
- More dimensions raise the likelihood of correlated features



More features require more training data

- More features aren't better if they don't add predictive information
- Number of training instances needed increases exponentially with each added feature
- Reduces real-world usefulness of models

Adding one feature

```
from tensorflow.python.keras.utils.layer_utils import
count_params


# Number of training parameters in Model #1
>>>
    count_params(model_1.trainable_variables)
        833

# Number of training parameters in Model #2 (with an added
feature)
>>>
    count_params(model_1.trainable_variables)
        1057
```

What do ML models need?

- No hard and fast rule on how many features are required
- Number of features to be used vary depending on
- Prefer uncorrelated data containing information to produce correct results

Why reduce dimensionality?

- Major techniques for dimensionality reduction

Storage

Computational

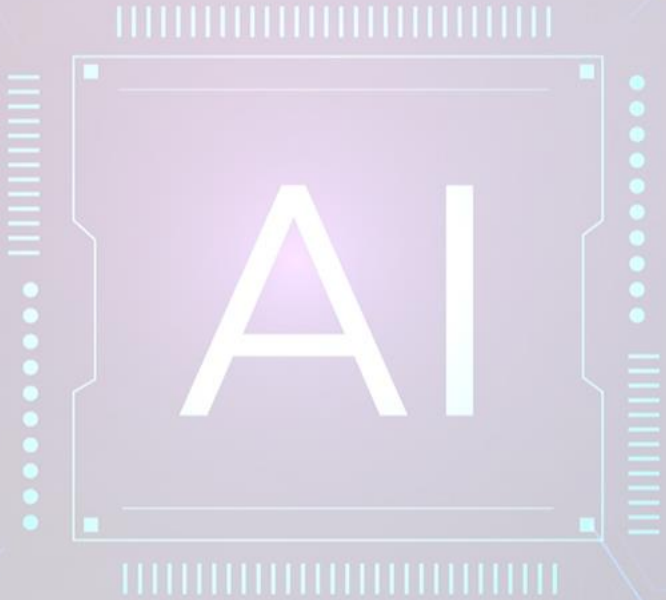
Consistency

Visualization

Engineering

Selection

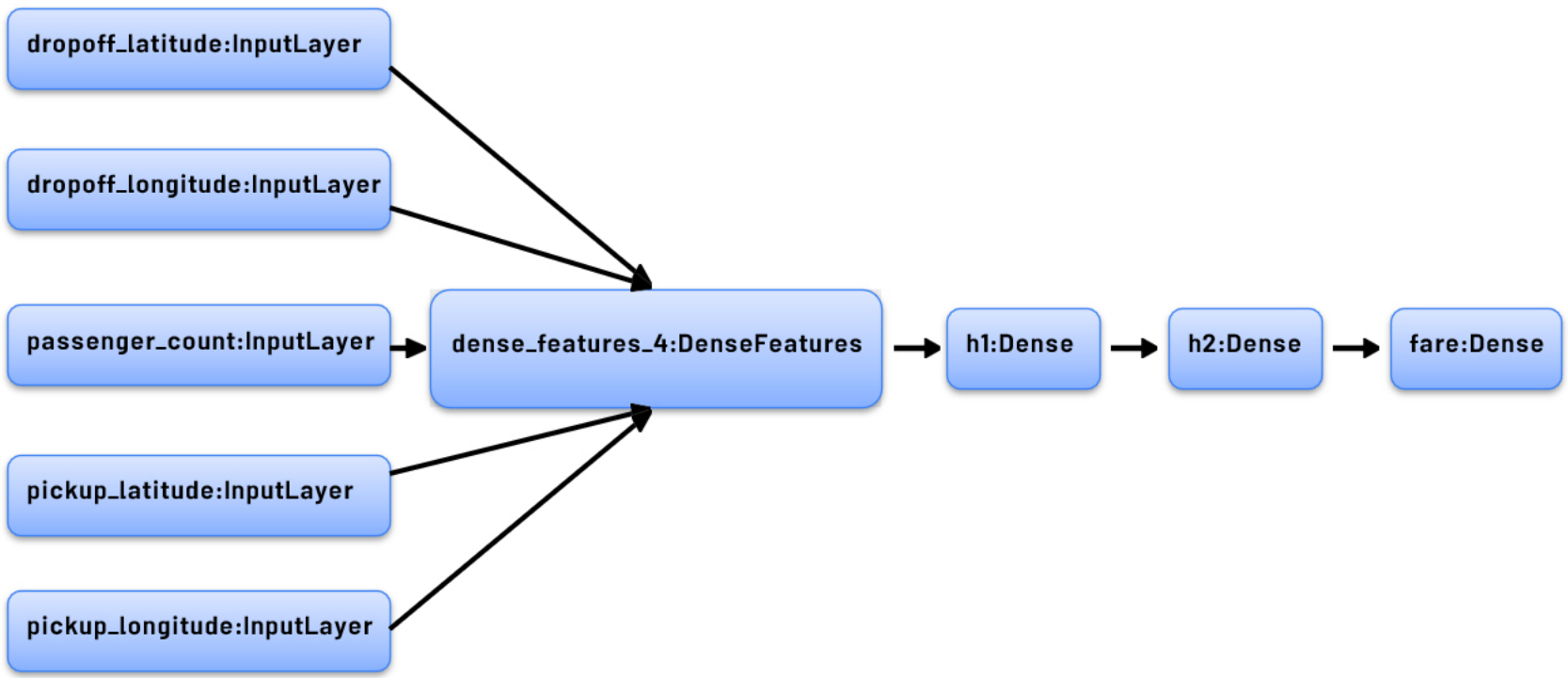
Case Study



Taxi Fare dataset

```
CSV_COLUMNS = [
     'fare_amount',
     'pickup_datetime', 'pickup_longitude', 'pickup_latitude',
     'Dropoff_longitude', 'dropoff_latitude',  'passenger_count',
     'key',
]

LABEL_COLUMN = 'fare_amount'
STRING_COLS = ['pickup_datetime']
NUMERIC_COLS = ['pickup_longitude', 'pickup_latitude',
                  'dropoff_longitude', 'dropoff_latitude',
                  'passenger_count']

DEFAULTS = [[0.0], ['na'], [0.0], [0.0], [0.0], [0.0], [0.0], ['na']]  DAYS =
['Sun', 'Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat']
```

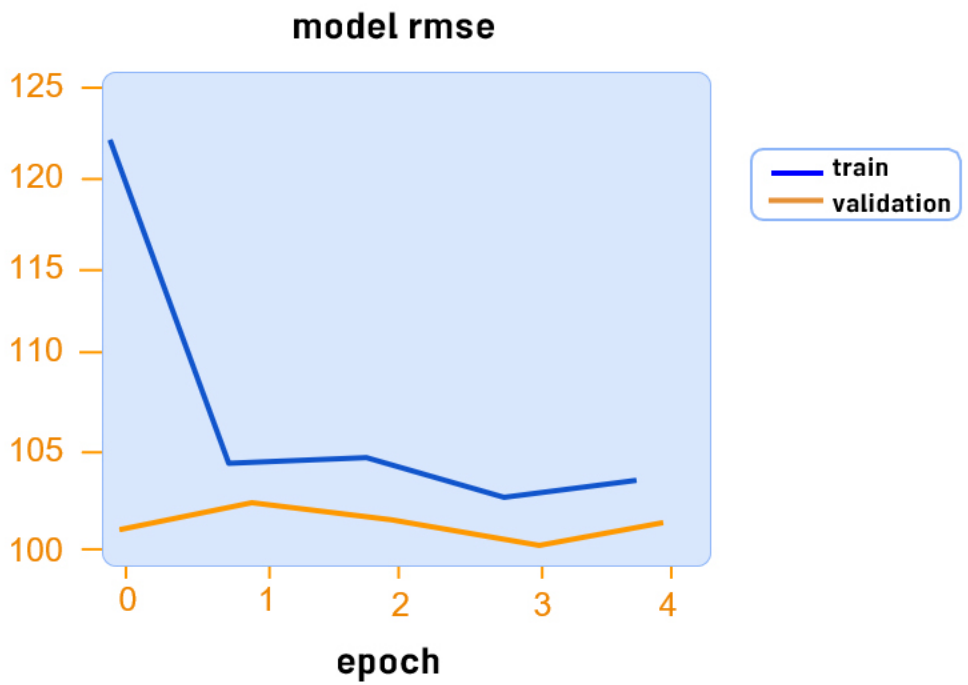
Build the model in Keras



Build a baseline model using raw features

```
from tensorflow.keras import layers
from tensorflow.keras.metrics import RootMeanSquared as RMSE

dnn_inputs = layers.DenseFeatures(feature_columns.values())(inputs)

h1 = layers.Dense(32, activation='relu', name='h1')(dnn_inputs)
h2 = layers.Dense(8, activation='relu', name='h2')(h1)

output = layers.Dense(1, activation='linear', name='fare')(h2)
model = models.Model(inputs, output)  model.compile(optimizer='adam',
loss='mse',metrics=[RMSE(name='rmse'), 'mse'])
```

Train the model



Increasing model performance with Feature Engineering

- **Carefully craft features for the data types**
  - Temporal (pickup date & time)
  - Geographical (latitude and longitude)

Handling temporal features

```
def parse_datetime(s):
      if type(s) is not str:
           s=s.numpy() .decode('utf-8')
      return datetime.datetime.strptime(s, "%Y-%m-%d  %H:%M:%S  %Z")
def get_dayofweek(s):
      ts= parse_datetime(s)
      return DAYS [ts.weekday()]
@tf.function
def dayofweek(ts_in):
      return tf.map_fn(
            lambda s: tf.py_function(get_dayofweek, inp=[s],
                                     Tout=tf.string),ts_in)
```

Geolocational features

```
def euclidean(params):
    lon1, lat1, lon2, lat2 =
    params  londiff = lon2 - lon1
    latdiff = lat2 - lat1
    return tf.sqrt(londiff * londiff + latdiff *
    latdiff)
```

Scaling latitude and longitude

```
def
    scale_longitude(lon_column)
    :  return (lon_column +
    78)/8.

def
    scale_latitude(lat_column)
    :  return (lat_column -
    37)/8.
```

Preparing the transformations

```
def transform(inputs, numeric_cols, string_cols, nbuckets):
    ...
    feature_columns = {
        colname: tf.feature_column.numeric_column(colname)  for colname in numeric_cols
    }
  for lon_col in ['pickup_longitude', 'dropoff_longitude']:  transformed[lon_col] =
        layers.Lambda(scale_longitude,
            ...)(inputs[lon_col])
  for lat_col in ['pickup_latitude', 'dropoff_latitude']:  transformed[lat_col] =
        layers.Lambda(
            scale_latitude,
            ...)(inputs[lat_col])
    ...
```

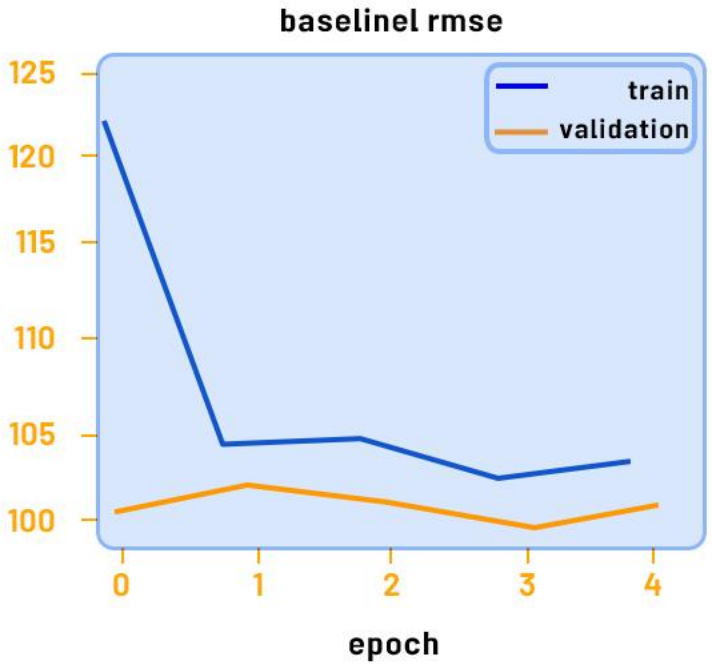
Bucketizing and feature crossing

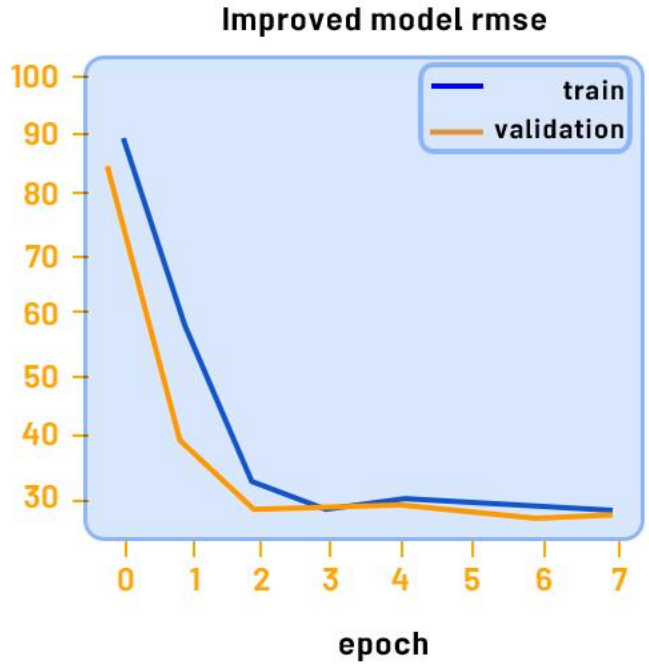
```
def transform(inputs, numeric_cols, string_cols,
nbuckets):
    ...
    latbuckets = np.linspace(0, 1,
    nbuckets).tolist()  lonbuckets = ... # Similarly
    for longitude
    b_plat = fc.bucketized_column(
        feature_columns['pickup_latitude'],
        latbuckets)
    b_dlat = # Bucketize 'dropoff_latitude'
    b_plon = # Bucketize 'pickup_longitude'
    b_dlon = # Bucketize'dropoff_longitude'
```

Bucketizing and feature crossing

```
ploc = fc.crossed_column([b_plat, b_plon], nbuckets *
nbuckets)  dloc = # Feature cross 'b_dlat' and 'b_dlon'
pd_pair = fc.crossed_column([ploc, dloc], nbuckets ** 4)


feature_columns['pickup_and_dropoff'] =
fc.embedding_column(pd_pair,  100)
```

Train the new feature engineered model

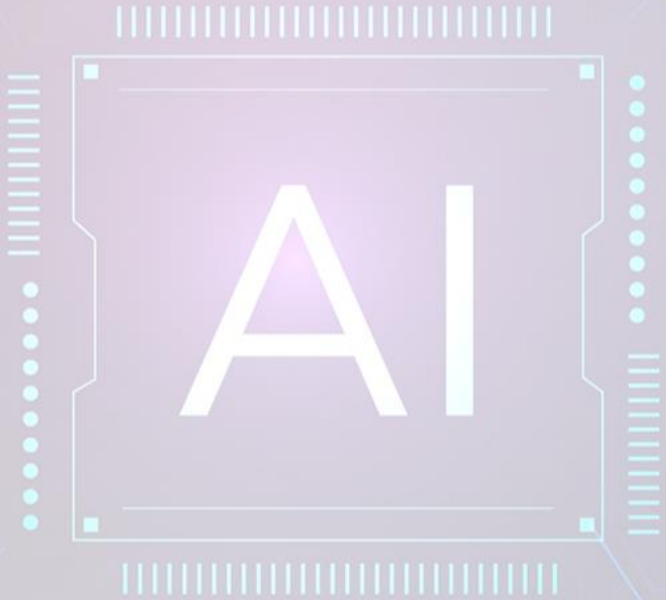




More dimensionality reduction algorithms

- **Unsupervised**
  - Latent Semantic Indexing/Analysis (LSI and LSA) (SVD)
  - Independent Component Analysis (ICA)
- **Matrix Factorization**
  - Non-Negative Matrix Factorization (NMF)
- **Latent Methods**
  - Latent Dirichlet Allocation (LDA)

Quantization & Pruning



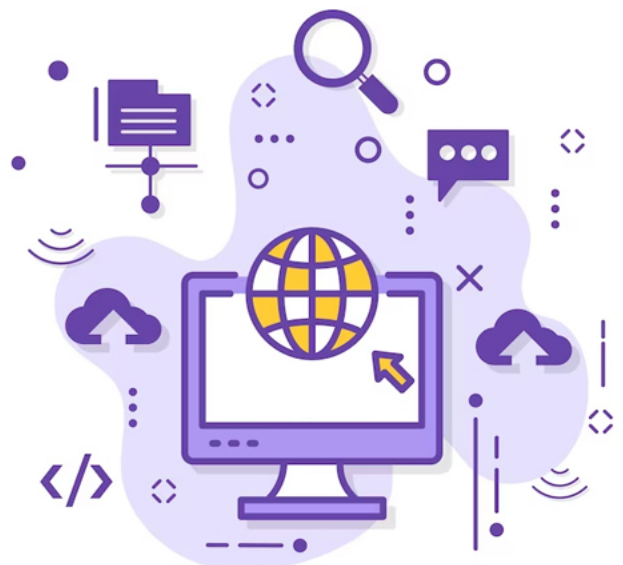
Trends in adoption of smart devices

Factors driving this trend

- Demands move ML capability from cloud to on-device
- Cost-effectiveness
- Compliance with privacy regulations

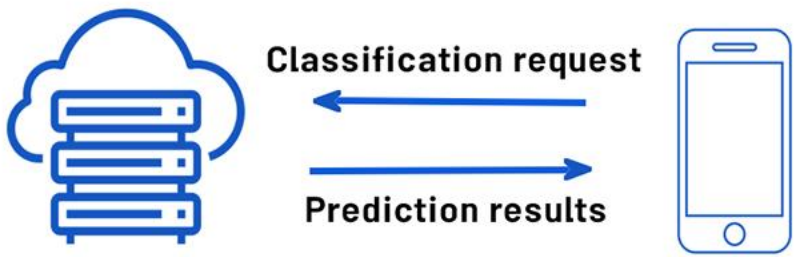
Online ML inference

- To generate real-time predictions you can:
  - Host the model on a server
  - Embed the model in the device
- Is it faster on a server, or on-device?
- Mobile processing limitations?



Mobile inference

Inference on the cloud/server



- **Pros**
  - Lots of compute capacity
  - Scalable hardware
  - Model complexity handled by the server
  - Easy to add new features and update the model
  - Low latency and batch prediction
- **Cons**
  - Timely inference is needed

Mobile inference

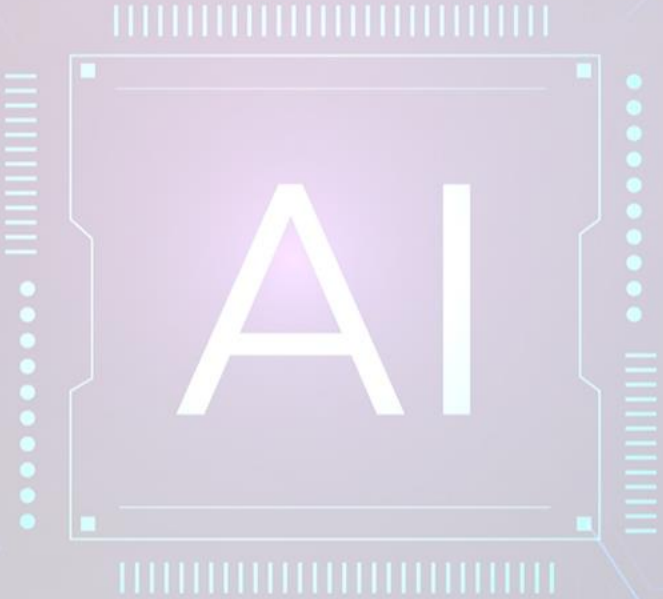
On-device Inference

- **Pros**
  - Improved speed
  - Performance
  - Network connectivity
  - No to-and-fro communication needed
- **Cons**
  - Less capacity
  - Tight resource constraints

Model deployment

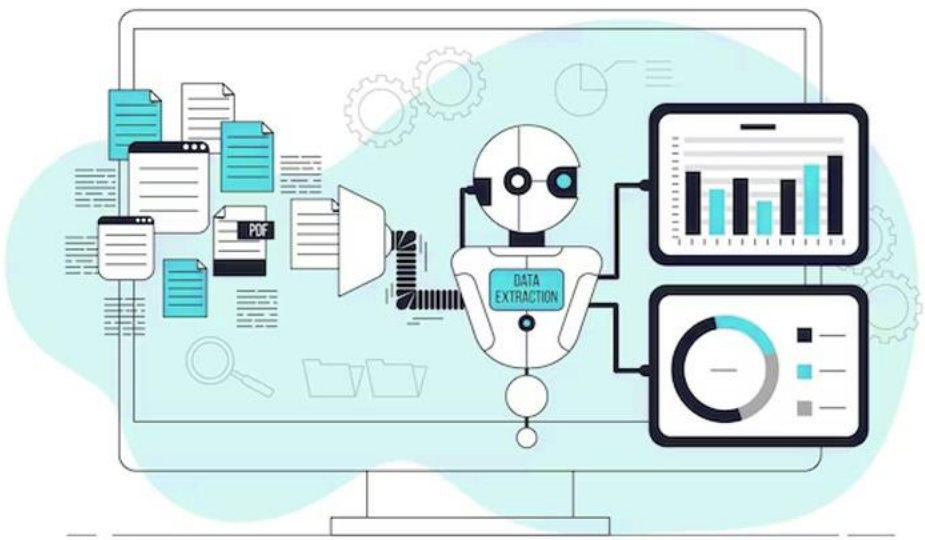
Options	On-device inference	On-device personalization	On-device training	Cloud-based web service	Pretrained models	Custom models
ML Kit	✓	✓		✓	✓	✓
Core ML	✓	✓	✓		✓	✓
TensorFlow Lite	✓	✓	✓		✓	✓
Pytorch Mobile	✓	✓			✓	✓

Quantization



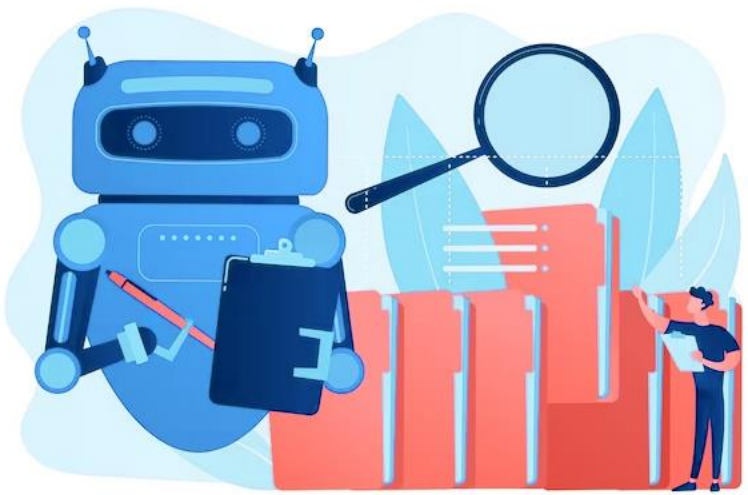
Why quantize neural networks?

- Neural networks have many parameters and take up space
- Shrinking model file size
- Reduce computational resources
- Make models run faster and use less power with low-precision

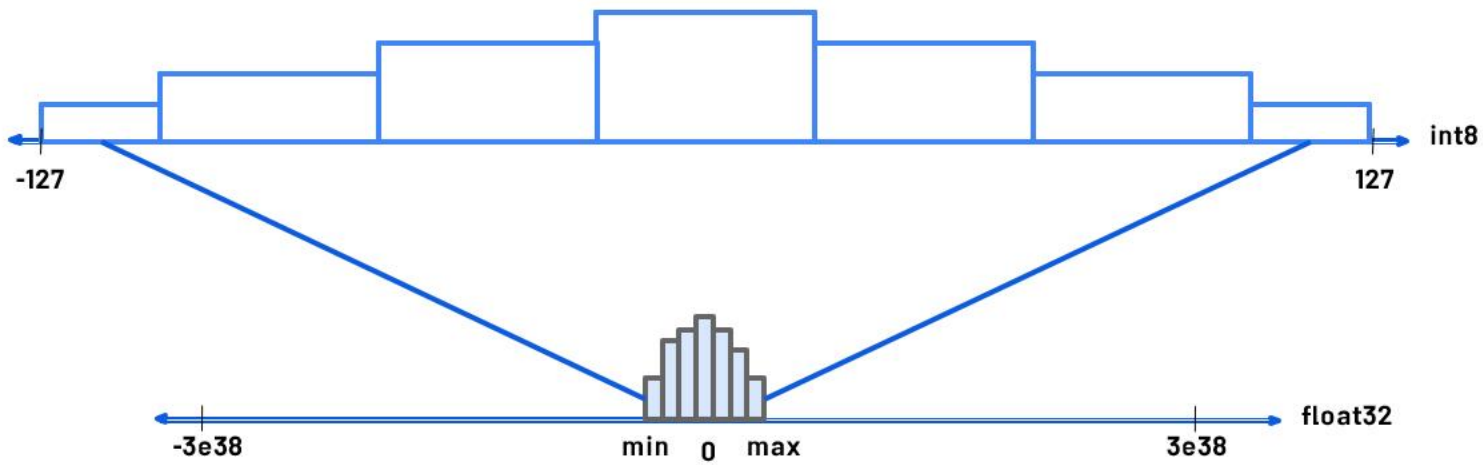


Benefits of quantization

- Faster compute
- Low memory bandwidth
- Low power
- Integer operations supported across CPU/DSP/NPUs

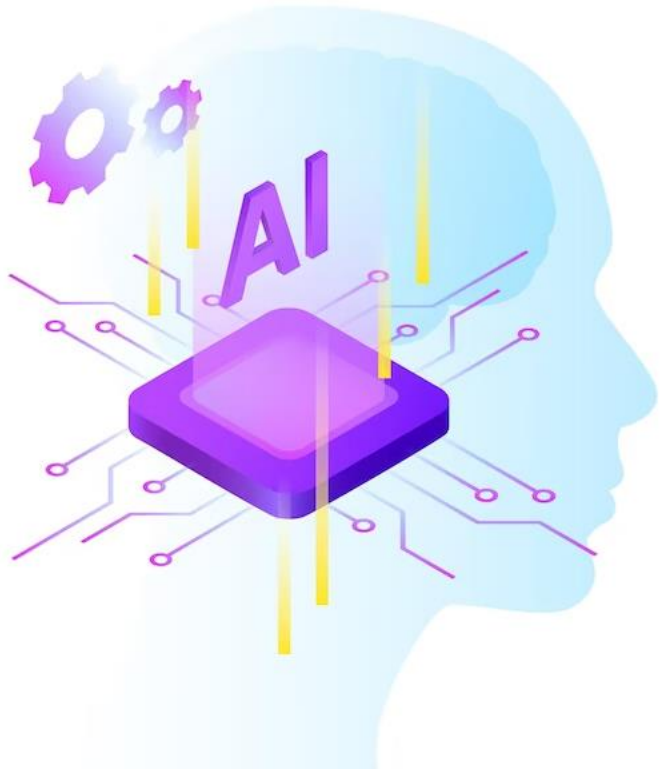


The quantization process



What parts of the model are affected?

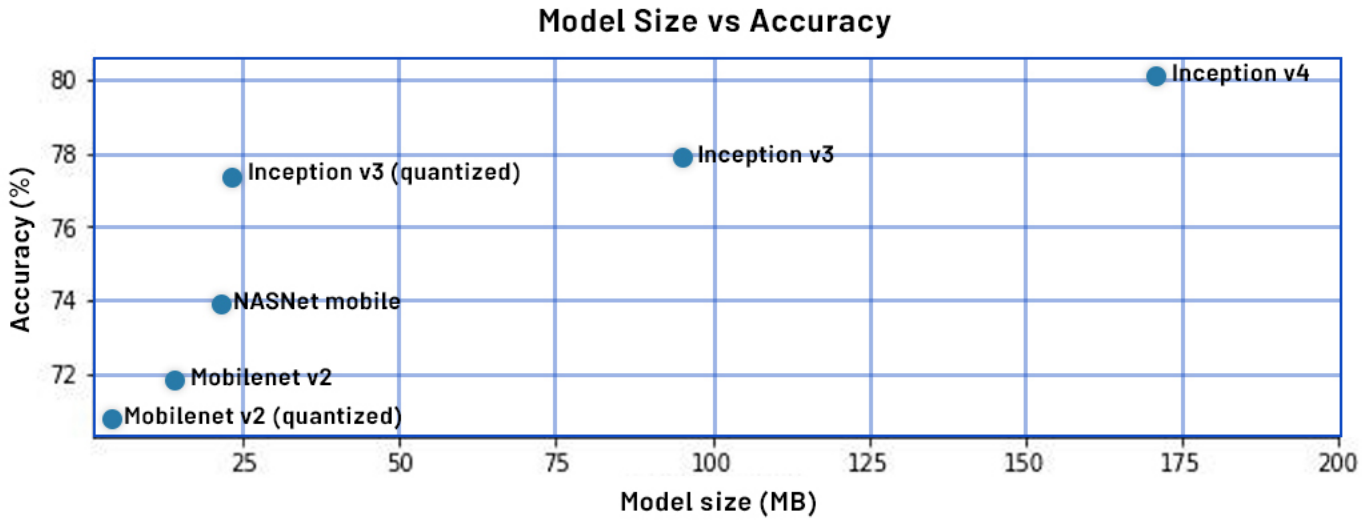
- Static values (parameters)
- Dynamic values (activations)
- Computation (transformations)

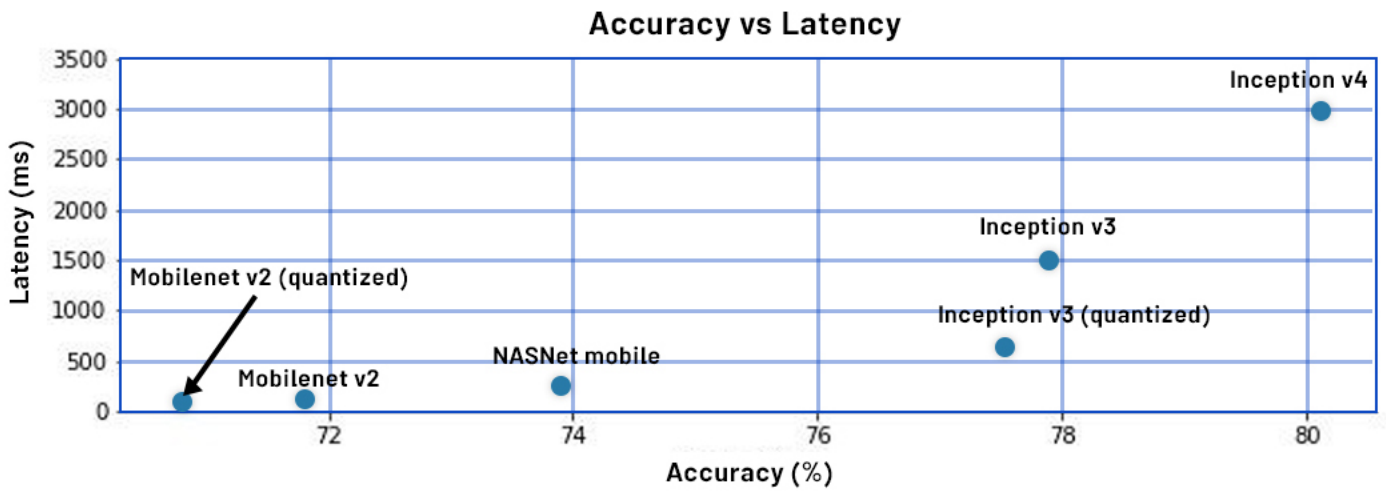


Trade-offs

- Optimizations impact model accuracy
  - Difficult to predict ahead of time
- In rare cases, models may actually gain some accuracy
- Undefined effects on ML interpretability

Choose the best model for the task





Post-training quantization

- Reduced precision representation
- Incur small loss in model accuracy
- Joint optimization for model and latency

Post-training quantization

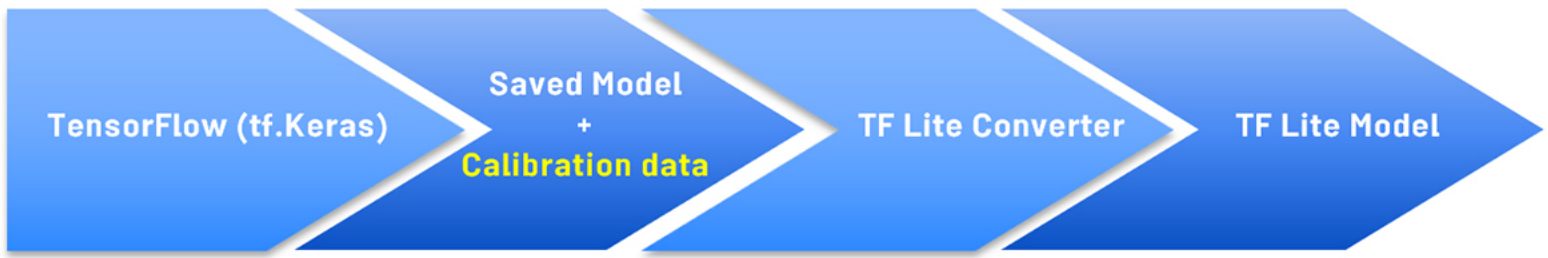
Technique	Benefits
Dynamic range quantization	4x smaller, 2x-3x speedup
Full integer quantization	4x smaller, 3x+ speedup
float16 quantization	2x smaller, GPU acceleration

Post-training quantization

```
import tensorflow as tf

converter = tf.lite.TFLiteConverter.from_saved_model(saved_model_dir)

converter.optimizations = [tf.lite.Optimize.OPTIMIZE_FOR_SIZE]


tflite_quant_model = converter.convert()
```

Post-training integer quantization

- INT8



Model accuracy

- Small accuracy loss incurred (mostly for smaller networks)
- Use the benchmarking tools to evaluate model accuracy
- If the loss of accuracy drop is not within acceptable limits, consider using quantization-aware training

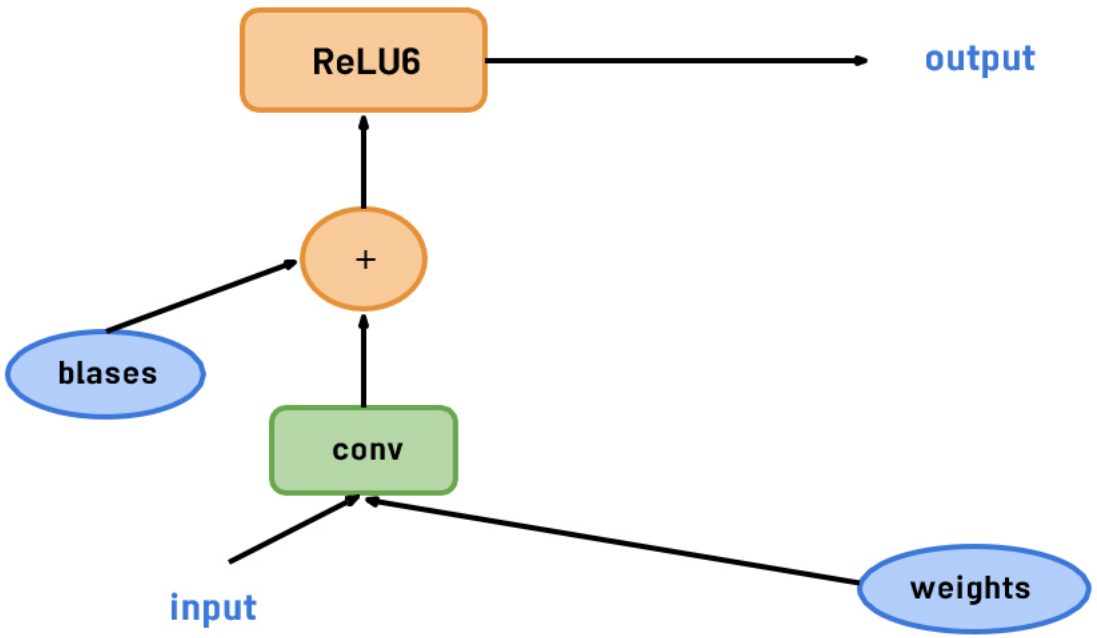
Quantization-aware training (QAT)

- Inserts fake quantization (FQ) nodes in the forward pass
- Rewrites the graph to emulate quantized inference
- Reduces the loss of accuracy due to quantization
- Resulting model contains all data to be quantized according to spec

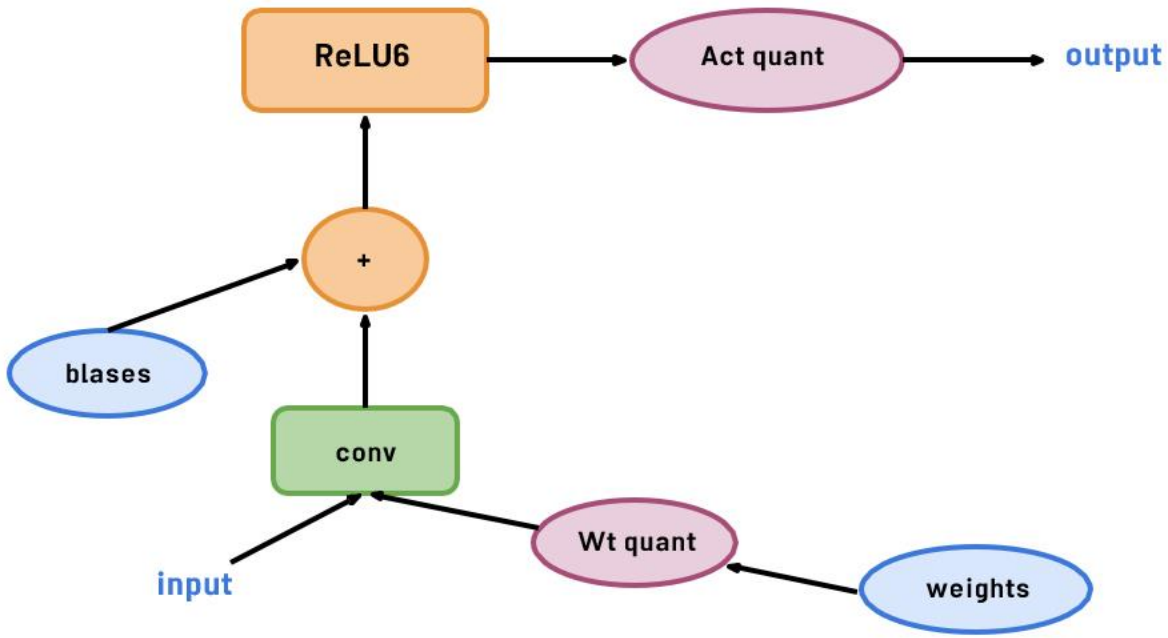
Quantization-aware training (QAT)

- INT8

Adding the quantization emulation operations



Adding the quantization emulation operations



QAT on entire model

```
import tensorflow_model_optimization as tfmot


model = tf.keras.Sequential([
   ...
])
# Quantize the entire model.
quantized_model =
tfmot.quantization.keras.quantize_model(model)

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

Quantize part(s) of a model

```
import tensorflow_model_optimization as tfmot
quantize_annotate_layer = tfmot.quantization.keras.quantize_annotate_layer
model = tf.keras.Sequential([
    ...
    # Only annotated layers will be quantized.
    quantize_annotate_layer(Conv2D()),
    quantize_annotate_layer(ReLU()),
    Dense(),
    ...
])
# Quantize the model.
quantized_model = tfmot.quantization.keras.quantize_apply(model)
```

Model Optimization Results - Accuracy

Model	Top-1 Accuracy (Original)	Top-1 Accuracy (Post Training Quantized)	Top-1 Accuracy (Quantization Aware Training)
Mobilenet-v1-1-224	0.709	0.657	0.70
Mobilenet-v2-1-224	0.719	0.637	0.709
Inception_v3	0.78	0.772	0.775
Resnet_v2_101	0.770	0.768	N/A

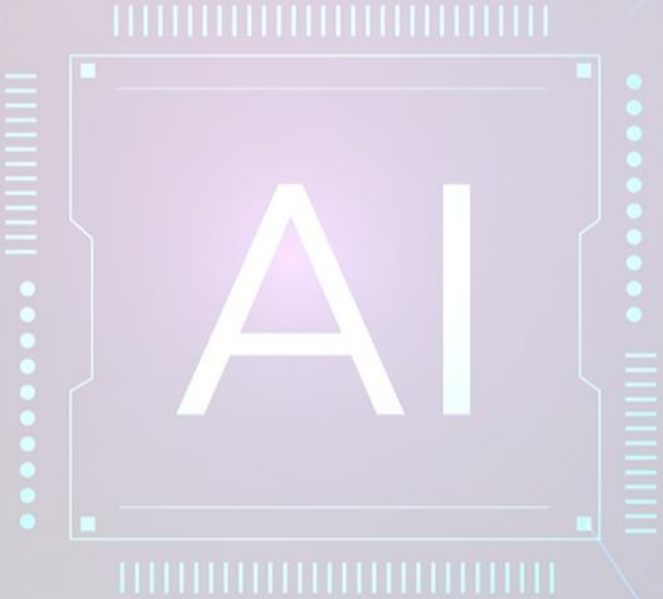
Model Optimization Results - Latency

Model	Latency (Original) (ms)	Latency (Post Training Quantized) (ms)	Latency (Quantization Aware Training) (ms)
Mobilenet-v1-1-224	124	112	64
Mobilenet-v2-1-224	89	98	54
Inception_v3	1130	845	543
Resnet_v2_101	3973	2868	N/A

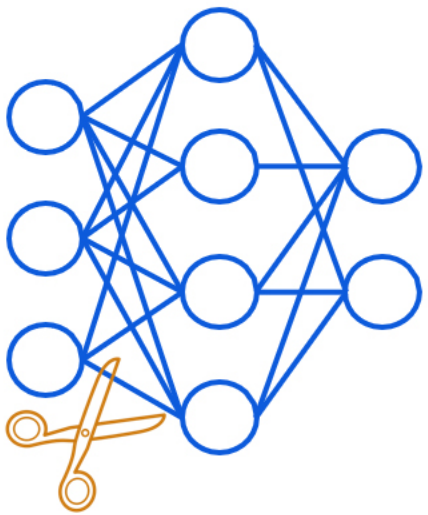
Model Optimization Results

Model	Size (Original) (MB)	Size (Optimized) (MB)
Mobilenet-v1-1-224	16.9	4.3
Mobilenet-v2-1-224	14	3.6
Inception_v3	95.7	23.9
Resnet_v2_101	178.3	44.9

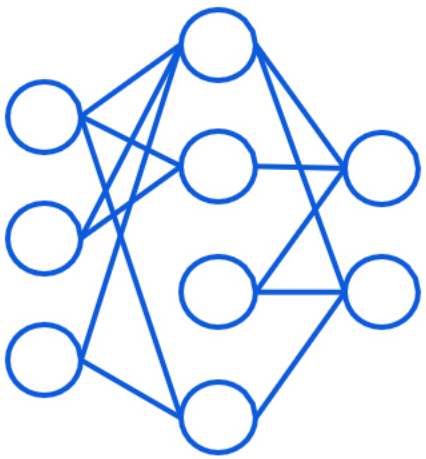
Pruning



Connection pruning

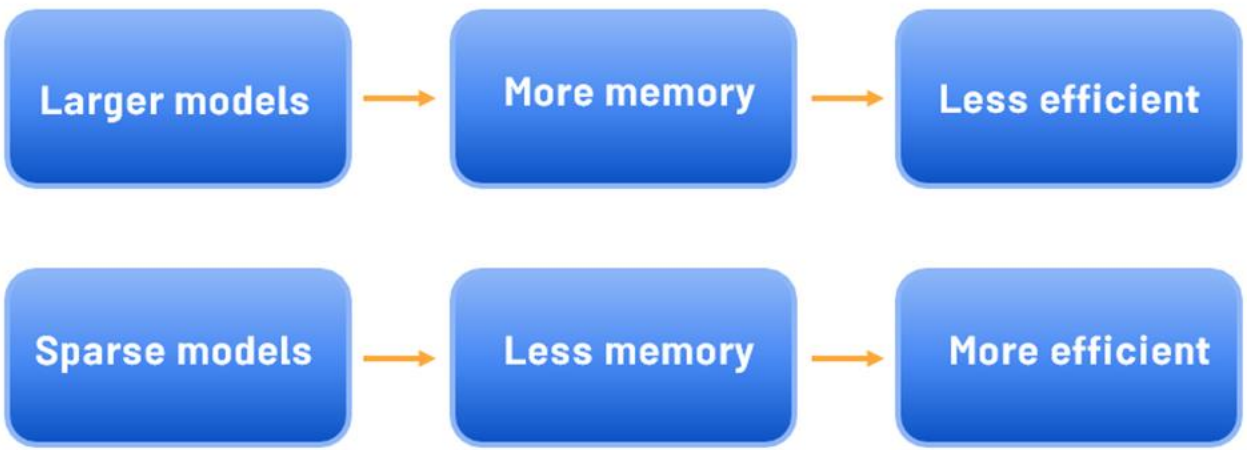


Before pruning

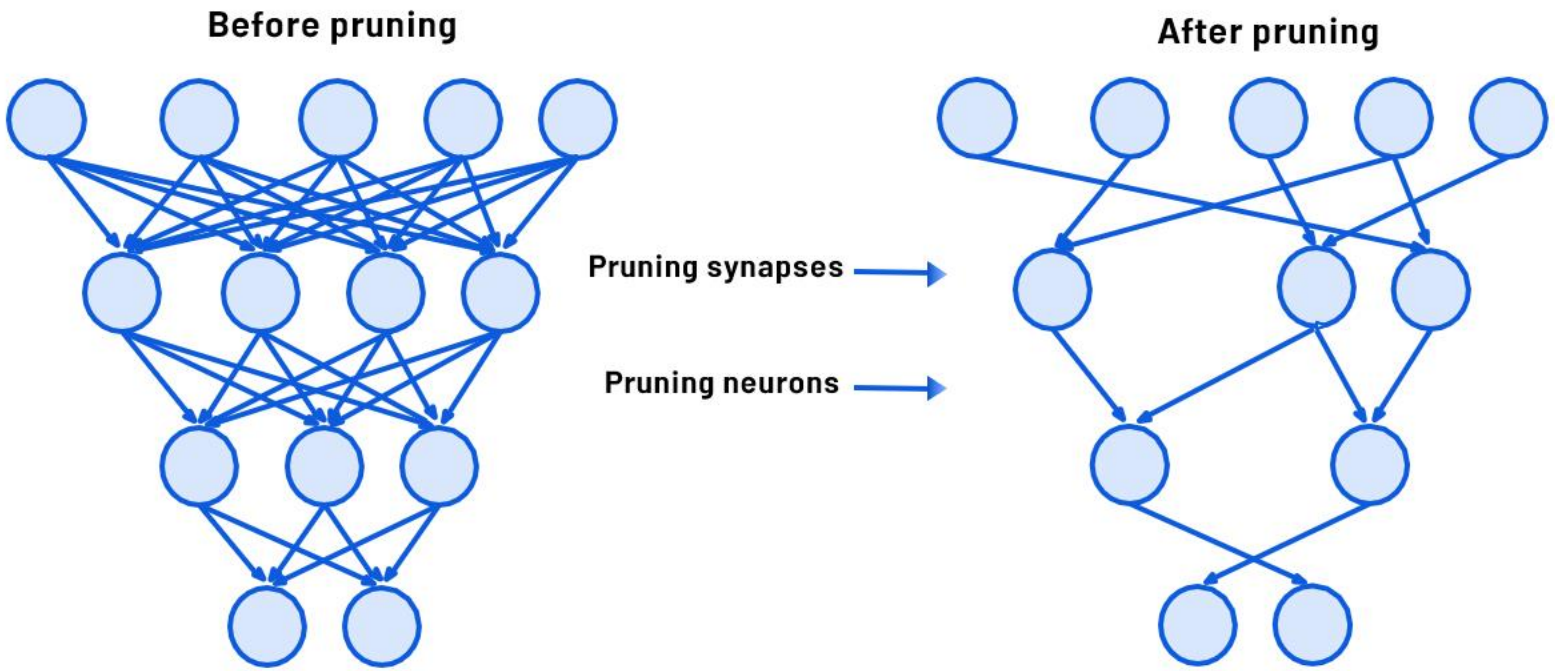


After pruning

Model sparsity



Origins of weight pruning



The Lottery Ticket Hypothesis

$$p = \frac{1}{3000000}$$

$$\bar{p} = 1 - p$$

$$p_n = 1 - (1 - p)^n$$

Finding Sparse Neural Networks

- "A randomly-initialized, dense neural network contains a subnetwork that is initialized such that — when trained in isolation — it can match the test accuracy of the original network after training for at most the same number of iterations"

  Jonathan Frankle and Michael Carbin

Pruning research is evolving

- The new method didn't perform well at large scale
- The new method failed to identify the randomly initialized winners
- It's an active area of research

Eliminate connections based on their magnitude

- Tensors with no sparsity (left), sparsity in blocks of 1x1 (center), and the sparsity in blocks 1x2 (right)

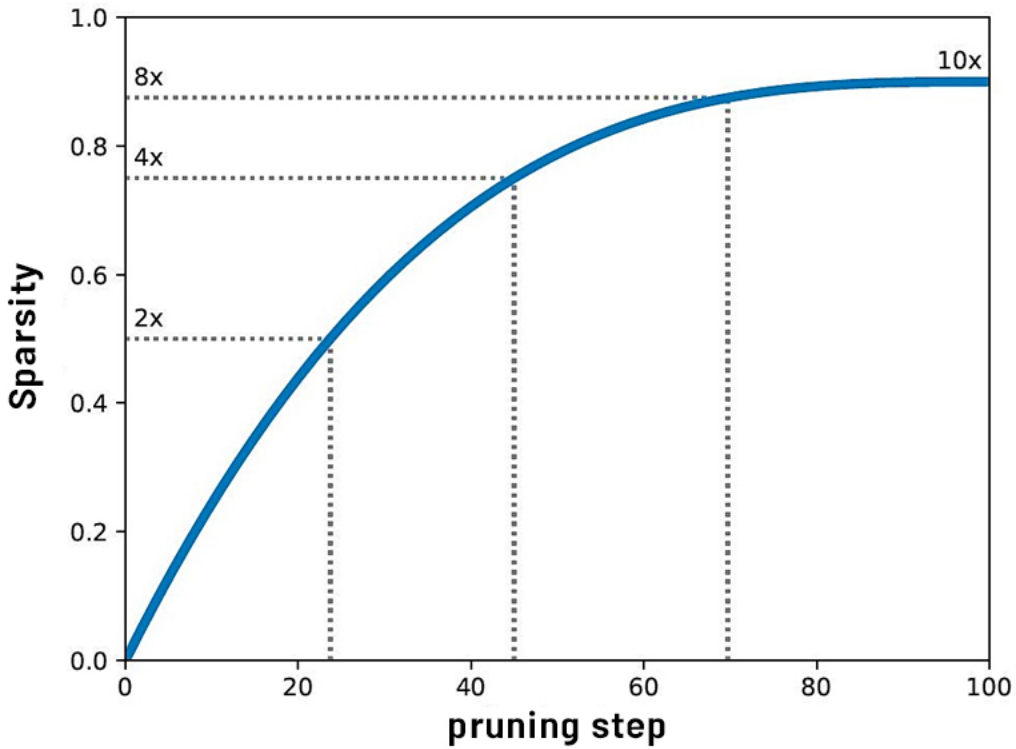
3	2	7	4
9	6	3	8
4	4	1	3
2	3	2	5

0	2	0	4
0	6	3	0
4	0	0	3
0	3	0	5

0	0	7	4
9	6	0	0
0	0	1	3
2	3	0	0

Apply sparsity with a pruning routine

- Example of sparsity ramp-up function with a schedule to start pruning from step 0 until step 100, and a final target sparsity of 90%.



What's special about pruning?

- Better storage and/or transmission
- Gain speedups in CPU and some ML accelerators
- Can be used in tandem with quantization to get additional benefits
- Unlock performance improvements

Pruning with TF Model Optimization Toolkit

- INT8

Pruning with Keras

```
import tensorflow_model_optimization as tfmot
       model = build_your_model()
pruning_schedule = tfmot.sparsity.keras.PolynomialDecay(
                      initial_sparsity=0.50,
                      final_sparsity=0.80,  begin_step=2000,
                      end_step=4000)

model_for_pruning = tfmot.sparsity.keras.prune_low_magnitude(
                       model,
                       pruning_schedule=pruning_schedule)

...
model_for_pruning.fit(...)
```

Results across different models & tasks

Model	Non-sparse Top-1 acc.	Sparse acc.	Sparsity
Inception V3	78.1%	78.0%	50%
		76.1%	75%
		74.6%	87.5%
Mobilenet V1 224	71.04%	70.84%	50%

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%