Dimensionality Effect on Performance

all about **model optimization** and **resource management**. We'll be talking about a lot of interesting issues including **dimensionality and ways to reduce it and why it's important**. Then we'll look at some really **resource constrained scenarios** : mobile and IOT deal with resource usage in those situations such as quantization and pruning.

The compute,storage and IOT Systems that your model requires will determine how much it costs to put your model into production and maintain it during its entire lifetime. This week we'll be taking a look at some important techniques that can help us manage model resource requirements.

We'll begin by discussing dimensionality and how it affects our models performance and resource requirements. In the not so distant past data generation and to some extent data storage was a lot more costly than it is today. Back then a lot of domain experts would carefully consider which features or variables to measure before designing their experiments and feature transforms. **As a result, data sets were expected to be well designed and potentially contain only a small number of relevant features.**

Today, data science tends to be more about integrating everything end to end, generating and storing data is becoming faster, easier and less expensive. So there's a tendency for people to measure everything they can and include ever more complex feature transformations. As a result, **datasets are often high dimensional, containing a large number of features, although the relevancy of each feature for analyzing this data is not always clear.**

Before going to deep, let's discuss a common misconception about neural networks. Many developers correctly assume that when they train their neural network models, the model itself, as part of the training process, will learn to ignore features that don't provide predictive information by reducing their weights to zero or close to zero. Well, this is true, the result is not an efficient model. Much of the model can end up being shut off when running inference to generate predictions but those unused parts of the model are still there. They **take up space** and they **consume compute resources** as the model server traverses the computation graph. Those unwanted features could also **introduce unwanted noise into the data**, which can **degrade model performance**.

And **outside of the model** itself each extra feature still **requires systems and infrastructure to collect that data, store it, manage updates,** etc, which adds cost and complexity to the overall system. That includes monitoring for problems with the data and the effort to fix those problems if and when they happen. Those costs continue for the lifetime of the product or service that you're deploying, which could easily be years.

A note about neural networks

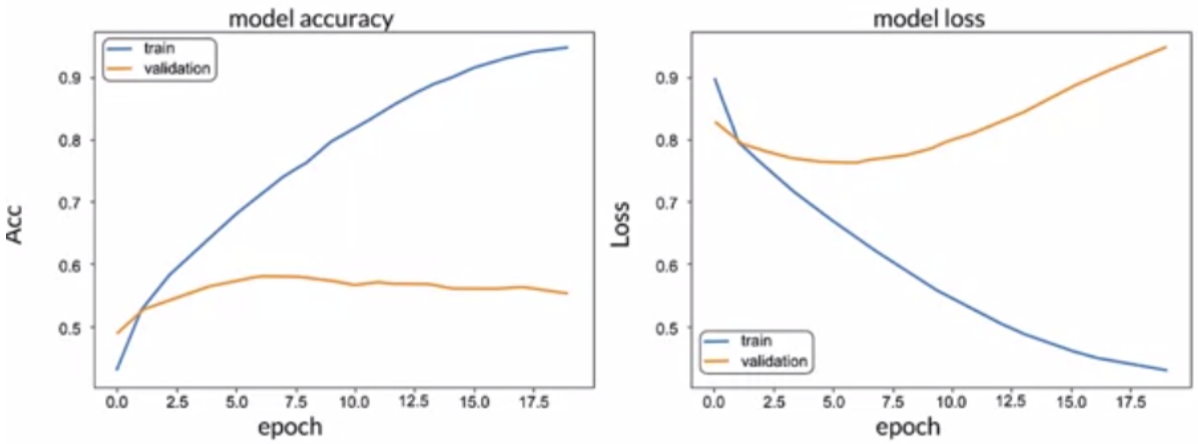
- Yes, neural networks will perform a kind of automatic feature selection
- However, that's not as efficient as a well-designed dataset and model
  - Much of the model can be largely "shut off" to ignore unwanted features
  - Even unused parts of the consume space and compute resources
  - Unwanted features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

In this case we have one dimension for each color channel in each pixel of the image. Some feature representations such as one hot encoding are problematic for working with text in high dimensional spaces as they tend to produce very sparse representations that do not scale well. One way to overcome this is to use an embedding layer that tokenizes the sentences and assigns a float value to each word. This leads to a more powerful vector representation that respects the timing and sequence of the words in a given sentence. This representation can be automatically learned during training. The cube labeled embedding layer in this figure is a conceptual representation of those vectors in a high dimensional space.

Let's start by **loading the necessary libraries** and modules into finding some important **parameters**. The reuters news data set that we will be working with contains 11,228 newswires labeled over 46 topics. The documents are already encoded in such a way that each word is indexed by an integer, its overall frequency in the data set. While loading the data set, we specify the number of words will work with 1000 so that the least repeated words are considered unknown.

Let's further **pre-process the data,** so it's ready for training a model. First this converts the training vector Y into a categorical variable for both train and test. Next, the code segments the input text into 20 word long sequences. Building the network is the next logical step. So here the choice is to embed a 1000 word vocabulary using all dimensions, here we're using all the dimensions of the data. The last layer is dense with dimension 46 since the target variable is a 46 dimensional vector of categories.

Example with a higher number of dimensions



Here is the accuracy as a function of training epics and the model loss as a function of training epics. **Notice that after about two epics are training data results in significantly higher accuracies and lower losses compared to the validation set. This is a clear indication that the model is severely overfitting**, this may be the **result of using all the dimensions of the data. So the model is picking up nuances in the training set that do not generalize well.** Let's try reducing the dimensionality and see how this affects model performance. For that let's embed a 1000 word vocabulary into 6 dimensions, this is roughly a reduction of a fourth root factor. The model remains unchanged otherwise. There may still be some overfitting, but with that one change, this model performs significantly better than the 1000 dimension version.

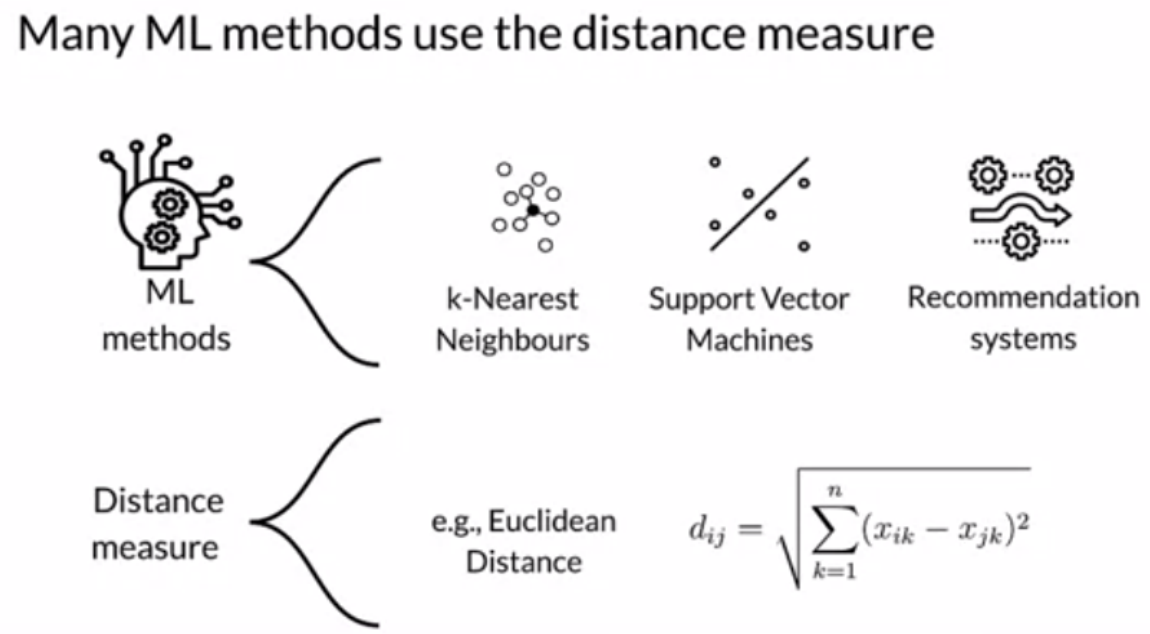
```
import tensorflow as tf
from tensorflow import keras
import numpy as np
from keras.datasets import reuters
from keras.preprocessing import sequence
num_words = 1000

(reuters_train_x,reuters_train_y),(reuters_test_x,reute
rs_test_y) =
tf.keras.datasets.reuters.load_data(num_words=num_words
)
n_labels = np.unique(reuters_train_y).shape[0]

from keras.utils import np_utils
reuters_train_y =
np_utils.to_categorial(reuters_train_y,46)
```

```
reuters_test_y =
np_utils.to_categorial(reuters_test_y,46)

reuters_train_x =
tf.keras.preprocessing.sequence.pad_sequences(reuters_t
rain_x,maxlen=20)
reuters_test_x =
tf.keras.preprocessing.sequence.pad_sequences(reuters_t
est_x,maxlen=20)

from tensorflow.keras import layers

model = tf.keras.Sequential(
    [
        layers.Embedding(num_words, 1000,
input_length=20),
        layers.Flatten(),
        layers.Dense(256),
        layers.Dropout(0.25),
        layers.Activation('relu'),
        layers.Dense(46),
        layers.Activation('softmax')
    ]
)

model.compile(loss="categorical_crossentropy",
optimizer="rmsprop", metrics=["accuracy"])
model_1 = model.fit(reuters_train_x,reuters_train_y,
validation_data=(reuters_test_x,reuters_test_y),
batch_size=128, epochs=20, verbose=0)
```

Curse of Dimensionality

Many common machine learning tasks like segmentation and clustering rely on computing distances between observations.

For example, supervised classification uses the distance between observations to assign a class, k-nearest neighbors is a basic example of this. Support vector machines or SVMs deal with projecting observations using kernels based on the distance between the observations after projection. Another example is recommendation systems that use a distance based similarity measure between the user and the item attribute vectors. There could even be other forms of distance being used. So distance plays an important role in understanding dimensionality.
One of the most common distance metrics is **Euclidean distance**, which is simply a linear distance between two points in a multi-dimensional space. The Euclidean distance between two dimensional vectors with Cartesian coordinates is calculated using this familiar formula.



In extreme cases where we have **more features and observations**, we run the risk of massively **overfitting our model**. But in the more general case when we have **too many features, observations become harder to cluster.**
Too many dimensions can cause every observation in your data set to appear equidistant from all the others. And because clustering using a distance measures such as Euclidean distance to quantify the similarity between observations, this is a big problem. If the distances are all approximately equal, all the observations appear equally alike and no meaningful clusters can be formed. **As dimensionality grows, the contrast provided by the usual metrics decreases**. In other words, **the distribution of norms in a given distribution of points tends to concentrate. That can cause unexpected behavior in high dimensional spaces. This phenomenon is called the curse of dimensionality.**

Why is high-dimensional data a problem?

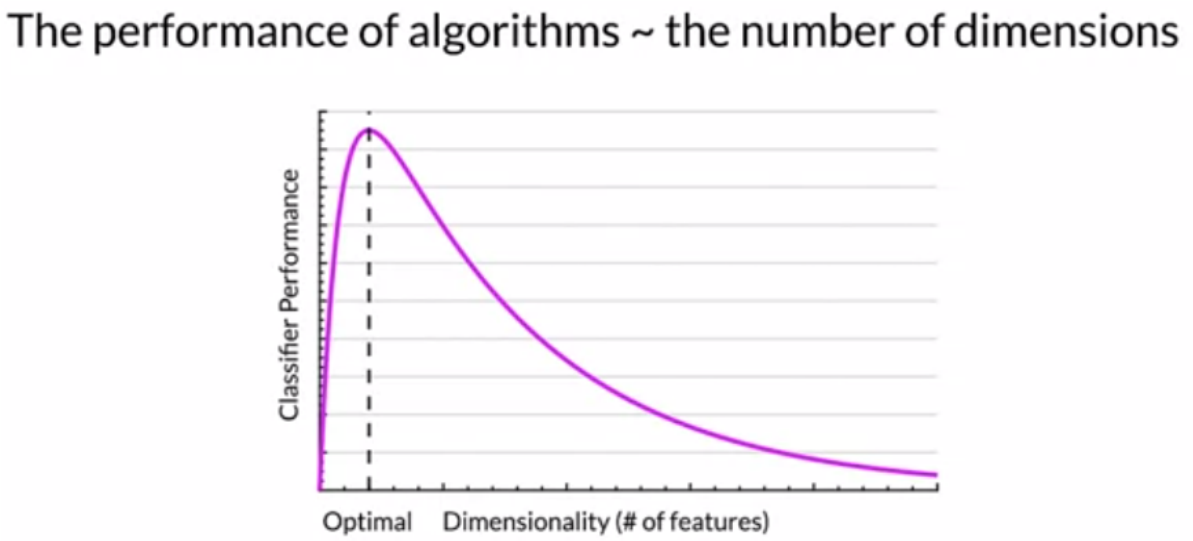
- More dimensions → more features
- Risk of overfitting our models
- Distances grow more and more alike
- No clear distinction between clustered objects
- Concentration phenomenon for Euclidean distance

It includes situations where non-intuitive properties of data are observed in these high dimensional spaces. This is specifically related to the usability and interpretation of distances and volumes. When it comes to the curse of dimensionality, there are two things to consider. **On the one hand**, machine learning is good at analyzing data when dealing with many dimensions. However, we humans aren't adept at finding patterns and data that may be spread out across several dimensions, especially if those dimensions are interrelated in counterintuitive ways. O**n the other hand,** as we add more dimensions, we also increase the processing power we need to analyze the data and at the same time we also increase the amount of training data required to make meaningful models. If you're curious, Richard Bellman first coined the term curse of dimensionality over half a century ago in 1961 in his book Adaptive Control Processes, A Guided Tour. So adding more features can easily create problems. This could include **redundant or irrelevant features** appearing in data. Moreover, **noise is added when features don't provide predictive power for our models**. On top of that, **more features make it harder for one to interpret and visualize data**. Finally, **more features mean more data, so you need to have more storage and more processing power to process it**. Ultimately, **having more dimensions often means our model is less efficient.**

Why are more features bad?

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

When you have problems getting your model to perform, you are often tempted to try adding more and more features. But as you add more features, you reach a certain point where your model's performance degrades. This graph shows this well. Here you see that as the dimensionality increases, the classifiers performance increases until the optimum number of features is reached.

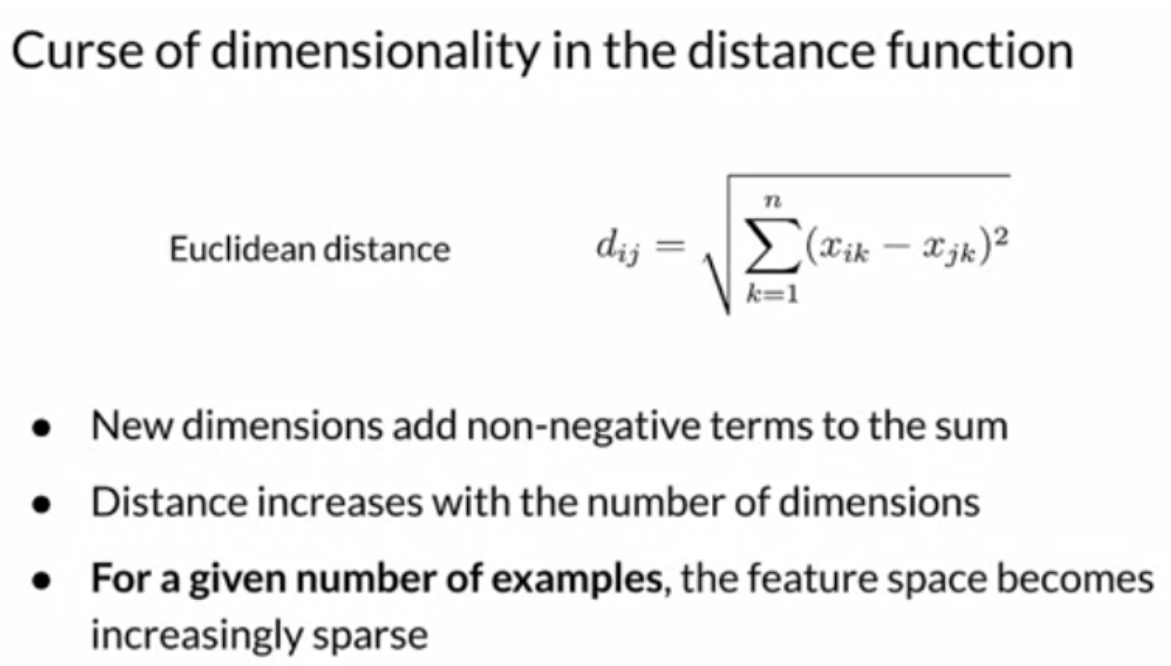


A key point to understand here is that you are increasing the dimensionality without increasing the number of training samples and that results in a steady decrease in classifier performance after the optimum. Let's look at another problem with dimensionality to uncover what is behind this behavior. Let's look deeper to try to understand why more dimensions can hurt your models.

Let's start by understanding **why the number of parameters of a function impact the difficulty of learning that function.**

Take for example, the parameters of a line function. In this case the list is finite. It simply means discretizing the features. Let's simplify this by using numbers from 1-5. Assuming that you have a function with a single parameter, then there are only five possible values that this parameter can take. What happens if you add a second parameter that can also take five values. Well, let's see. There are now 5 times 5 or 25 possible pairs. This is a simple example using discrete parameter values, but of course it's even worse with continuous variables. What happens if you had a third parameter? Now the representation is a cube, you probably see the formula behind this reasoning. If we have n values that a parameter can take and m parameters, you end up with n to the m possible parameter values. The number of parameter values grows exponentially. Now, how big of a problem is it? Well, it's a very big problem indeed which is why this is called the curse of dimensionality. **An increase in the number of dimensions of a data set means there are more entries in the feature vector representing each training example.**

Let's focus on a Euclidean space and Euclidean distance measure. Each new dimension adds a non-negative term to the sum, so the distance increases with the number of dimensions for distinct factors. In other words, **as the number of features grows for a given number of training examples, the feature space becomes increasingly sparse with more distance between training examples. Because of that the lower data density requires more training examples to keep the average distance between data points the same.**



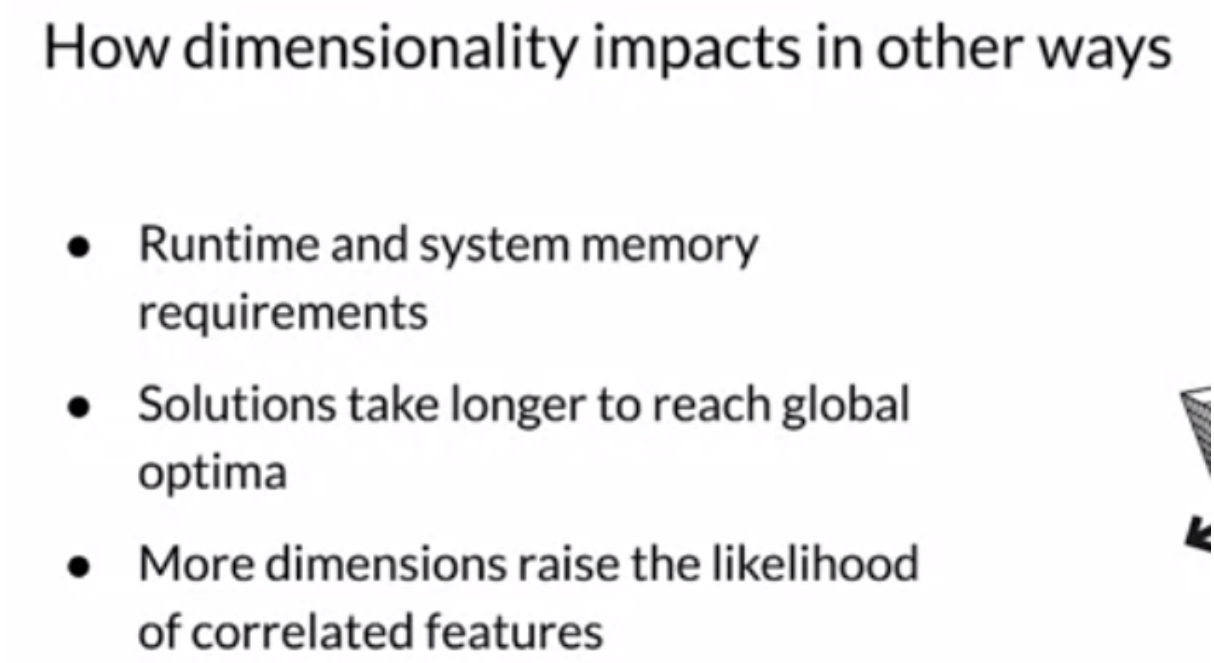
It's also important that the examples that you add are significantly different from the examples that you already have that are already present in the sample. Here the argument is built using Euclidean distance, but it is true for any properly defined distance measure.

When the distance between observations grows, supervised learning becomes more difficult because **predictions for new samples are less likely to be based on learning from similar training examples. The size of the feature space grows exponentially as the number of features increases making it much harder to generalize efficiently. The variance increases and there's a higher chance of overfitting to noise in more dimensions resulting in poor generalization performance**.
In practice, features can also be **correlated** or do not exhibit much variation. For these reasons, there is a need to reduce dimensionality. The challenge is **to keep as much of the predictive information as possible using as few features as possible**.
Regardless of which modeling approach you're using, increasing dimensionality has another problem especially for **classification** which is known as the **Hughes effec**t. **This is a phenomenon that demonstrates the improvement in classification performance as the number of features increases until we reach an optimum where we have enough features**. **Adding more features while keeping the training set the same size will degrade the classifiers performance.** We saw this earlier in our graph. In classification, the goal is to find a function that discriminates between two or more classes. You can do this by searching for hyperplanes in space that separate these categories. The more dimensions you have, the easier it is to find a hyperplane during training, **but at the same time the harder it is to match that performance when generalizing to unseen data.** And the less training data you have, the less sure you are that you identify the dimensions that matter for discriminating between categories.

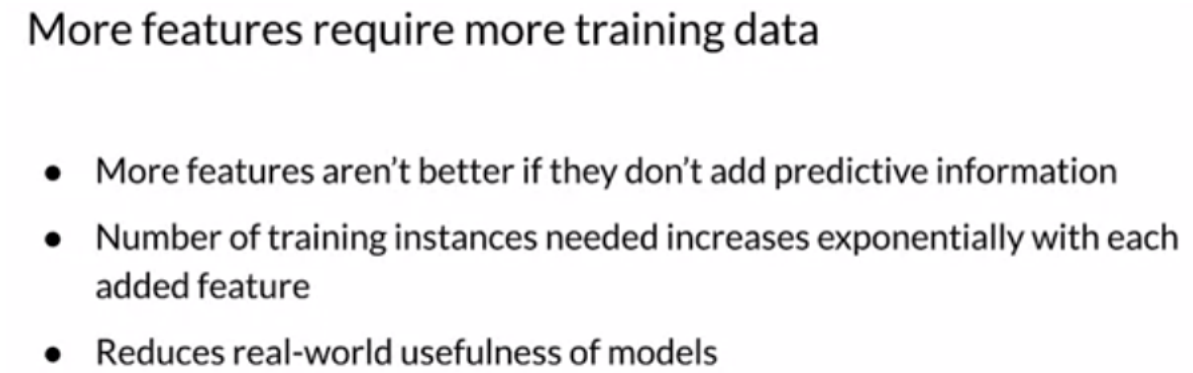
Curse of Dimensionality

Let's look at an example of how dimensionality reduction can help our models perform better, apart from distances and volumes. Increasing the number of dimensions can create other

problems. **Processor and memory** requirements often scale non linearly with an increase in the number of dimensions, due to an exponential rise in feasible solutions many optimization methods cannot reach a global optima and get stuck in a local optima. More dimensions also often increases the likelihood of having correlated features and parameter estimation can often be challenging in regression models.

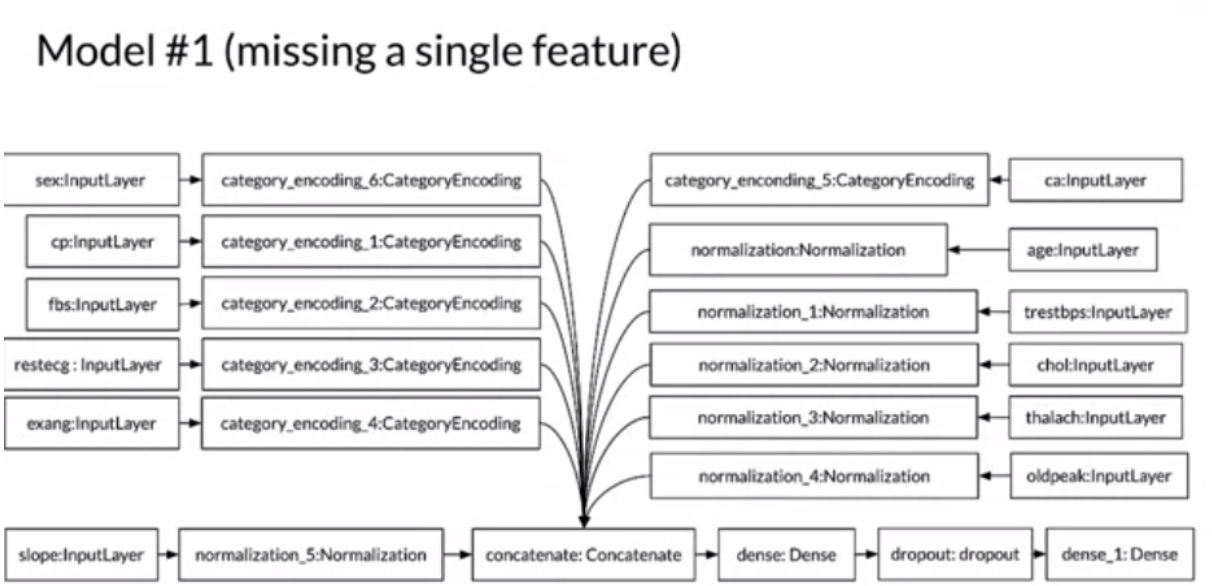


So let's look at how more features can make training a model harder. With an example, when you create a model, you design it for a certain number of features or dimensions, you might be tempted to add more features to get a better model, but more features can actually hurt your model. Each feature holds information that may or may not help your model predict accurately, **as you add more and more features, you need to add more and more training examples along the range of values for those features.** The amount of training data needed increases exponentially with each added feature. That means that t**he volume of training data increases exponentially.** And we need to make sure that the **training data covers the same regions of the feature space as the prediction requests that will receive,** all of these can reduce the ability of your model to generalize Well, along with this, the number of trainable variables in the model also increases.



To demonstrate this, let's look at an example of a binary classification model for the Cleveland heart disease data set when a single additional feature is added. Let's start by creating a structured classification model for the Cleveland heart disease data set. This dataset has 14 features to predict whether or not a patient has heart disease. This is a binary classification

problem. This first model omits one of the original features called foul, go look at this and how adding a feature to the dataset impacts the number of trainable variables in the model. So let's add back that signal additional feature that we removed in the first model. For this let's encode this as a categorical string feature using Keras preprocessing layers which is available in tensorflow. Next, let's see how adding it impacts your original model in terms of the number of trainable parameters. If you compare the number of trainable parameters between the two, even adding only one feature results in a 27% increase. That's a considerable growth in the number of parameters to say the least. That will make training slower and more expensive. You'll also need to increase the size of the training data set which will make the training even slower and more expensive.



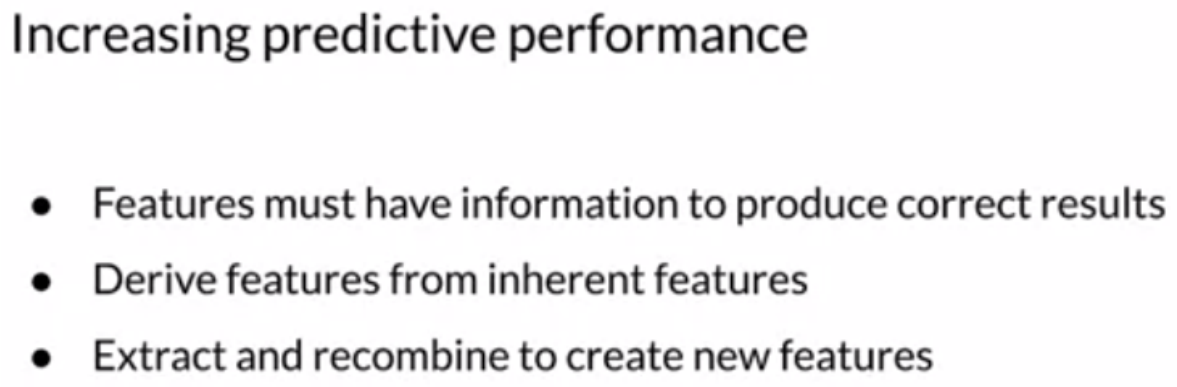

```
from tensorflow.python.keras.utils.layer_utils import count_params

# 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
```

The main point in this section is that when data dimensionality becomes too large, the performance of a classifier decreases and the demand for resources increases. The question, that is, w**hat does too large really mean**? Unfortunately, there is **no fixed rule** for how many features should be used in a machine learning problem. In fact, this depends on the **amount of training data available,** the **variance in that data, t**he **complexity of the decision surface and the type of classify are used.** It also **depends on which features actually contain predictive information** that will help your model train. You want enough data with the best

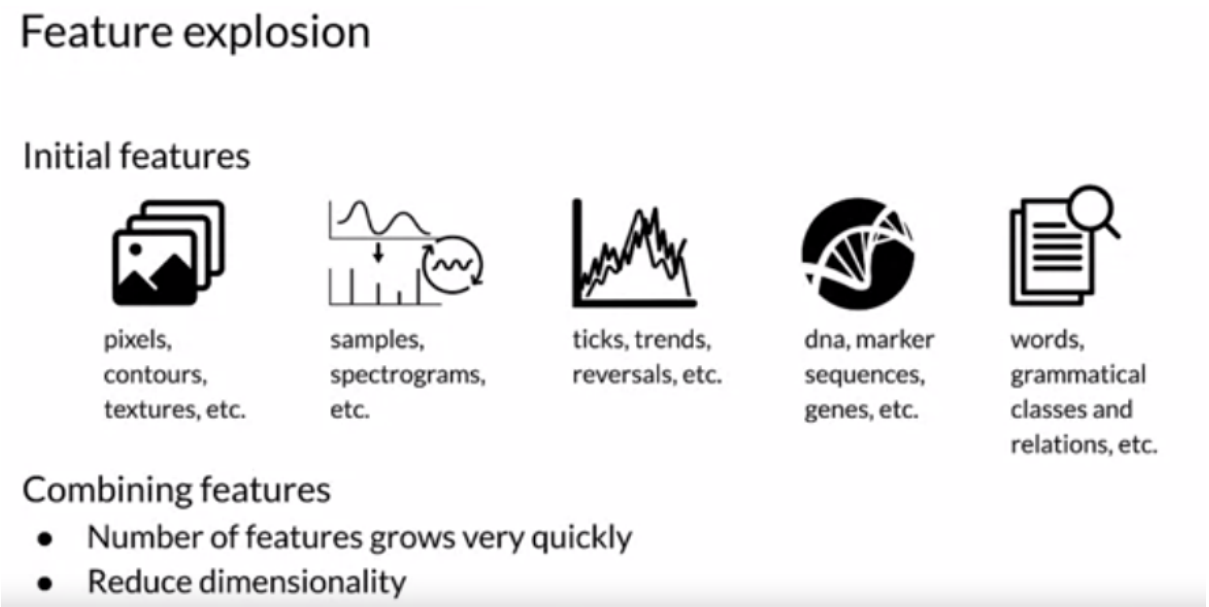
features and enough variety in the values of those features and enough predictive information in those features to maximize the performance of your model while simplifying it as much as possible.

Manual Dimensionality

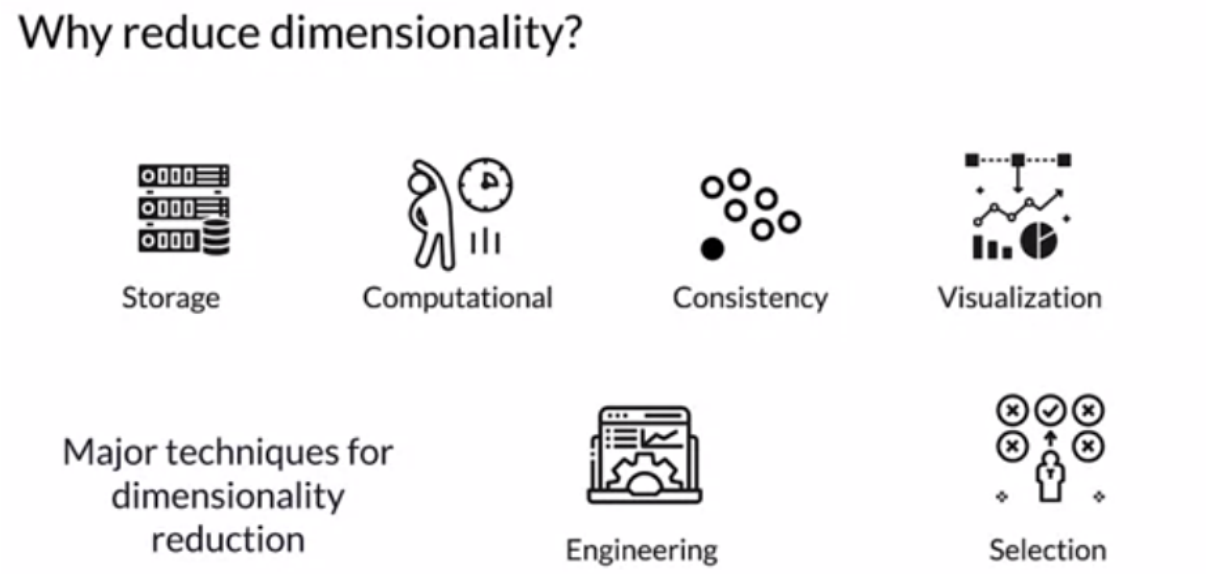
When pre processing a set of features to create a new feature set, it's important to retain as much predictive information as possible, without predictive information all the data in the world won't help your model learn. Features must be representative of the predictive information in the data set. This information also needs to be **in a form that will help your model learn**. While some inherent features can be obtained **directly from raw data,** you often need **derived features, normalized, engineered or embedded features**. A poor model fed with important features will perform better than a fantastic model fed with low quality or bad features.



Many domains involve huge numbers of features and dimensions. Often the first pick of features is an expression of domain knowledge, that can often result in more features than we really need or want. As we saw in our discussion of the curse of dimensionality this has inherent drawbacks. This means that you need to reduce dimensionality, or more precisely, the number of features you're including in your dataset while retaining or improving the amount of predictive information contained in the data.



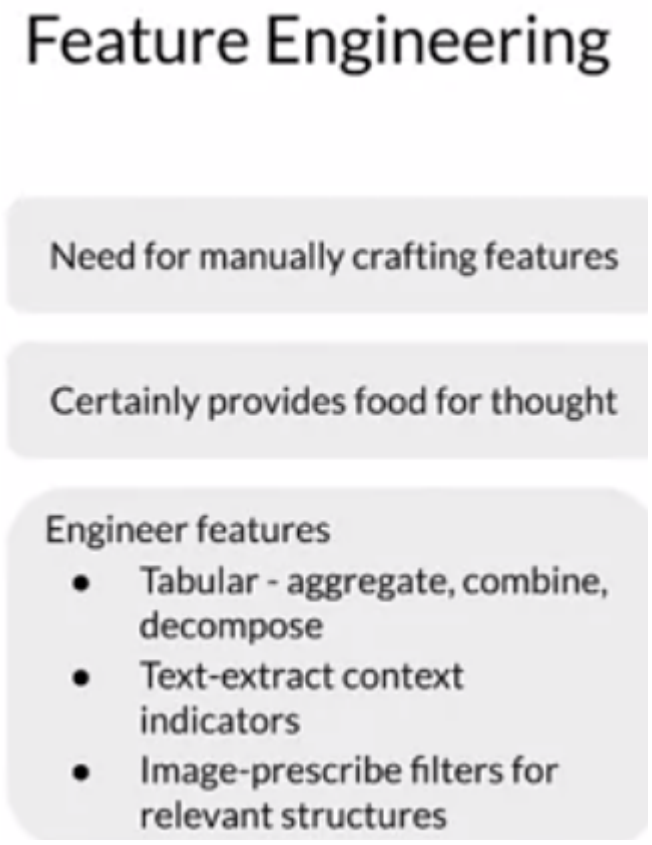
Dimensionality reduction looks for patterns and data and uses these patterns to re express the data in a lower dimensional form. This makes computation much more efficient, which can be a significant factor in a world of big models and big data sets. However, dimensionality reductions most essential function is to **reduce the data set to its bare bones, discarding noisy features that cause significant problems for supervised learning tasks like regression and classification.** In many real world applications it is the dimensionality reduction that makes predictions possible. Your data collection and management infrastructure will be simplified, also. Another factor to consider is that some algorithms do not perform well when we have large dimensions. It also reduces multicollinearity by removing redundant features, it helps when we're trying to visualize the data. And as we discussed earlier, it isn't easy to visualize data in higher dimensions, so reducing our space to 2D or 3D may help us to plot and observe patterns more clearly.



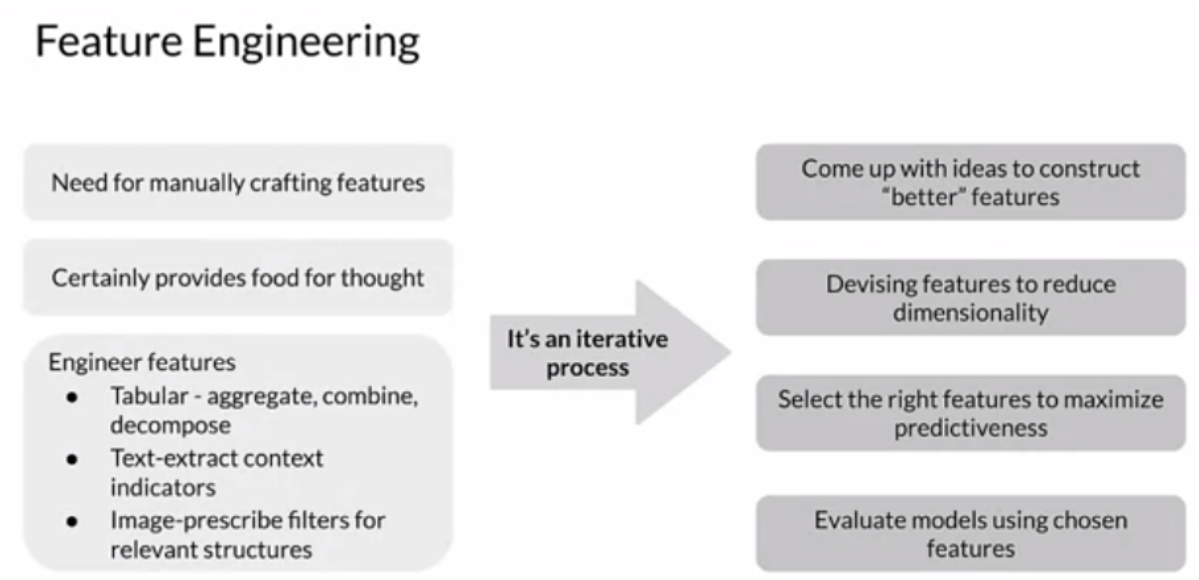
Feature engineering helps meet these requirements. It builds valuable information from raw data by **reformatting**, **combining** and t**ransforming primary features into new** ones until it yields a new set of data that results in a better model. In addition, **features selection examines** a set of potential features, select some of them and discards the rest. **Feature selection is**

applied either to prevent redundancy and or to remove irrelevancy in the original features or just get to a limited number of features to avoid issues.

The best results come down to you, the practitioner crafting the features. This is one of the areas where machine learning engineering is somewhat of an art form. **Feature importance** and **feature selection** can help inform you about the objective utility of features, but those features have to come from somewhere. You often need to manually create them. This requires spending a lot of time with the actual sample data and thinking about the **underlying form of the problem,** the **structures in the data a**nd how best to **express them for predictive modeling** algorithms. With tabular data It often means a mixture of aggregating and or combining features to create new features and decomposing or splitting features to also create new features. With textual data, it often means devising document or content specific indicators relevant to the problem. With image data, it can often mean using filters to pick out relevant structures like pixels, contours, shapes and textures.



It tends to be an iterative process that involves data selection and model evaluation again and again. The process usually starts with brainstorming features. Here you really get into the problem, look at a lot of data, study feature engineering on other problems and see what you can learn. Then you move on to devising new features. It depends on your problem, but you may use automatic feature extraction, manual feature engineering or a mixture of the two. Next you pick the right features using feature important scoring and feature selection methods to prepare one or more views of your data. Finally, you measure the model's performance on unseen data using the chosen features.



Manual Dimensionality reduction

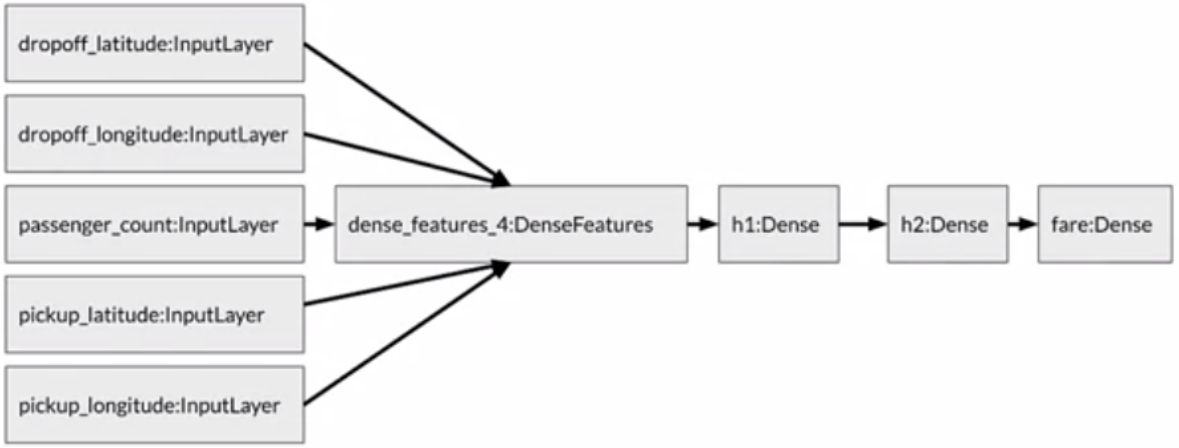
The data set consists of 106,545 taxi rides. The objective is to predict the fair amount of each ride based on a variety of features such as time and location of pickup, time travel and distance, number of passengers etcetera. As usual, the first steps are downloading the data set which is in CSV format separating the variables into string and numeric types and defining useful constants and parameters. Let's build a baseline model to predict the fair. We'll try using these features. Drop off, latitude, drop off longitude passenger count, pick up latitude and pick up longitude. The network consists of a concatenation of dense hidden layers with the last one producing a fair prediction output. We'll build the model in Keras using the functional API Unlike the sequential API you'll need to specify the input and hidden layers. Note that you're creating a linear regression baseline model with no feature engineering as a quick reminder, a baseline model is a naive implementation that helps with setting expectations for model performance. After setting up the model for training and creating the data sets, you're ready to train the baseline model. To train the model simply call model dot fit. Let's look at training and validation performance using the root mean squared error loss over the trading epics, ideally you want the validation RMSE to be close to the training set. Now, let's try to improve the model. To improve the model's performance, let's create two new feature, engineering types, temporal and geographical, for example, will work with the temporal feature, pick up date time as a string and we will need to handle this within the model. First, you'll include pickup date time as a feature and then you'll need to modify the model to handle it as a string feature. The pickup or drop off longitude and latitude data are crucial to predicting the fair amount since fair amounts in new york city taxis are largely determined by the distance traveled. As such we need to teach the model of the Euclidean distance between the pickup and drop off points. Recall that latitude and longitude allows us to specify any location on Earth using a set of coordinates. The dataset contains information regarding the pickup and drop off coordinates. However, there is no information regarding the distance between the pickup and drop off points. So let's create a new feature that calculates the distance between each pair of pick up and drop off points. You can do this using the Euclidean distance, which is a straight line distance between any two coordinate points, but note that this will only be a rough indicator of the actual driving distance. It's very important for numerical variables to get scaled before they're fed into the neural network. Let's use min max

scaling, also called normalization on the geo location features. Later in our model, you'll see that these values are shifted and re scaled so they end up ranging from 0 to 1. We'll use domain knowledge to create a function named scale longitude where you pass all the longitude values and add 78 to each value. Note that are scaling longitude values range from negative 72 negative 78. So the value 78 is the maximum longitudinal value. The difference or delta between negative 70 and negative 78 is eight. The function adds 78 to each longitudinal value and then divides by eight to return a scaled value. Similarly, let's create a function named scale latitude where you pass in all the latitudinal values and subtract 37 from each value. Note that are scaling latitude range is from 37 to 45. Thus the value 37 is the minimal latitudinal value. The delta or difference between negative 37 and negative 45 also happens to be eight. The function that subtracts 37 from each latitudinal value, and then divides by eight to return a scaled value. Next let's create a geo transform function. This function passes in your numerical and string column features as inputs to the model and then scales the longitude and latitude as we saw in the last slide. Then we compute the Euclidean distance based on the geo location parameters. Unless the specific geometry of the earth is relevant to your data, a bucketized version of the map is likely to be more useful than the raw inputs. This requires bucketizing the dimensions of latitude and longitude separately and then cross them effectively doing a two dimensional bucketizing of location data. In this example you bucketize these latitude and longitude features and create feature crosses out of the geo locational features here the code creates bucket sized columns for pick up and drop off latitude and longitude and then proceeds to create crossed columns for each. The code combines these results in an embedding comb. This is the new architecture of your model. As with your first attempted model, you need to create a model in Keras is using the functional API. This will, of course, leverage all the feature engineering that you've done so far. Let's take a look at the performance of this new model. Looking at the results for training and validation. It's clear that the model with feature engineering on the right is a significant improvement over the baseline model on the left.

Principle Compoments Analysis

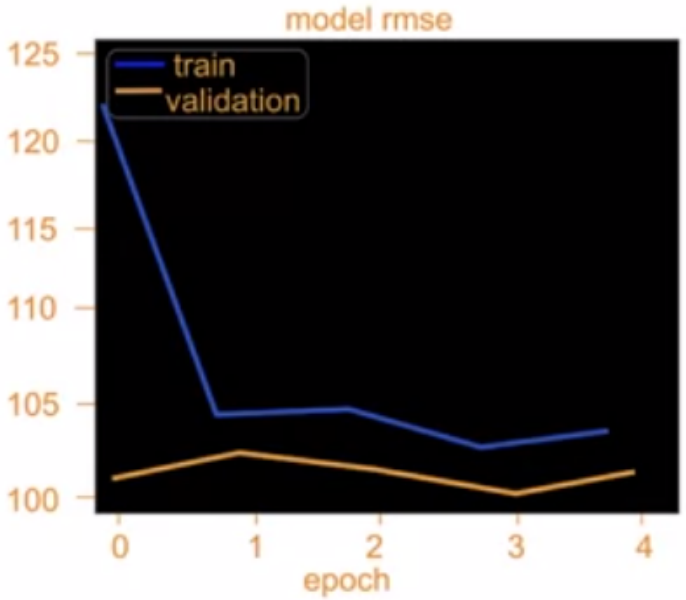
```
CSV_COLUMNS = [
    'fare_amount',
    'pickup_datetime', 'pickup_longitude', 'pickup_latitude',
    'Dropoff_longitude', 'dropoff_latitude',
    'passenger_count', 'key',
]

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




```
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




```
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)
```

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

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

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

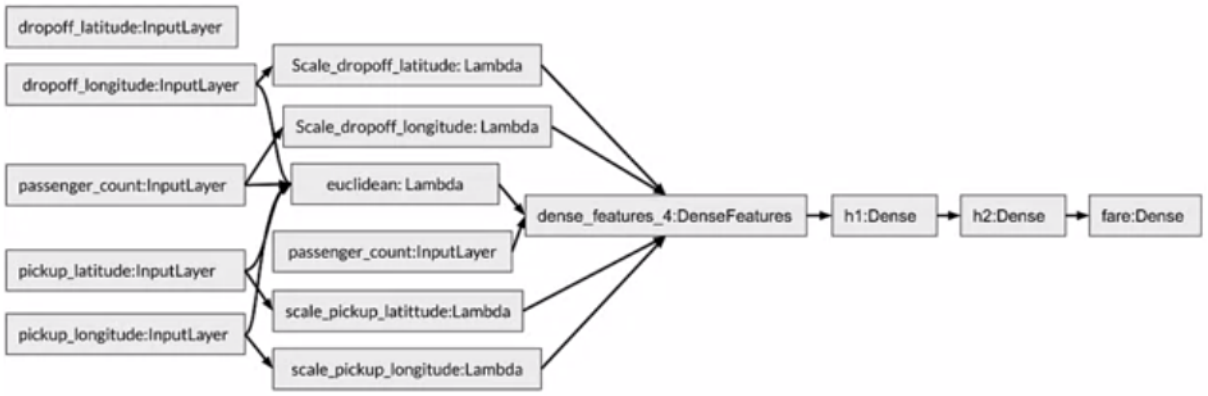
```
def transform(inputs, numeric_cols, string_cols, nbuckets):
    ...
    transformed['euclidean'] = layers.Lambda(
        euclidean,
        name='euclidean')([inputs['pickup_longitude'],
                           inputs['pickup_latitude'],
                           inputs['dropoff_longitude'],
                           inputs['dropoff_latitude']])
    feature_columns['euclidean'] = fc.numeric_column('euclidean')
    ...
```

```
def transform(inputs, numeric_cols, string_cols, nbuckets):
    ...
    transformed['euclidean'] = layers.Lambda(
        euclidean,
        name='euclidean')([inputs['pickup_longitude'],
                           inputs['pickup_latitude'],
                           inputs['dropoff_longitude'],
                           inputs['dropoff_latitude']])
    feature_columns['euclidean'] = fc.numeric_column('euclidean')
    ...
```

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)
```

Build a model with the engineered features



Algorithmic Dimensionalit Reduction

In addition to manually reducing the dimensionality of your datasets, you can also apply several **algorithmic approaches** to do dimensionality reduction. Let's look at some of those now. Let's look at techniques that you can use to reduce dimensionality **automatically**.

First, let's build some intuition on how **linear dimensionality reduction actually works**. In this approach, you linearly project **n-dimensional data** onto a **smaller k- dimensional subspace**. Here**, k is usually much smaller than n.** There are infinitely many dimensional subspaces that we can project data onto. Which subspace do we choose? To understand how sub-spaces are chosen. Let's take a step backwards and look how one can **project data onto a line**. To start, let's think of features as vectors existing in a high-dimensional space. Visualizing them would reveal a lot about the distribution of the data though it's impossible for us humans to see so many dimensions all at once. Instead, you need to project the data onto a lower dimension, which

might allow you to visualize the data more directly. **This projection is called an embedding. Computing this requires taking each sample and calculating a single number to describe it. A benefit of reducing to one-dimension is that the numbers and the examples can be sorted on a line.** In this example, we're taking images and reducing the information they contain to just one-dimension their average pixel brightness, which we can then visualize as a point on a line. Coming back to subspaces, there are s**everal ways to choose these k-dimensional subspaces.** For example, in a **classification** tests, you typically want to have the maximum separation among classes. **Linear discriminant analysis, or LDA,** generally works well for that. For **regression**, you want to maximize the correlation between the projected data and the output, where **Partial least squares, or PLS,** works well. Finally and **unsupervised** tasks, we typically want to retain as much of the variance as possible. **Principal component analysis, or PCA,** is the most widely used technique for doing that.

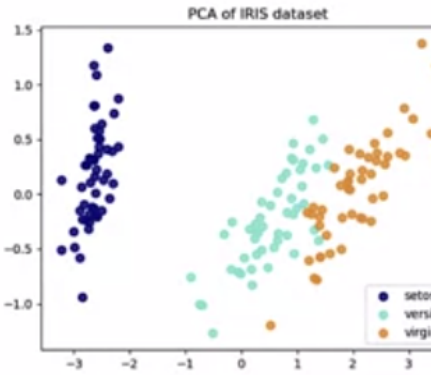
PCA

- unsuperviesed algorithm that creates linear combination of the original features.
- keep as much as variance as possible from original data in a low dimensional space
- only for square matrices
- steps
    - **decorrelation**
        - **PCA rotates the samples so that they are aligned with the coordinate axes**.
        - **PCA also shifts the samples so that they have a mean of zero.**
        - **PCA is called principal component analysis because it learns the principal components of the data. It is the principal components that**

PCA aligns with the coordinate axis.

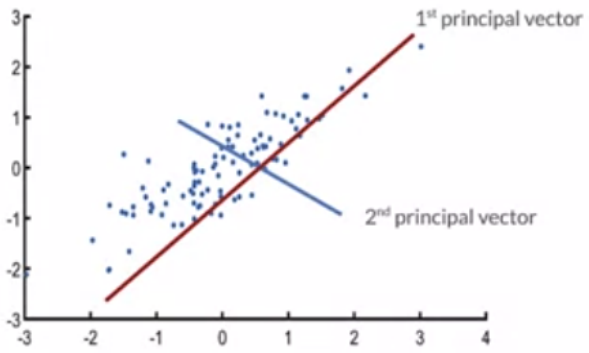
Principal component analysis (PCA)

- PCA is a minimization of the orthogonal distance
- Widely used method for unsupervised & linear dimensionality reduction
- Accounts for variance of data in as few dimensions as possible using linear projections



Principal components (PCs)

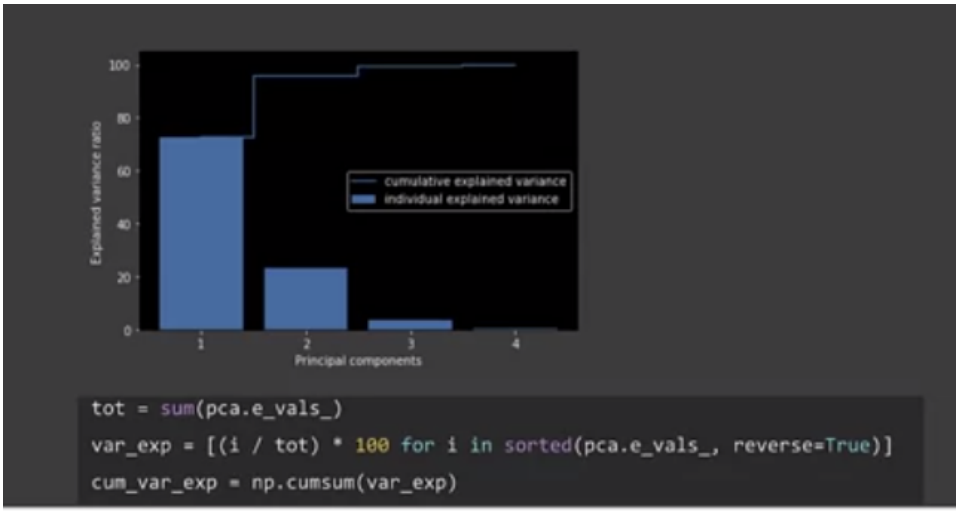
- PCs maximize the variance of projections
- PCs are orthogonal
- Gives the best axis to project
- Goal of PCA: Minimize total squared reconstruction error



goal

- find a lower dimensional surface onto which to project the data so as to **minimize the squared projection error/** to minimize the square of the distance between each point and the location of where it gets projected.
- The result will be to **maximize the variance of the projections. The first principal component is the projection direction that maximizes the variance of the projected data. The second principal component is the projection direction that is orthogonal to the first principal component and maximizes the remaining variance of the projected data**. Here's a toy example consisting of a cloud of points in 2D. Let's try to apply PCA to this two-dimensional data and see what happens. The first principal component is a projection direction that maximizes the variance of the projected data. In

the plot, you can see three attempts at producing such a line. In this case, it's quite obvious that the variance is maximized in the direction indicated by the red line. The second principal component is the projection direction that is orthogonal to the first principal component and maximizes the remaining variance of the projected data indicated here by the green line. The full set of principal components comprises a new orthogonal basis for feature space whose axis follow the maximum variances of original data. These projections are simply transformed to the new k-dimensional reduced space. This reconstruction will of course, have some amount of **error**, but this is often **negligible** and **acceptable** given the other benefits of dimensionality reduction.Now assuming you've applied PCA again using four components instead of two, let's visualize how much variance has been explained using these four components. If you look at the relative variance, you might lose some information, but if the **eigenvalues are small**, **not much information is lost. Principal components** are orthogonal in nature as we've seen before and this means that they are **uncorrelated.** Also, they are **ranked in order of their explained variance. The first principle component explains the most variance in the dataset, and the second explains the second most variance and so on. Therefore, you can reduce dimensionality by limiting the number of principal components to keep based on the cumulative explained variance.**



The factor loadings are the unstandardized values of the eigenvectors. We can interpret the loadings as the covariances or correlations. Scikit-learn has an implementation of PCA which includes both fit and transform methods, just like the standard scalar operation, as well as a fit transform method which combines both fit and transform. The **fit** method learns how to shift and rotate the samples, but it doesn't actually change them. The **transform** method, on the other

hand, applies the transformation the fit learned. In particular, the transfer method can be applied to new unseen samples.

```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn import datasets

# Load the data
digits = datasets.load_digits()

# Standardize the feature matrix
X = StandardScaler().fit_transform(digits.data)
```

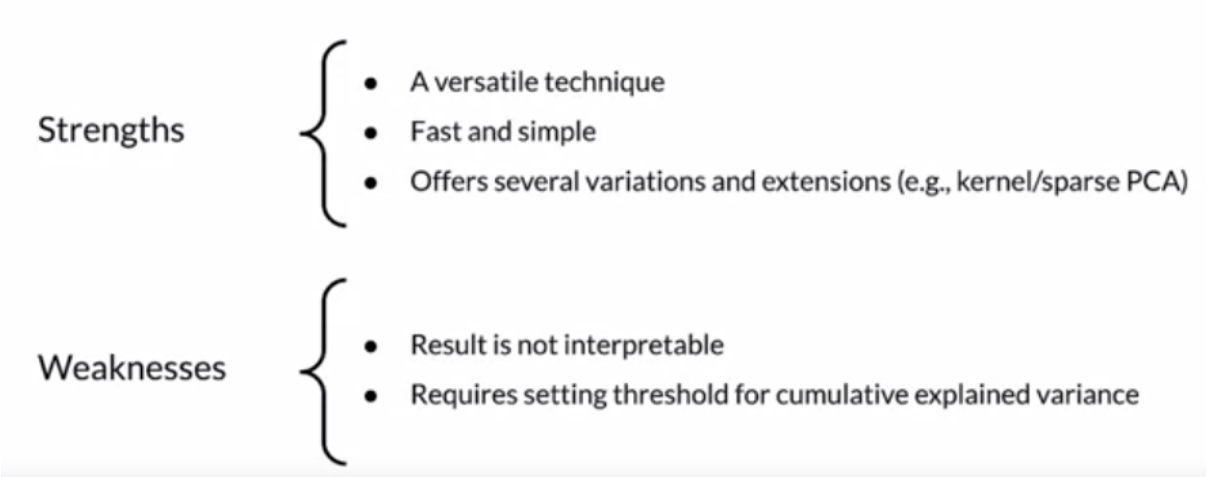
Before applying PCA, let's use the **standard scaler** on the features. This code creates a PCA instance that will retain 99 percent of the variance fitted to the data and apply the transform which was learned.

```
# Create a PCA that will retain 99% of the variance
pca = PCA(n_components=0.99, whiten=True)

# Conduct PCA
X_pca = pca.fit_transform(X)
```

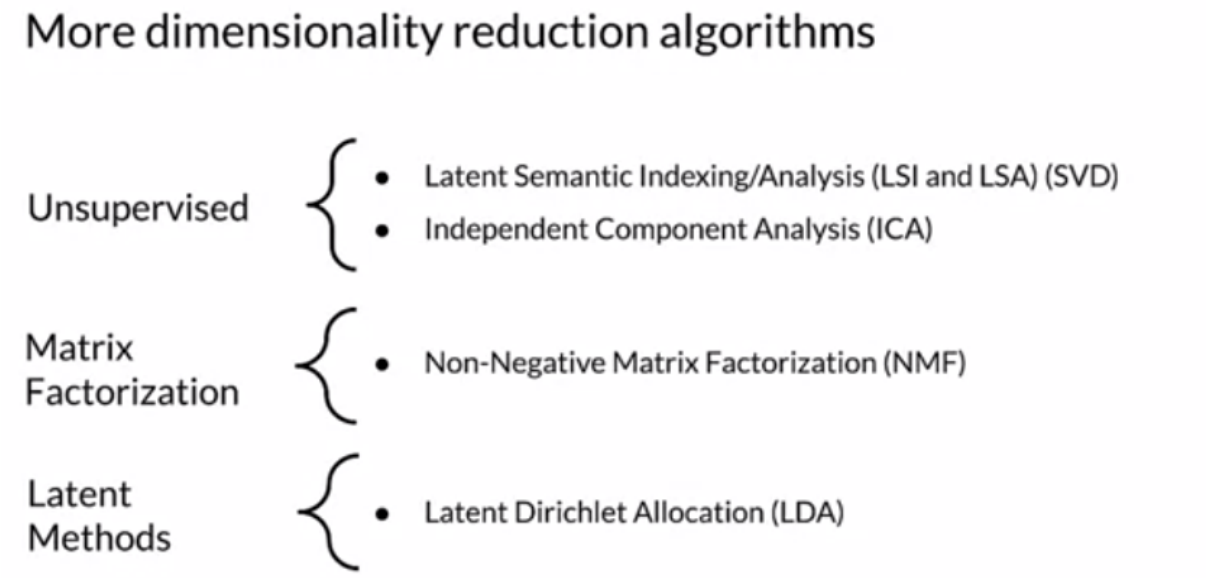
Summary:

- It's fast and **simple** to implement, which means you can easily test algorithms with and without PCA to compare performance.
- PCA offers several variations and **extensions**. For example, kernel PCA or sparse PCA, etc., to tackle specific roadblocks.
- However, the resulting principal components are **not interpretable**, which may be a deal breaker in some settings where interpretability is important.
- In addition, you must still **manually** set or tune a threshold for cumulative explained variance. Other than this, PCA is especially useful when visually studying clusters of

observations in high dimensions. This could be when you are still exploring the data. For example, you may have reason to believe that the data are inherently low rank, which means that there are many attributes, but only a few attributes which mostly determine the rest through a linear association.



Other Techniques



- **single value decomposition or SVD**

- in some cases, rare words contribute more. In general, the importance of words increases if the number of occurrences of these words within the same document also increases. On the other hand, the importance will be decreased for words which occur frequently in the corpus. The challenges that the resulting matrix is **very sparse and not square.** To decompose these types of matrices, which can't be decomposed with eigendecomposition, we can use techniques such as singular value decomposition or SVD. SVD decomposes our original dataset into its constituents, resulting in a reduction of dimensionality, it's **used to remove redundant features** for the dataset. Independent component analysis

- SVD decomposes non-square matrics
- useful for sparse matrics as prduced by TF-IDF
- removes redundant features from the dataset

independent component analysis or ICA.

- looks for **independent** factors.
    - uncorrelated
        - no linear relation between them.
    - independent,
        - not dependent on other variables.
- separates a multivariant signal into **additive components** that are maximally independent
- separating superimposed signals 叠加信号. Since the model does not include a noise term, for the model to be correct, **whitening** must be applied. This can be done in various ways, including using one of the **PCA variants**.
- ICA further assumes that there exists independent signals, S, and a linear combination of signals, Y. The goal of ICA Is to recover the original signals, S, from Y, ICA assumes **that the given variables are linear mixtures of some unknown latent variables**. It also assumes **that these latent variables are mutually independent.** In other words,

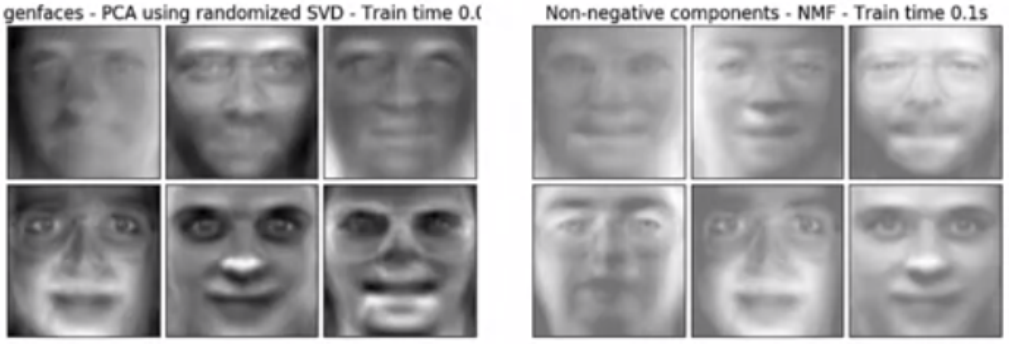
comparation PCA and ICA

- Let's compare PCA and ICA visually to get a better understanding of how they're different. Both are statistical transformations, that is PCA uses information extracted from second order statistics, while ICA goes up to higher order statistics. Both are used in various fields like **blind source separation**, **feature extraction** and also in **neuroscience**. ICA is an algorithm that **finds directions in the feature space corresponding to projections which are highly non-Gaussian**.. Unlike PCA, **these directions need not be orthogonal in the original feature space, but they are orthogonal in the whitened feature space**, in which all directions correspond to the same variance. PCA, on the other hand, finds orthogonal directions in the raw feature space that corresponded directions accounting for maximum variance.

In Matrix Factorization techniques, non-negative matrix factorizatio

Non-negative Matrix Factorization (NMF)

- NMF models are interpretable and easier to understand
- NMF requires the sample features to be non-negative



NMF expresses samples as a combination of interpretable parts. For example, it represents documents as combinations of topics, and images in terms of commonly occurring visual patterns. NMF, like PCA, is a dimensionality reduction technique, in contrast to PCA, however, NMF models are interpretable. This means NMF models are easier to understand and much easier for us to explain to others. NMF can't be applied to every dataset however, it requires the sample features to be non-negative, so the values must be greater than or equal to zero. It has been observed that when carefully constrained, NMF can produce a parts-based representation of the dataset, resulting in interpretable models. This example displays 16 sparse components found by NMF from the images in the Olivetti faces dataset on the right, compared with the PCA eigenfaces on the left.

Latent Dirichlet Allocation or LDA is one of the more popular latent dimensionality reduction methods 潜在降维方法

Mobile. IoT and Smilar Use Cases

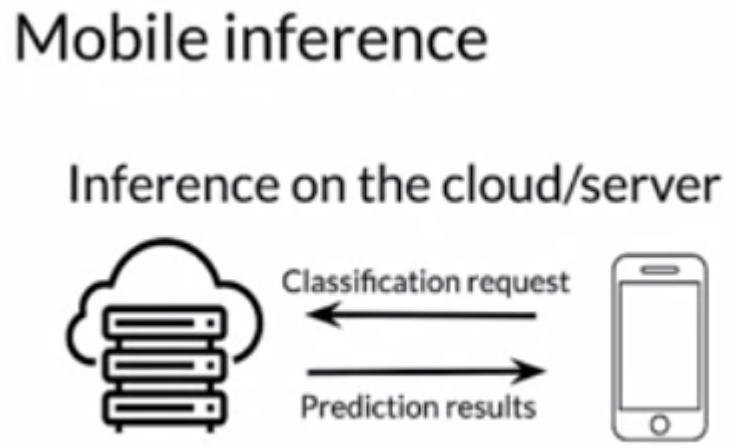
Model optimization is another area of focus where you can further optimize performance and resource requirements. The goal is to create models that are as **efficient** and **accurate** as possible and to achieve the **highest performance** at the least cost.
Machine learning is increasingly becoming part of more and more devices and products. This includes the rapid growth of mobile and IoT applications, including devices which are situated everywhere from farmers fields to train tracks. Businesses are using the data which these devices generate to train machine learning models to improve their business processes, products, and services. Even digital advertisers spend more on mobile than desktop. There are already billions of mobile and edge computing devices, and that number will continue to grow rapidly in the next decade. McKinsey predicts that by 2025, the overall economic impact of IoT

and mobile could reach trillions of dollars, surpassing many sectors like automation of knowledge work or Cloud technology. As these devices become more and more ubiquitous and powerful, many of the machine learning tasks, which you think of as requiring months of high powered compute time, will become part of more and more fairly common devices.
Traditionally, you can think of deploying machine learning models in the Cloud. This requires a server to run inference and return the results. But with the advance of machine learning research for applications on **lower power devices**, this processing can be **offloaded** to a device and **run locally**. This enables more opportunities for including machine learning is part of a device's core functionality. Moreover, the hardware costs for these devices continues to fall, which enables lower price points and higher volumes. A key aspect of **on-device machine learning** is that in most cases it ensures **greater compliance with privacy regulations by keeping user data on the device.**
To generate real-time predictions you can:

- host the model on a server
- embed the model in the device
    - network connection
    - model small
    - fast to perform
    - mobile devices limited processing capabilites
    - all access it needs to the data that it needs
    - need historical data?

How should you deploy your models so that they can be used to generate real value? If you host them on a server, the mobile or IoT device needs to be connected so that it can make a network request. Another option is to embed the model on a mobile device directly. In your case, can you always rely on the device to have a network connection? Also is your model small enough and fast enough to perform inference on the device? Additionally, mobile devices offer limited processing capabilities which might affect which types of models you can embed in them. Furthermore, does the device have all the access it needs to the data that it needs? Or does it need things like historical data that are only available on a server?

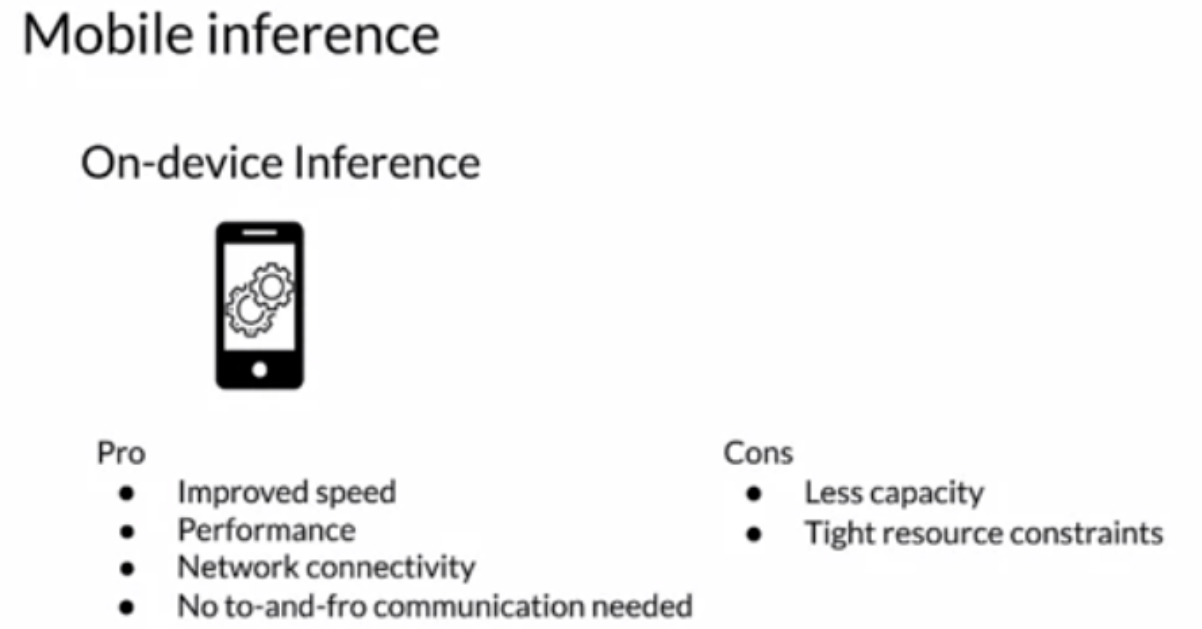
Suppose you're trying to build an app that applies different effects to photos. In a scenario where the models being hosted on a server, the app needs to first send the photo to the server, and then the server feeds the picture through a model to apply the desired effect, and a few seconds later, it sends the modified image back to the app.



Using a server for inference has the **advantage** that it keeps the mobile app simple. The server encapsulates all of the model complexity. This means that you can update the model or add new

features anytime you want. To deploy the improved model, you update the model on the server. That means that you probably don't have to update the app itself, unless you need to change the request that the app sends. One big drawback is the timely inference is a strong requirement in this setting.

In case of on-device inference, you load the trained model into the app. Since the model runs in the app, you don't need to send a request over the Internet and wait for a reply. Instead, the prediction happens fast and you don't need a network connection. There's an increasing demand for sophisticated AI enabled services like image and speech recognition, natural language processing, visual search, and personalized recommendations. At the same time, datasets are growing. Networks are becoming more complex. Privacy is increasingly becoming an issue and latency requirements are tightening to meet user expectations. All of these trends influence the choice of where to generate predictions from your trained models, which in turn affects the architecture and complexity of the models that you train.



deploy model to devices

Now let's take a look at some of the options available today to deploy models to mobile apps. ML Kit for Firebase offers ready to use APIs. You can also deploy your own TensorFlow Lite models if you don't find a base API that covers your use case. It targets mobile platforms and uses TensorFlow Lite, the Google Cloud Vision API and Android Neural Networks API to provide on-device machine learning, such as facial recognition, barcode scanning, and object detection among others. ML Kit gives you both on-device and Cloud APIs, meaning you can also use the APIs when there's no network connection. The Cloud based APIs make use of the Google Cloud Platform. With ML Kit, you can upload models through the Firebase Console and let the service

take care of hosting and serving the models to your apps users. Another advantage is that since ML Kit is available through Firebase, it's possible to take advantage of the broader Firebase platform.
With Core ML, you can build your model or use a pretrained model. To use your model, you first need to create a model using third-party frameworks. Then you convert your model to the Core ML model format. Supported frameworks includes Scikit-learn, Keras, Caffe, and XGBoost.
There are also some pre-trained models ready for use. TensorFlow Lite was developed by Google and has APIs for many programming languages including Java, C++, Python, Swift, and Objective-C. It's optimized for on-device applications and provides an interpreter tuned for on-device machine learning. Custom models are converted to TensorFlow Lite format and their size is optimized to increase efficiency. TensorFlow Lite also supports optimizing models for IoT and embedded applications, for devices with as little as 20k of memory. TensorFlow Lite models can be trained and evaluated in TFX pipelines, which is important when the model will become part of a production, product, or service.

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 *	✓	✓	✓		✓	✓

* Also supported in TFX

Benefits and process of Quantization

- https://medium.com/tensorflow/introducing-the-model-optimization-toolkit-for-tensorflow-254aca1ba0a3
- https://blog.tensorflow.org/2020/04/quantization-aware-training-with-tensorflow-model-optimization-toolkit.html
-

optimizing your models. Especially for deployment scenarios, such as mobile and IoT, where the capabilities of the device are extremely limited compared to running on a server or in the Cloud. However, before doing so, let's clarify that these techniques can benefit any model regardless of where it is deployed since they reduce the compute resources required to serve the model.

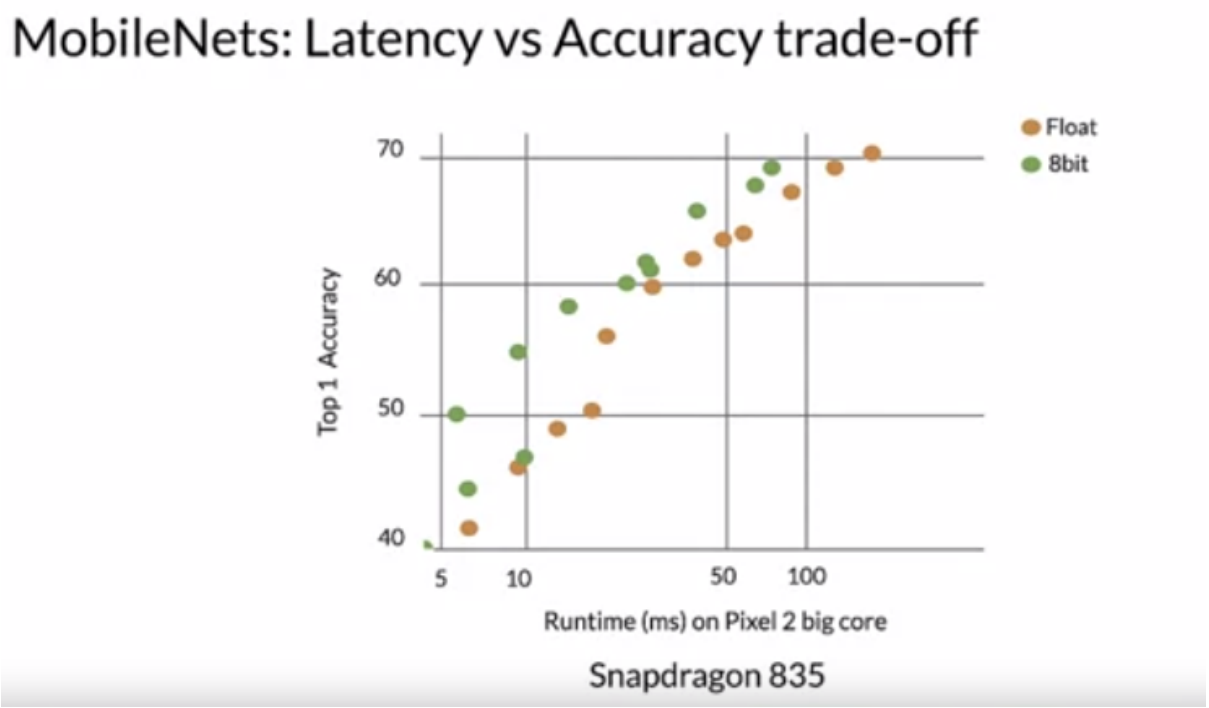
Quantization involves transforming a model into an equivalent representation that uses **parameters and computations at a lower precision**. This improves the model's execution performance and efficiency, but it can often result in lower model accuracy. Let's use an analogy

to understand this better. Think of an image. As you might know, a picture is a grid of pixels where each pixel has a certain number of bits. Now if you try reducing the continuous color spectrum of real-life to discrete colors, we're quantizing or approximating the image. In this animation, you can see that a black and white image could be represented with one bit per pixel, while a typical picture with color has 24 bits per pixel. Quantization, in essence, lessens or reduces the number of bits needed to represent information. However, you may notice that as you reduce the number of pixels beyond a certain point, depending on the image, it may get harder to recognize what that image is. Neural network models can take up a lot of this space. For example, AlexNet which requires around 200 megabytes of disk space. Nearly all of that size is taken up with the weights for the neural connections, as there are often many millions of these in a single model. Because they're all slightly different floating-point numbers. Simple compression-like zipping doesn't compress them well unless we make models less dense. Most straightforward **motivation for quantization is to shrink file sizes.** For mobile apps, especially it's often impractical to store a 200-megabyte model on the phone just to run a single app. Compressing higher precision models is necessary. Another reason to quantize is to **reduce the computational resources** that you need to do inference calculations by running them entirely with low precision inputs and outputs. This is a lot more difficult since it requires changes everywhere you do calculations, but it offers potential rewards. Doing this will help you **run your models faster and use less power,** which is especially important on mobile devices. It also opens the door to a lot of embedded systems that can't run floating-point efficiently, enabling many applications in the IoT world.

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**

Now, let's take a look at what **quantization means**. MobileNets are a family of architectures that achieve **a state-of-the-art trade-off between on-device latency and ImageNet classification accuracy.** A recent publication demonstrated how integer-only quantization could further improve the trade-off on common hardware. The authors of the paper benchmarked the MobileNet architecture with varying depth multipliers and resolutions on ImageNet on three types of Qualcomm cores. This plot is for the Snapdragon 835 chip. You can see that for any given level of accuracy, latency time is lower for the 8-bit version of the model.

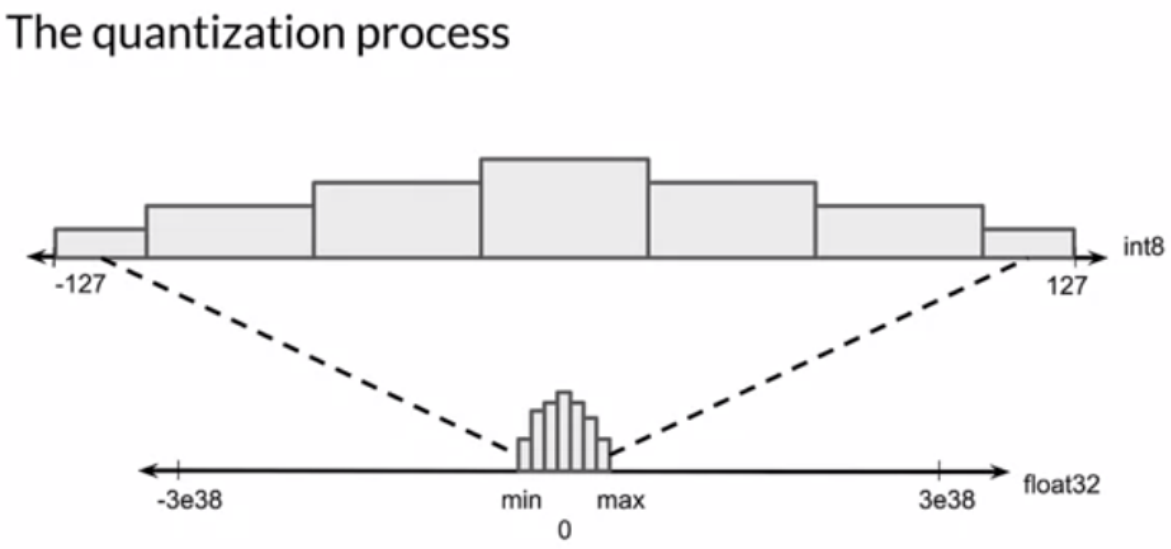


Arithmetic with lower bit depth is faster, assuming that the hardware supports it. Even though floating-point computation is no longer slower than integer on modern CPUs, operations with 32-bit floating-point will almost always be slower than, say, eight-bit integers. Moving from 32 bits to eight bits, we usually get **speedups of 4x reduction** in memory. Lighter deployment models mean they have less storage space and are easier to share over smaller bandwidths and easier to update. Lower bit depths also mean we can **squeeze more data** into the same caches and registers. This makes it possible to build applications with better caching capabilities that reduce power usage and run faster. Floating-point arithmetic is hard, which is why it may not always be supported on microcontrollers and on some ultra low-powered embedded devices, such as drones, watches, or IoT devices. **Integer support, on the other hand, is always readily available.**

Benefits of quantization

- **faster compute**
- **low memory bandwidth**
- **low power**
- **integer operations supported across cpu dsp npu**
-

Neural networks consist of activation nodes, the connections between the nodes, a weight parameter associated with each connection, and a bias term. When it comes to quantizing these networks, it is these weight parameters and activation node computations that we're trying to quantize. Quantization squeezes a small range of floating-point values into a fixed number of information buckets. As you can see in this diagram. This process is lossy in nature. **But the weights and activations of a particular layer often tend to lie in a small range, which can be estimated beforehand. This means we don't need the ability to store a range in the same data type, allowing us to concentrate our precious fewer bits within a smaller range. Say negative three to positive three**. As you might imagine, it will be crucial to accurately know this smaller range. If done right, **quantization causes only a small loss of precision, which usually doesn't change the output significantly.**



Now, let's see what parts of a model are affected after applying quantization. One of them could be static parameters like the **weights of layers,** and others could be dynamic ones like **activations inside networks**. You could also have **transformations** like adding, modifying, or removing operations, coalescing different operations, and so on. In some cases, transformations may need extra data. You'll see how this is the case in one of the techniques of quantization where some unlabeled data is used to determine scaling parameters.

What parts of the model are effected?

- **static values (parameters)**
- **dynamic values (activations)**
- **computation (transformations)**

Optimizations can often result in changes in model **accuracy**, which must be considered during the application development process. The accuracy changes depend on the individual model and data being optimized and are difficult to predict ahead of time. Generally, models that are optimized for size and latency will lose some amount of accuracy. Depending on your application, this may or may not impact your user's experience. In rare cases, certain models may actually gain some accuracy as a result of the optimization process. In terms of interpretability, there are some effects which may be imposed on the model after quantization. This means that it's hard to evaluate whether transforming a layer was going in the right or wrong direction.

Trade-offs

- **optimizations impact model accuracy**
    - **difficult to predict ahead of time**
- **in rare cases, models may acutally gain some accuracy**

undefined effects on ML interpretability

Mobile and embedded devices have limited computational resources, so it's important to keep your application resource-efficient. Depending on the task, you will need to make a trade-off between model accuracy and model complexity. If your **task requires high accuracy, then you may need a large and complex model.** For tasks that **require less precision, it's better to use a smaller, less complex model.** Because they not only use less disk space in memory, but they are also generally **faster and more energy-efficient.** For example, these graphs show accuracy and latency trade-offs for some common image classification models. One example of models optimized for mobile devices are MobileNets, which are optimized for mobile vision

applications. Once you've selected a candidate model that is right for your task, it's a good practice to profile and benchmark your model.

Post Training quantization

You can do **quantization** during training or after the model has been trained. Let's look, first, at post-training quantization. Post-training quantization is a conversion technique that can reduce model size while also improving CPU and hardware accelerator latency with little degradation in model accuracy. **You can quantize an already trained TensorFlow model when you convert it to TensorFlow Lite format using the TensorFlow Lite converter**. It's easy to use since it's integrated into the TFLite converter directly. What post-training quantization basically does is to convert, or more precisely, **quantize the weights from floating point numbers to integers in an efficient way.** By doing this, you can gain up to three times lower latency without taking a major hit on accuracy. With the default optimization strategy, the converter will do its best to apply a post-training quantization, trying to **optimize the model for both size and latency.** This is recommended, though you can always customize this behavior. There are several post-training quantization options to choose from. This is a summary of the choices and the benefits they provide. If you're looking for a decent speed-up, like 2-3 times faster, while being two times smaller, you can consider dynamic range quantization. On the other hand, if you want to squeeze out even more performance from your model, then full integer quantization or float16 quantization may result in faster performance. Float16 is especially useful when you plan to use a GPU.

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

With **dynamic range quantization**, during inference, the weights are converted from eight bits to floating point, and the activations are computed using floating point kernels. This conversion is done once and cached to reduce latency. This optimization provides latencies which are close to **fully fixed point** inference.

```
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 quantization takes only two lines of code. Let's begin by importing TensorFlow and defining a converter with TFLite. Then you set the converter to optimize the model for size using the optimize for size option. You then apply the converter to your model. The other available optimization modes include optimize for latency, which reduces a latency of your model, while default mode basically tries to optimize it for both speed and storage. Enhanced optimizations can be applied by providing a representative dataset.

Post-training integer quantization

Using dynamic range quantization, you can reduce the model size and/or latency, but this comes with a limitation as it requires inference to be done with floating point numbers. This may not always be ideal since some hardware accelerators only support integer operations, for example, Edge TPUs. The optimization toolkit also supports post-training integer quantization. This enables users to take an already trained floating point model and fully quantize it to use only eight bits signed integer, which enables fixed point hardware accelerators to run these models. When targeting greater CPU improvements or fixed point accelerators, this is often a better option. Post-training integer quantization works by gathering calibration data, which it does by running inferences on a small set of inputs so as to determine the right scaling parameters needed to convert the model to an integer quantized model. Post-training quantization can result in a loss of accuracy, particularly for smaller networks, but it is often fairly negligible. On the plus side, this will speed up execution of the heaviest computations by using lower precision and the most sensitive computations with higher precision, thus typically resulting in little or no final loss of accuracy. Pre-trained fully quantized models are also available for specific networks in the TensorFlow Lite model repository. It's important to check the accuracy of the quantized model to verify that any degradation in accuracy is within acceptable limits. TensorFlow Lite includes a tool to evaluate model accuracy. Alternatively, if the loss of accuracy is too great,

consider using quantization aware training. However, doing so requires modifications during model training to add fake quantization nodes, while post-training quantization techniques are fairly simple.

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

Post-training quantization:

first train it in full precision and then simply quantize the weights to fixed point.

Quantization aware training:

- applies quantization to the model while it is being trained.
- simulates low precision inference time computation in the forward pass of the training process.

By **inserting fake quantization nodes**, the rounding effects 舍入效果 of quantization are assimilated in the forward pass, as it would normally occur in actual inference.

Goal: **fine-tune the weights to adjust for the precision loss**.

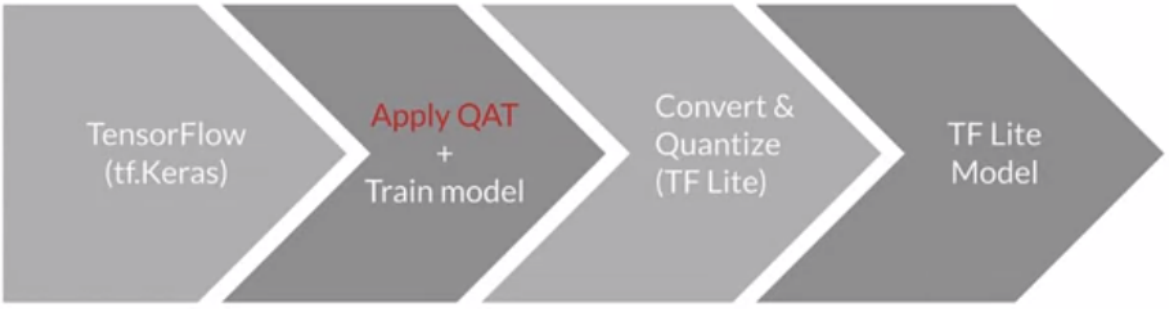
Method: If fake quantization nodes are included in the model graph at the points where quantization is expected to occur, for example, convolutions. Then in the forward pass, the flood values will be rounded to the specified number of levels to simulate the effects of quantization. This introduces the quantization error as noise during training and is part of the overall loss which the optimization algorithm tries to minimize., The model learns parameters that are more robust to quantization.

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

Process,

Quantization-aware training (QAT)

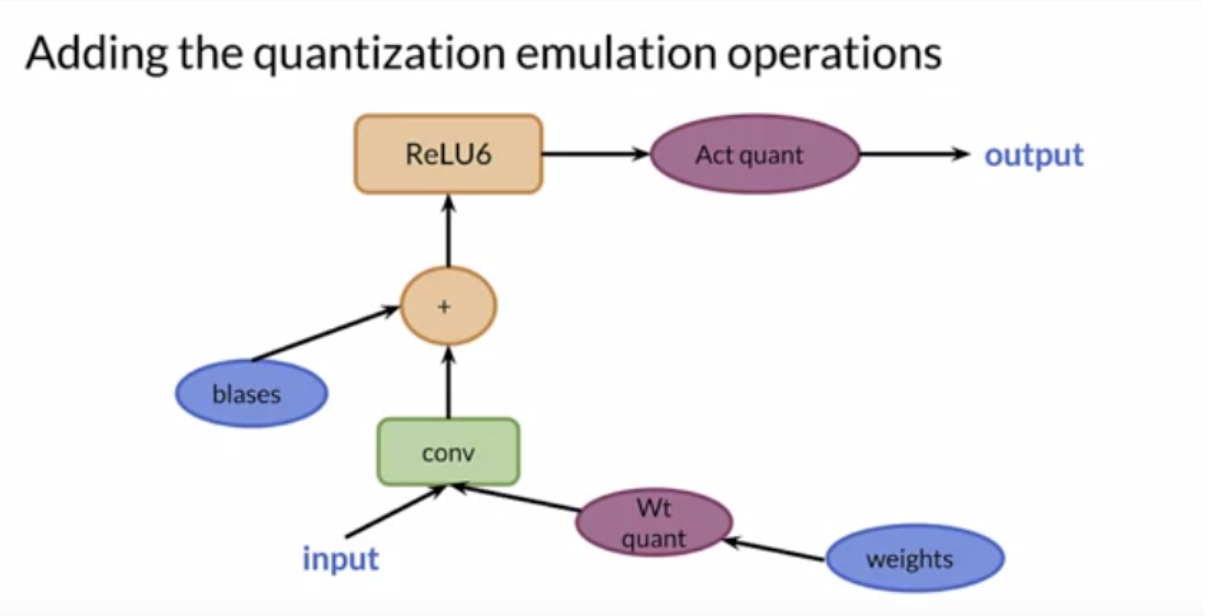


,

- build a model like you usually would and make it quantization aware using the **TensorFlow model optimization toolkits**, APIs.

- Finally, you train this model with the quantization emulation operations to get our integer-only quantized model.

- The next step is to add quantization emulation operations.



The quantization emulation operations need to be placed in the training graph such that they're consistent with the way that the quantized graph will be computed. The **weight quant** and **activation quant Ops** introduce losses in the forward pass of the model to simulate actual quantization loss during inference. Note how there is **no quant operation between convolution and Relu6. This is because Relu6 gets fused in TensorFlow Lite.** The quantization where training API makes it easy to train with quantization awareness for an entire model or only parts of it. Then export it for deployment with **TensorFlow Lite.** To make the whole model aware of quantization, we apply **tfmot.quantization.keras.quantize_model(model).** The API is also quite flexible and capable of handling far more complicated use cases.

```
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(...)
```

```
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)
```

```
 quantize_annotate_layer =
 tfmot.quantization.keras.quantize_annotate_layer
 quantize_annotate_model =
 tfmot.quantization.keras.quantize_annotate_model
 quantize_scope = tfmot.quantization.keras.quantize_scope

 model = quantize_annotate_model(tf.keras.Sequential([
    quantize_annotate_layer(CustomLayer(20, input_shape=(20,)),
                            DefaultDenseQuantizeConfig()),
    tf.keras.layers.Flatten()
 ]))
```

```
# `quantize_apply` requires mentioning `DefaultDenseQuantizeConfig` with
`quantize_scope`
with quantize_scope(
  {'DefaultDenseQuantizeConfig': DefaultDenseQuantizeConfig,
   'CustomLayer': CustomLayer}):
  # Use `quantize_apply` to actually make the model quantization aware.
  quant_aware_model = tfmot.quantization.keras.quantize_apply(model)
```

For example, it allows you to control quantization precisely within a layer. Create custom quantization algorithms, and handle any custom layers that you may have written. You can selectively quantize layers of a model to explore the trade-off between accuracy, speed, and model

size. For example, try quantizing the later layers instead of the first layers. Always remember to avoid quantizing critical layers like the attention mechanism in transformer architectures for example. If you happen to have activations or other operations that aren't yet supported by the quantization aware framework. You can use a quantization configuration to solve this. For example, in this code snippet calls a custom config, like **DefaultDenseQuantizeConfig() to** quantize a custom layer. Finally, let's include your custom config in your quantized scope before calling quantize apply. Here are some results showing the loss of accuracy on a few models. This should give you a feel for what to expect in your own models. Let's look at the latency for a few models. Remember that lower numbers are better in this case. Finally, let's look at the model size. Lower numbers are better.

Pruning

Rruning: increase the efficiency of models

How: reduce the number of parameters and operations involved in generating a prediction by removing network connections (lower the parameter count) - that did not contribute substantially to producing accurate results (without too much loss of accuracy) . Optimizing machine learning programs can take several different forms. Fortunately, neural networks have proven resilient to various transformations aimed to the skull. When you consider more extensive neural networks with more layers and nodes, reducing their storage and computational cost becomes critical, especially for some real time applications. Model compression can be used to address this problem. As machine learning models were pushed into imbedded devices like mobile phones, compressing neural networks grew in importance. Pruning in deep learning is a biologically inspired concept that we'll discuss next.

Connection sparsity has long been a foundational principle in neuroscience research

Benefits:

- A sparse network is not only smaller, but it is also faster to train and use.

- Where hardware is limited, such as in embedded devices are smart phones, speed and size can make or break a model,

- more complex models are more prone to overfitting. In some sense, restricting the search space can also act as a regularizer.

Challenges: reducing the model's capacity can also lead to a loss of accuracy. As in many other areas, there is a delicate balance between complexity and performance.

Iterative pruning methods: It was a iterative pruning method. The first step was to train a model, and then the saliency of each weight was estimated, which was defined by the change in the

loss-function upon applying a perturbation to the nodes in the network. The smaller the change, the less the effect the weight would have on the training. Finally, they eliminate the weights with the lowest saliency. This is equivalent to setting them to zero. Finally, this pruned model was retrained. One particular challenge arises with this method when the prune network is retrained. It turned out that due to its decreased capacity, retraining was much more difficult. The solution to this problem arrived later, along with an insight called the lottery ticket hypothesis. The probability of winning the jackpot of a lottery is very low. For example, if you're playing Powerball, you have odds of exactly one in about 3 million for the winning ticket. What are your chances if you purchase n tickets? If the probability of winning is 1 over 3 million, then what about the chances of not winning? It's the compliment of 1 minus p. Extend this when buying n tickets and we have the probability of 1 minus p to the power of n. From this, it follows that the probability of at least one of them winning is simply the complement again. What does this have to do with neural networks? Before training, the weights of a model are initialized randomly. Can it happen that there is a sub-network of a randomly initialized network? Which one? The initialization lottery? Some researchers set out to investigate the problem and answer the question. Most notably Frankle and Carbin 2019 found that fine-tuning the weights after training was not required for these new prune networks. In fact, they showed that the best approach was to reset the weights to their original value and then retrain the entire network. This would lead to models with even higher accuracy compared to both the original dense model and the post-pruning plus fine-tuning approach proposed by Han and colleagues. This discovery led them to propose an idea considered wild at first, but now commonly accepted. That over parameterized dense networks containing several sparse subnetworks with varying performances, and one of these subnetworks is the winning ticket, which outperforms all others.

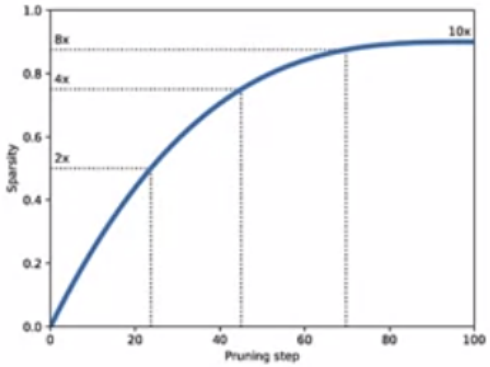
Limitation of this method:

- it does not perform well for l**arger-scale problems and architectures.** The original paper, the authors stated that for more complex datasets like ImageNet and deeper architectures like ResNet, the method fails to identify the winners of the initialization lottery.

- In general, achieving a good sparsity accuracy tradeoff is a difficult problem. Is a very active research field and the state of the art keeps improving.

TensorFlow includes a Keras-based weight pruning API, which uses a straightforward yet broadly applicable algorithm designed to **iteratively remove connections based on their magnitude during training.** Fundamentally a final target sparsity is specified along with a schedule to perform the pruning. In this figure here, you can see that during training, a pruning routine will be scheduled to execute. Removing the weights with the lowest magnitude values that are closest to zero until the current sparsity target is reached. Every time the pruning routine is scheduled to execute, the current sparsity target is recalculated starting from zero percent until it reaches the final target sparsity at the end of the pruning schedule. By gradually increasing it according to **a smooth ramp-up function.** Just like the schedule, the ramp-up function can be tweaked as needed.

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%.

For example, in certain cases, it may be convenient to schedule the training procedure to start after a certain step when some convergence level has been achieved. Or end pruning earlier than the total number of training steps in your training program to further fine-tune the system at the final target sparsity level. Sparsity increases as training proceeds. You need to know when to stop. That means at the end of the training procedure, the tensors corresponding to the pruned Keras layers will contain zeros where weights have been pruned according to the final sparsity target for the layer.

An immediate benefit that you can get out of pruning is **disk compression.** That's because sparse tensors are compressible. Thus by applying simple file compression to the prune TensorFlow checkpoint or the converted TensorFlow Lite model. We can reduce the size of the model for storage and/or transmission. In some cases, you can even gain speed improvements in CPU and machine-learning accelerators that exploit integer precision efficiencies. Moreover, across several experiments, we found that weight pruning is compatible with quantization, resulting in compound benefits. In the upcoming exercise, we show we can further compress the pruned model from two megabytes to just about half of a megabyte by applying post-training quantization. In the relatively near future, TensorFlow Lite will add first-class support for sparse representation in computation. Thus expanding the compression benefit to runtime memory and unlocking performance improvements. Sparse tensors allow you to skip otherwise unnecessary computations involving the zeroed values. Or depending on when you're watching this, it may already be included.

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 addtional benefits**
- **unlock performance imrovements**

To use the pruning API you first create a TensorFlow Keras model. Then we add sparsity to some of the layers in the model and retrain it or train it. Finally, you can also read the benefits of quantization by converting the pruned model to TFLite. Let's apply pruning to the whole model. In this example, you start with 50 percent sparsity. 50 percent zeros and weights and end up with 80 percent sparsity. You can also prune only a part of the model or specific layers for model accuracy improvements. Later, you'll see how to create sparse models with the TensorFlow model

optimization toolkit API for both TensorFlow and TFLite. You then combine pruning with post-training quantization for additional benefits. Also, this technique can be successfully applied to different types of models across distinct tasks. From image processing convolutional-based neural networks to speech processing using recurrent neural networks. This table shows some of these experimental results.

```
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(...)
```

hat was quite a week. We started with understanding **dimensionality** and looked at a few ways to control it and reduce it. Then we went into some resource **constraints scenarios**, including mobile and IoT applications. We looked at some of the issues around that and ways to deal with that as well. Including **quantization** of a couple of different kinds and **pruning**.