Data Lifecycle in Production

Part 2: Feature Engineering, Transformation and Selection

Ramin Toosi

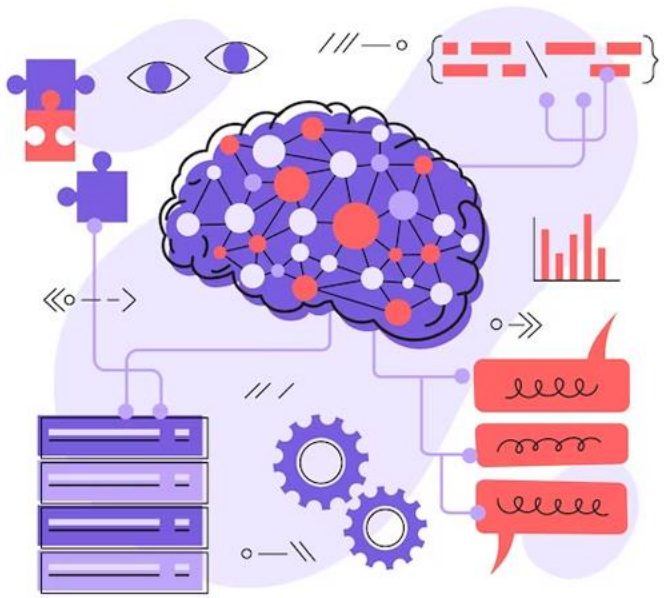
Feature Engineering

- "Coming up with features is difficult, time-consuming, and requires expert knowledge. Applied machine learning often requires careful engineering of the features and dataset."

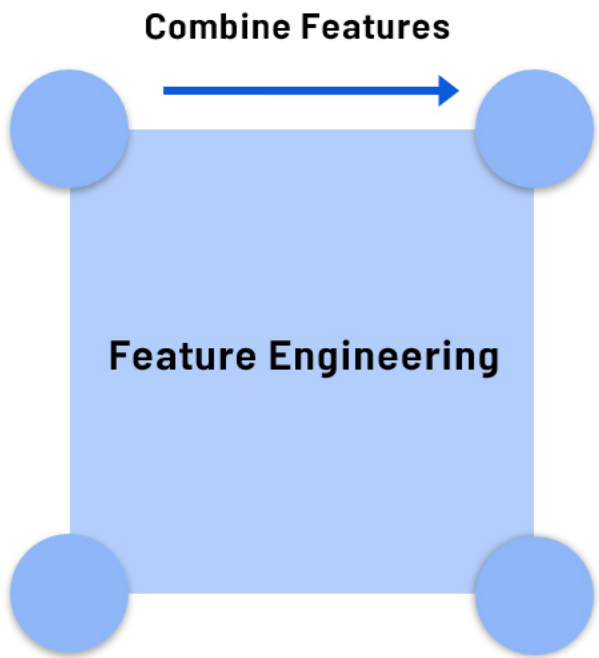
Andrew Ng

Squeezing the most out of data

- Making data useful before training a model
- Representing data in forms that help models learn
- Increasing predictive quality
- Reducing dimensionality with feature engineering



Art of feature engineering



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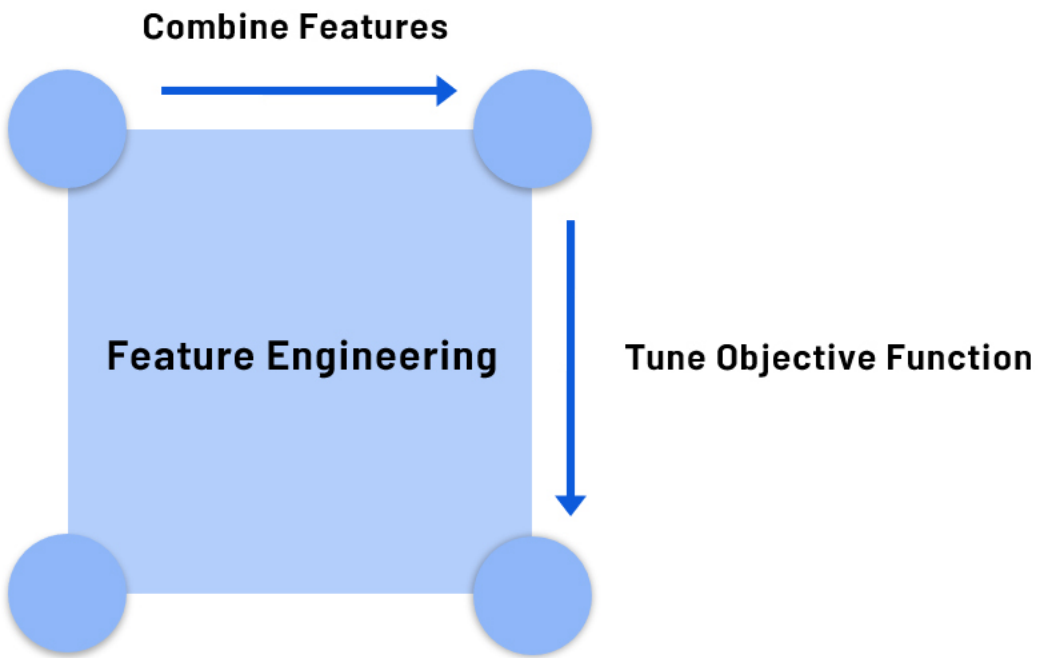

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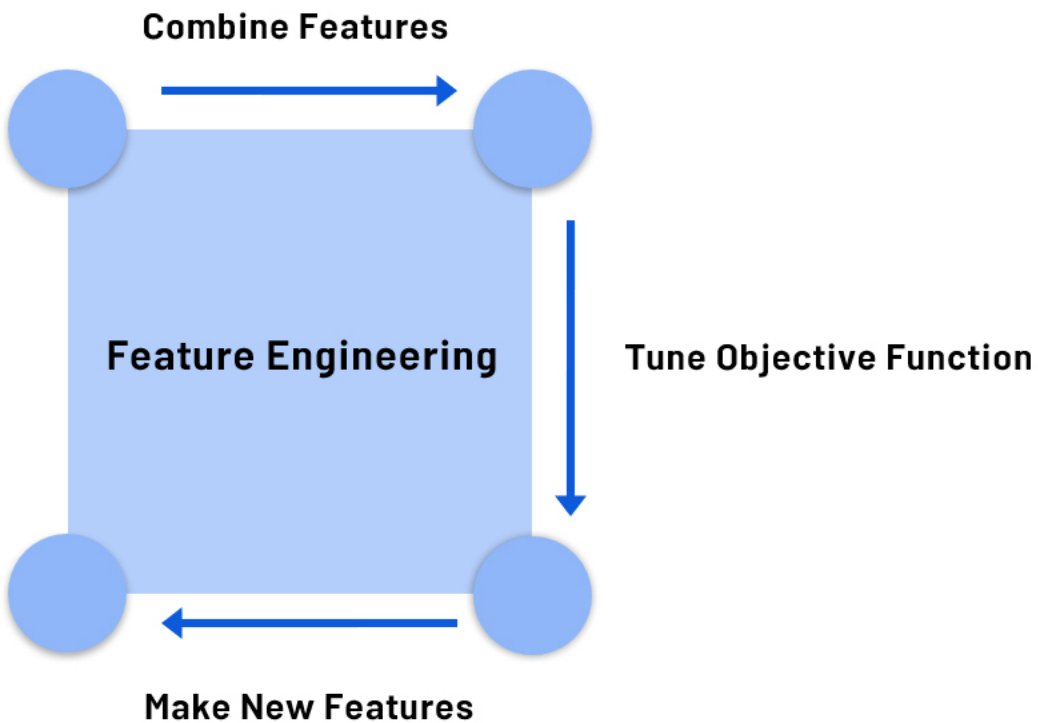

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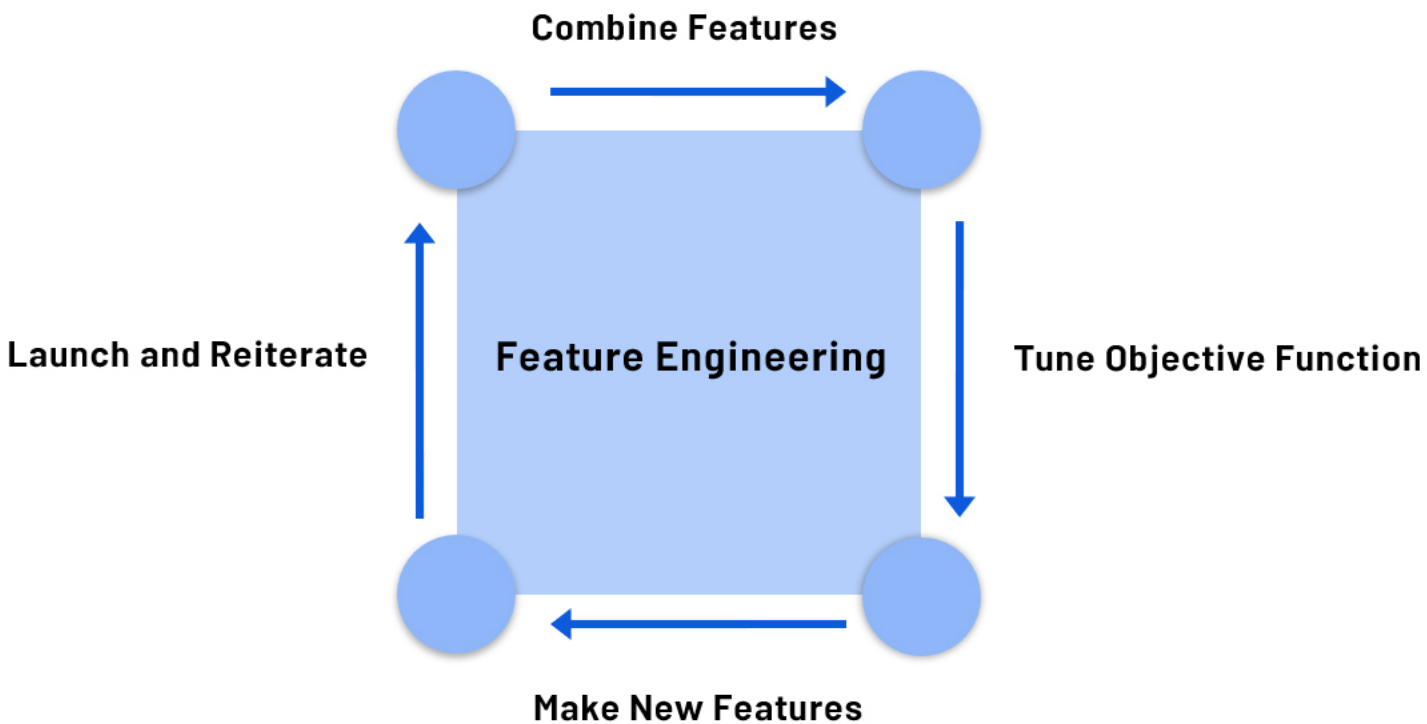

Main preprocessing operations

Data cleansing

Feature tuning

Representation transformation

Feature extraction

Feature construction

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Mapping raw data into features

Raw Data

```
0: {
 house_info : {
 num_rooms : 6
 num_bedrooms : 3  street_name:
 “Shorebird Way”
```

Mapping raw data into features

Raw Data

```
0: {
  house_info : {
  num_rooms : 6
  num_bedrooms : 3  street_name:
  “Shorebird Way”
  ...num_basement_rooms: -1

   }
}
```

Mapping raw data into features

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Raw data doesn't come to us as feature vectors

Mapping raw data into features

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Raw data doesn't come to us as feature vectors

Feature Engineering

Feature Vector

```
[
6.0,
1.0,
0.0,
0.0,
9.321,
-2.20,
1.01,
0.0,
...,
]
```

Mapping raw data into features

Raw Data

```
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  house_info : {
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Raw data doesn't come to us as feature vectors

Feature Engineering

Feature Vector

```
[
6.0,
1.0,
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9.321,
-2.20,
1.01,
0.0,
...,
]
```

Process of creating features from raw data is feature engineering

Mapping categorical values

Street names

{'Charleston Road', 'North Shoreline Boulevard', 'Shorebird Way', 'Rengstorff Avenue'}

Raw Data

```
0: {
  house_info : {
  num_rooms : 6
  num_bedrooms : 3
  street_name: "Shorebird Way"
  num_basement_rooms: -1
...
   }
}
```

String Features can be handled with one-hot encoding

Feature Engineering

Feature Vector

One-hot encoding
This has a 1 for "Shorebird way" and 0 for all others

```
street_name feature=
[0,0, ..., 0, 1, 0, ..., 0]
```

Categorical Vocabulary

```
# From a vocabulary list

vocabulary_feature_column = tf.feature_column.categorical_column_with_vocabulary_list(

                            key=feature_name,

                            vocabulary_list=["kitchenware", "electronics", "sports"])

# From a vocabulary file

vocabulary_feature_column = tf.feature_column.categorical_column_with_vocabulary_file(

                             key=feature_name,

                             vocabulary_file="product_class.txt",

                             vocabulary_size=3)
```

Empirical knowledge of data

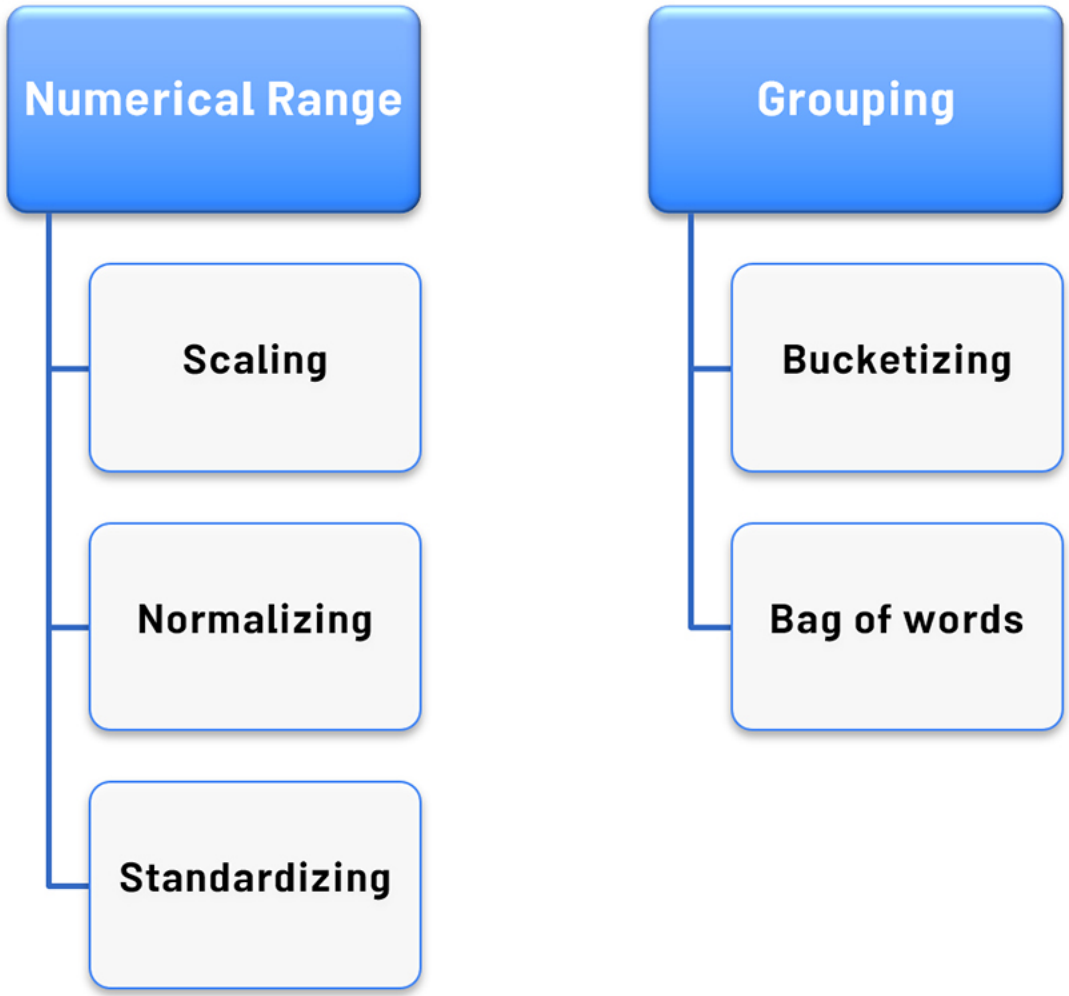
Text: stemming, lemmatization, TF-IDF, n-grams, embedding lookup

Images: clipping, resizing, cropping, blur, Cannyfilters, Sobel filters, photometric distortions

Feature engineering techniques

- **Numerical Range**
  - Scaling
  - Normalizing
  - Standardizing

Feature engineering techniques



Scaling

- Converts values from their natural range into a prescribed range
  - E.g. Grayscale image pixel intensity scale is [0,255] usually rescaled to [-1,1]

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```
image = (image - 127.5) / 127.5
```

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  - E.g. Grayscale image pixel intensity scale is [0,255] usually rescaled to [-1,1]

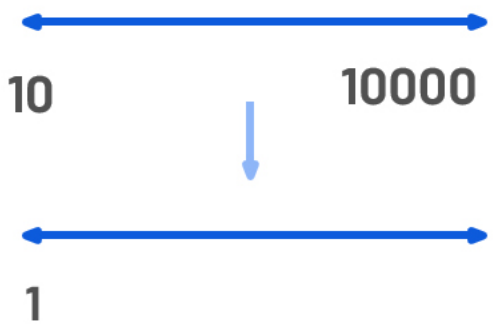
```
image = (image - 127.5) / 127.5
```

- Benefits
  - Helps neural nets converge faster
  - Do away with NaN errors during training
  - For each feature, the model learns the right weights

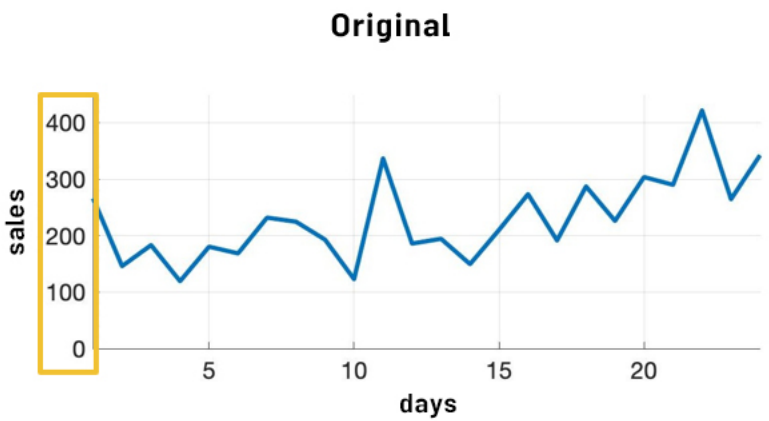
Normalization

$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$$

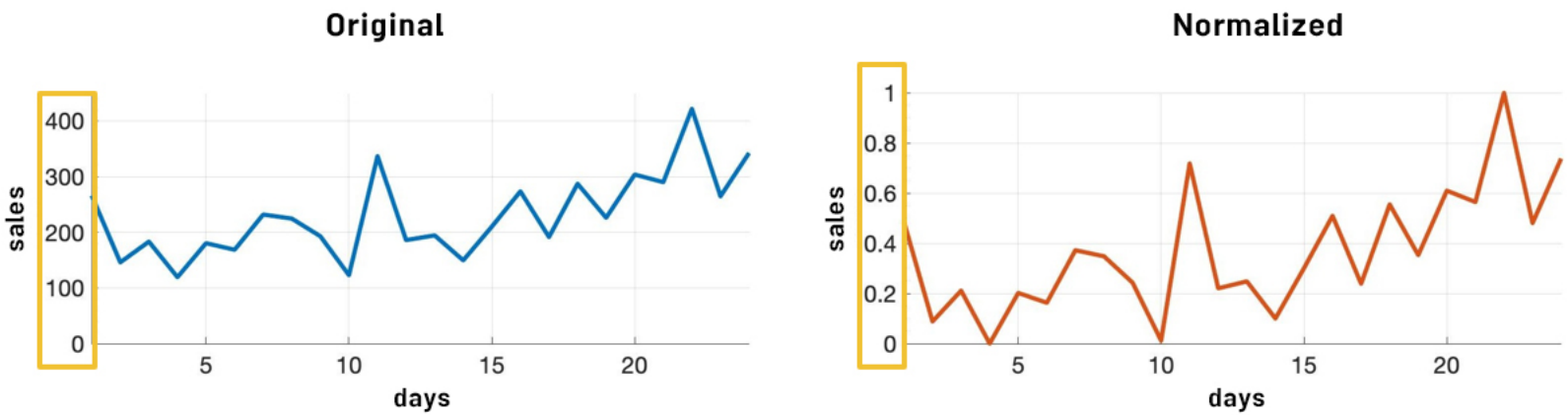
$$X_{\text{norm}} \in [0, 1]$$



Normalization



Normalization

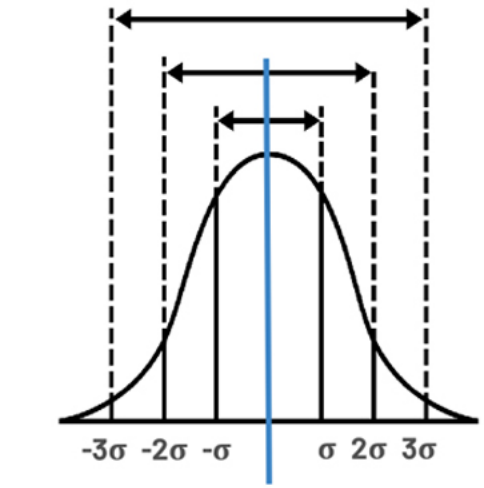


Standardization (z-score)

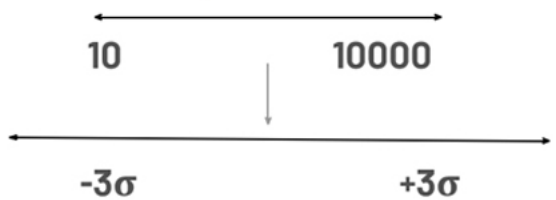
- Z-score relates the number of standard deviations away from the mean
- Example:

$$X_{\text{std}} = \frac{X - \mu}{\sigma}$$

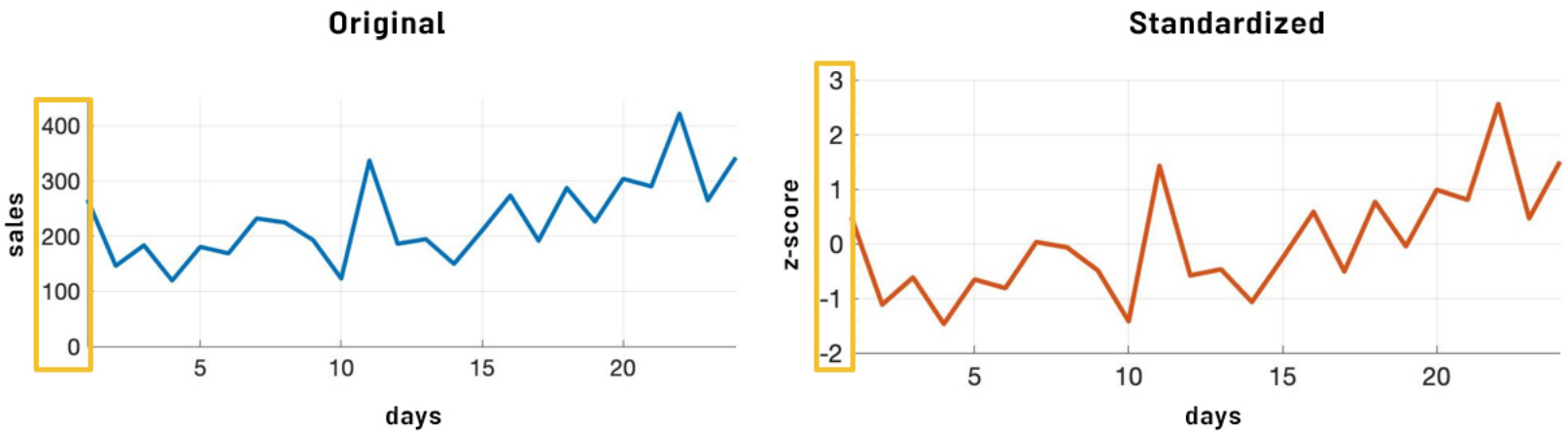
$$X_{\text{std}} \sim \mathcal{N}(0, \sigma)$$



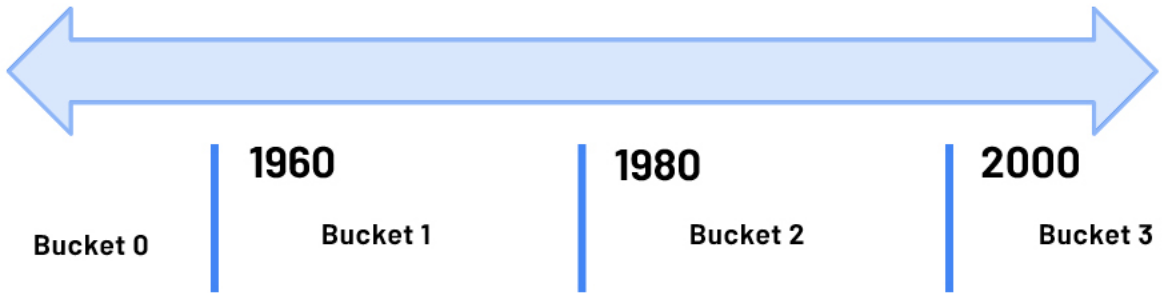
$\mu = 0$



Standardization (z-score)



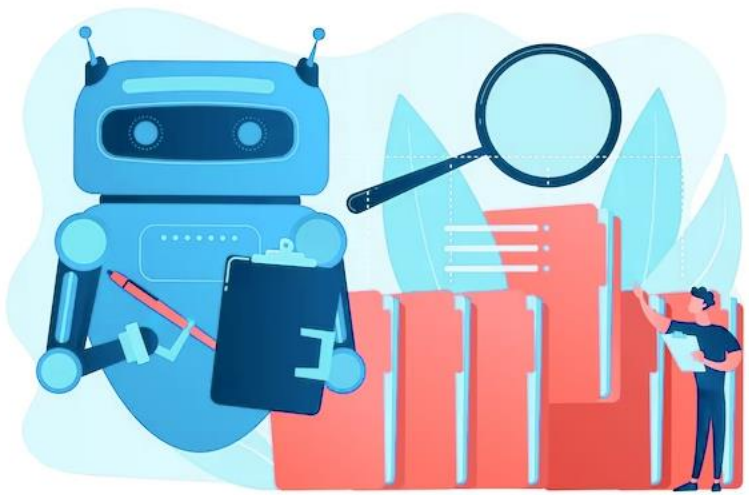
Bucketizing / Binning



Date Range	Represented as...
< 1960	[1, 0, 0, 0]
>= 1960 but < 1980	[0, 1, 0, 0]
>= 1980 but < 2000	[0, 0, 1, 0]
>= 2000	[0, 0, 0, 1]

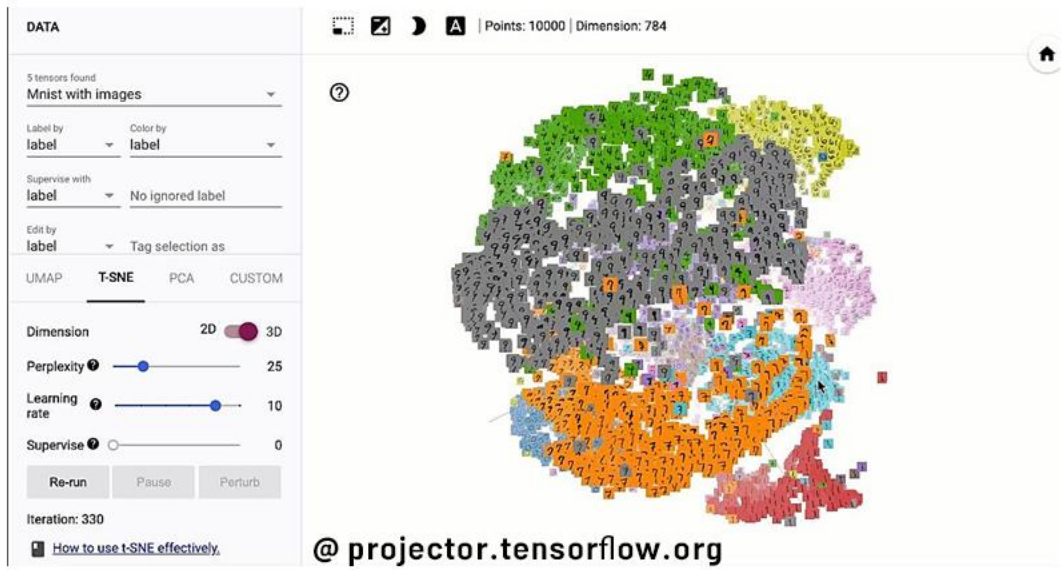
Other techniques

- **Dimensionality reduction in embeddings**
  - Principal component analysis (PCA)
  - t-Distributed stochastic neighbor embedding (t-SNE)
  - Uniform manifold approximation and projection (UMAP)
- **Feature crossing**



TensorFlow embedding projector

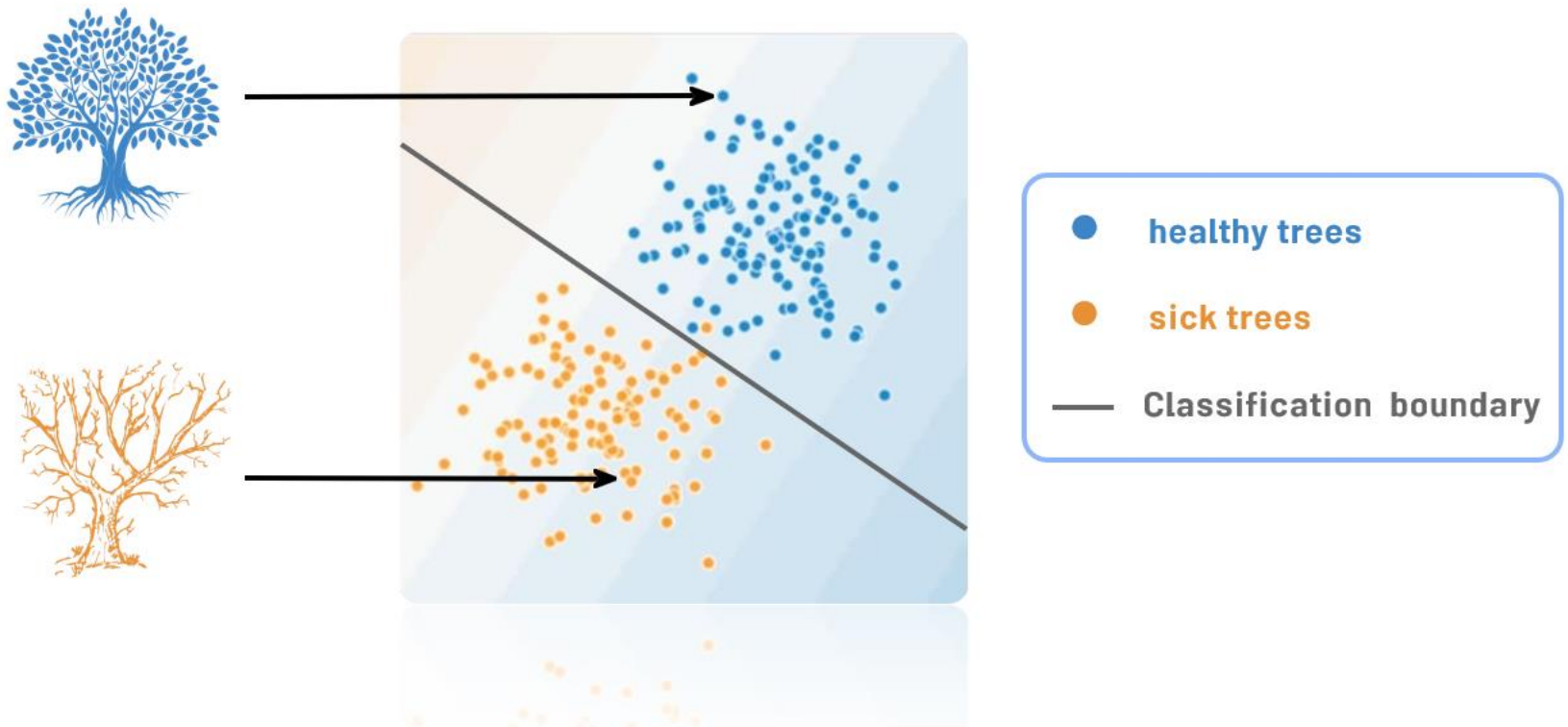
- Intuitive exploration of high-dimensional data
- Visualize & analyze
- Techniques
  - PCA
  - t-SNE
  - UMAP
  - Custom linear projections
- Ready to play



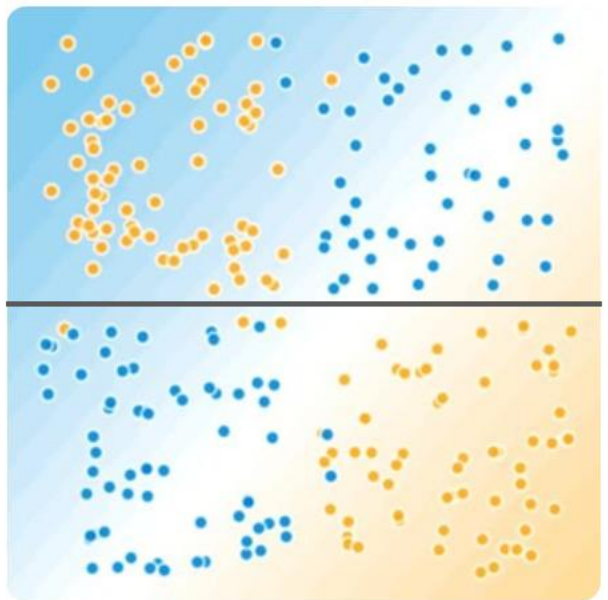
Feature crosses

- **We can create many different kinds of feature crosses**
  - Combines multiple features together into a new feature
  - Encodes nonlinearity in the feature space, or encodes the same information in fewer features
  - [A X B]: multiplying the values of two features
  - [A x B x C x D x E]: multiplying the values of 5 features
  - [Day of week, Hour] => [Hour of week]

Encoding features



Need for encoding non-linearity

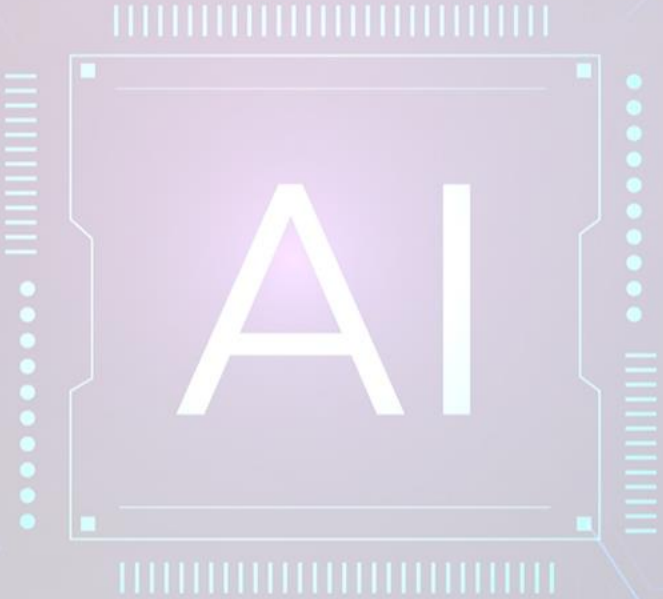


healthy trees

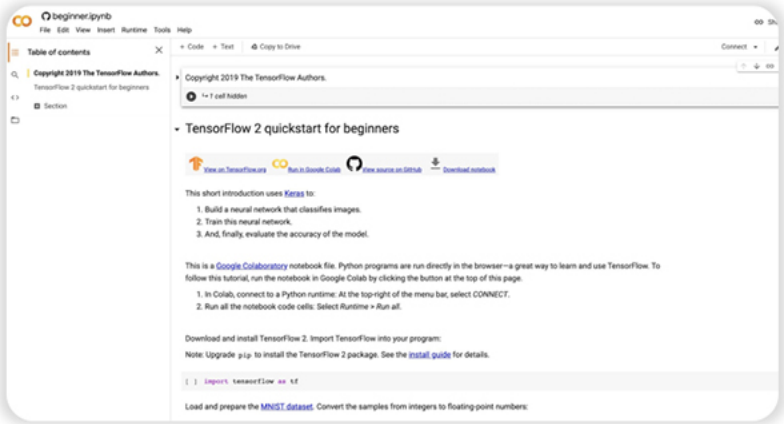
sick trees

Classification boundary

Preprocessing data at scale



From development to production



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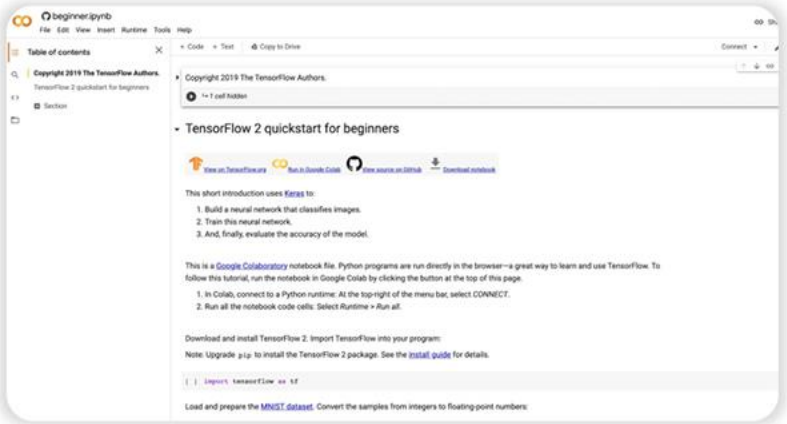

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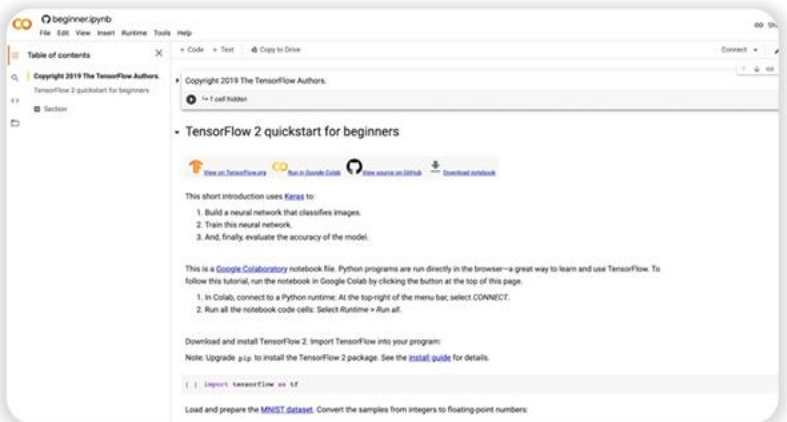
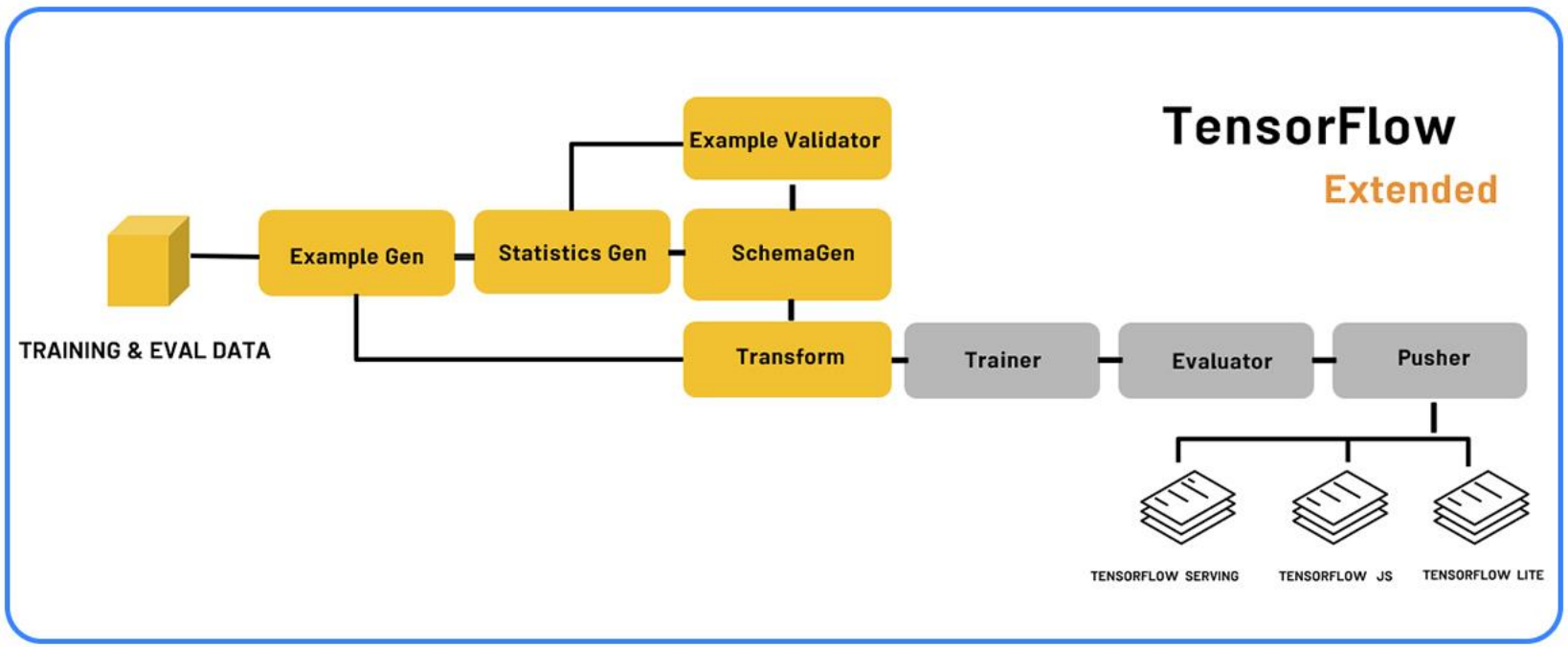


Python

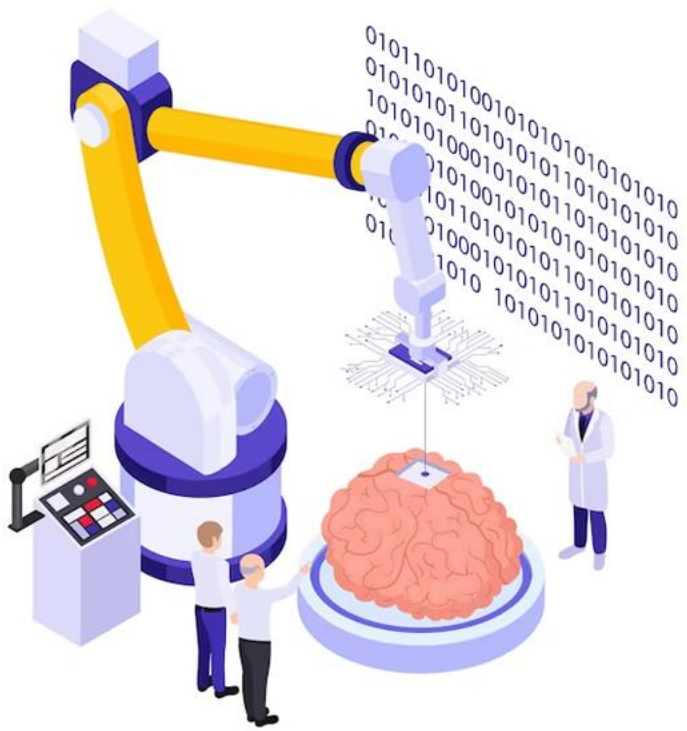
Java

ML Pipeline


TensorFlow
Extended
Example Validator
Example Gen
Statistics Gen
SchemaGen
TRAINING & EVAL DATA
Transform
Trainer
Evaluator
Pusher
TENSORFLOW SERVING
TENSORFLOW JS
TENSORFLOW LITE

Preprocessing

- Inconsistencies in feature engineering
- Preprocessing granularity
- Pre-processing training dataset
- Optimizing instance-level transformations



Challenges

Real-world models:
terabytes of data

Large-scale data

Consistent transforms
between training & serving

Inconsistencies in feature engineering

Training & serving code paths are different

Diverse deployments scenarios

- Mobile (TensorFlow Lite)
- Server (TensorFlow Serving)
- Web (TensorFlow JS)

Risks of introducing training-serving skews

Skews will lower the performance of your serving model

Preprocessing granularity

Transformations	
Instance-level	**Full-pass**
Clipping	Minimax
Multiplying	Standard scaling
Expanding features	Bucketizing
etc.	etc.

When do you transform?

Pre-processing training dataset

Pros	Cons
Run-once	Transformations reproduced at serving
Compute on entire dataset	Slower iterations

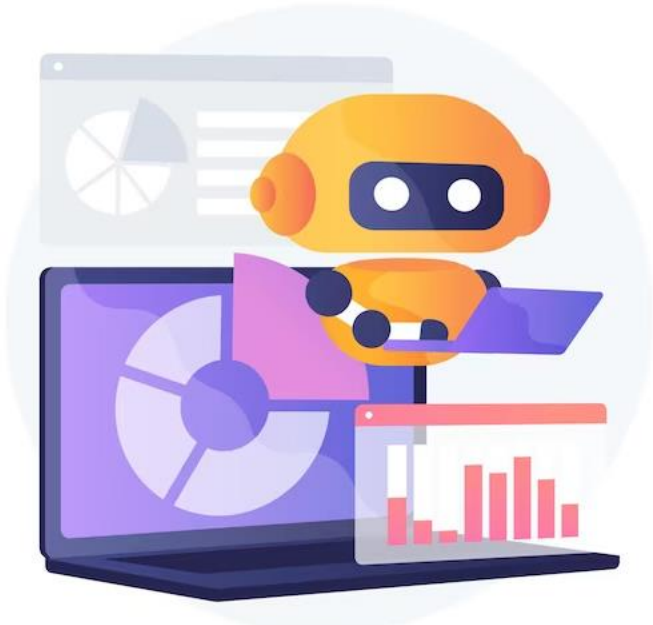
How about 'within' a model?

Transforming within the model

Pros	Cons
Easy iterations	Expensive transforms
Transformation guarantees	Long model latency
	Transformations per batch: skew

Why transform per batch?

- For example, normalizing features by their average
- Access to a single batch of data, not the full dataset
- Ways to normalize per batch
  - Normalize by average within a batch
  - Precompute average and reuse it during normalization

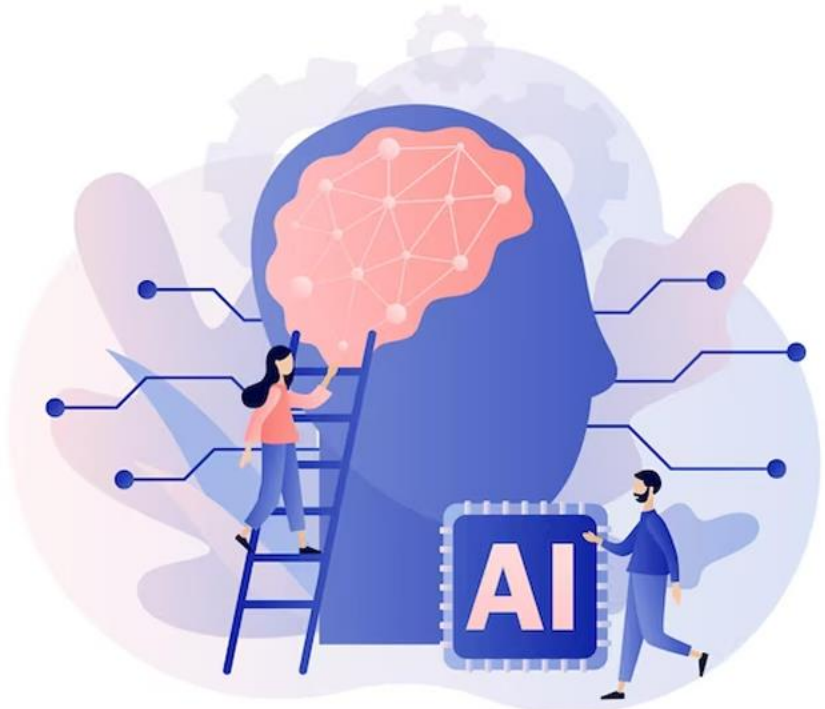


Optimizing instance-level transformations

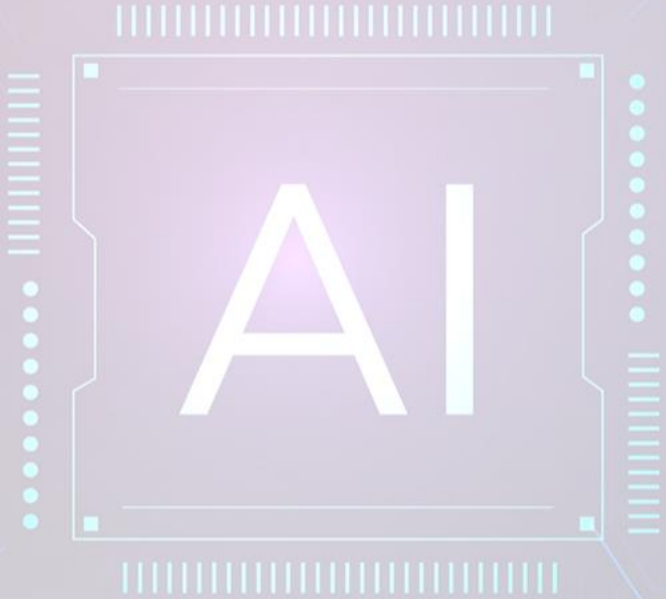
- Indirectly affect training efficiency
- Typically accelerators sit idle while the CPUs transform
- Solution:
  - Prefetching transforms for better accelerator efficiency

Summarizing the challenges

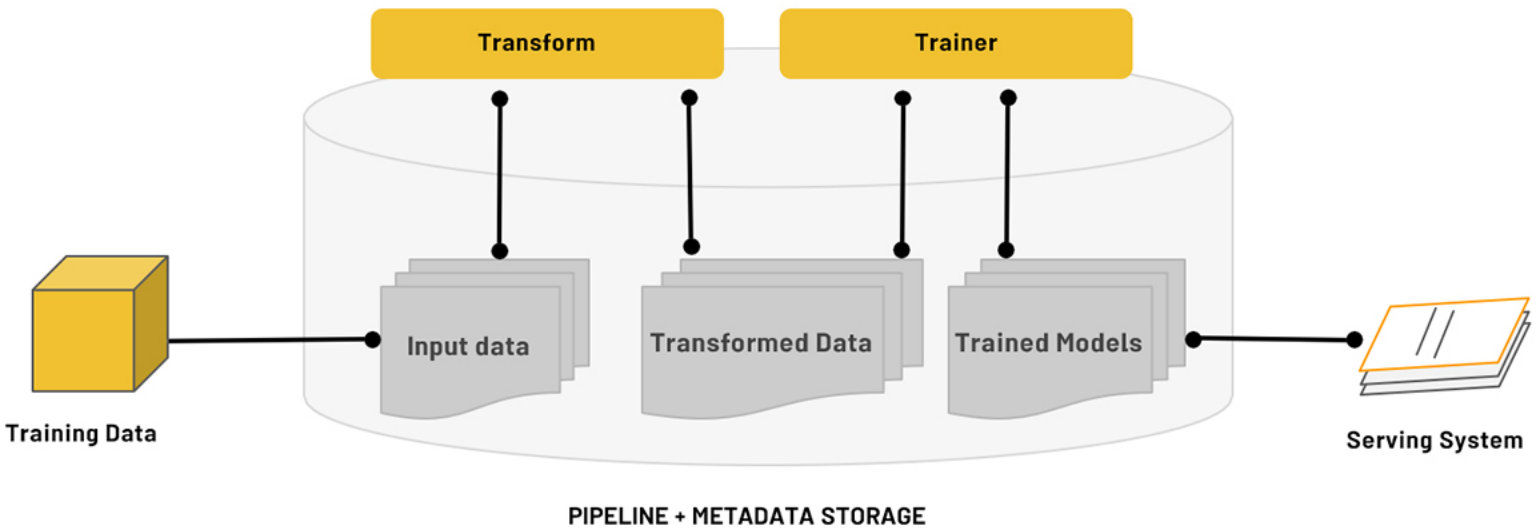
- Balancing predictive performance
- Full-pass transformations on training data
- Optimizing instance-level transformations for better training efficiency (GPUs, TPUs, ...)



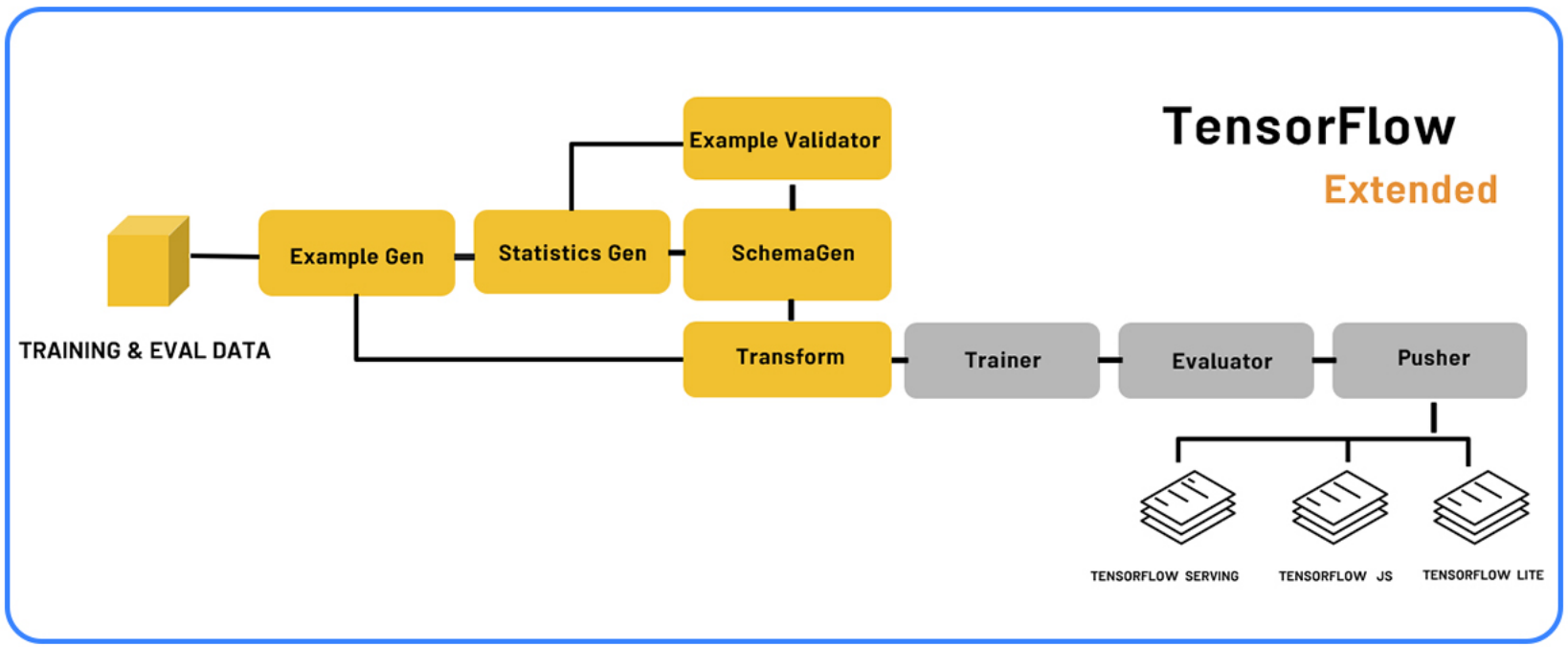
TF Transform



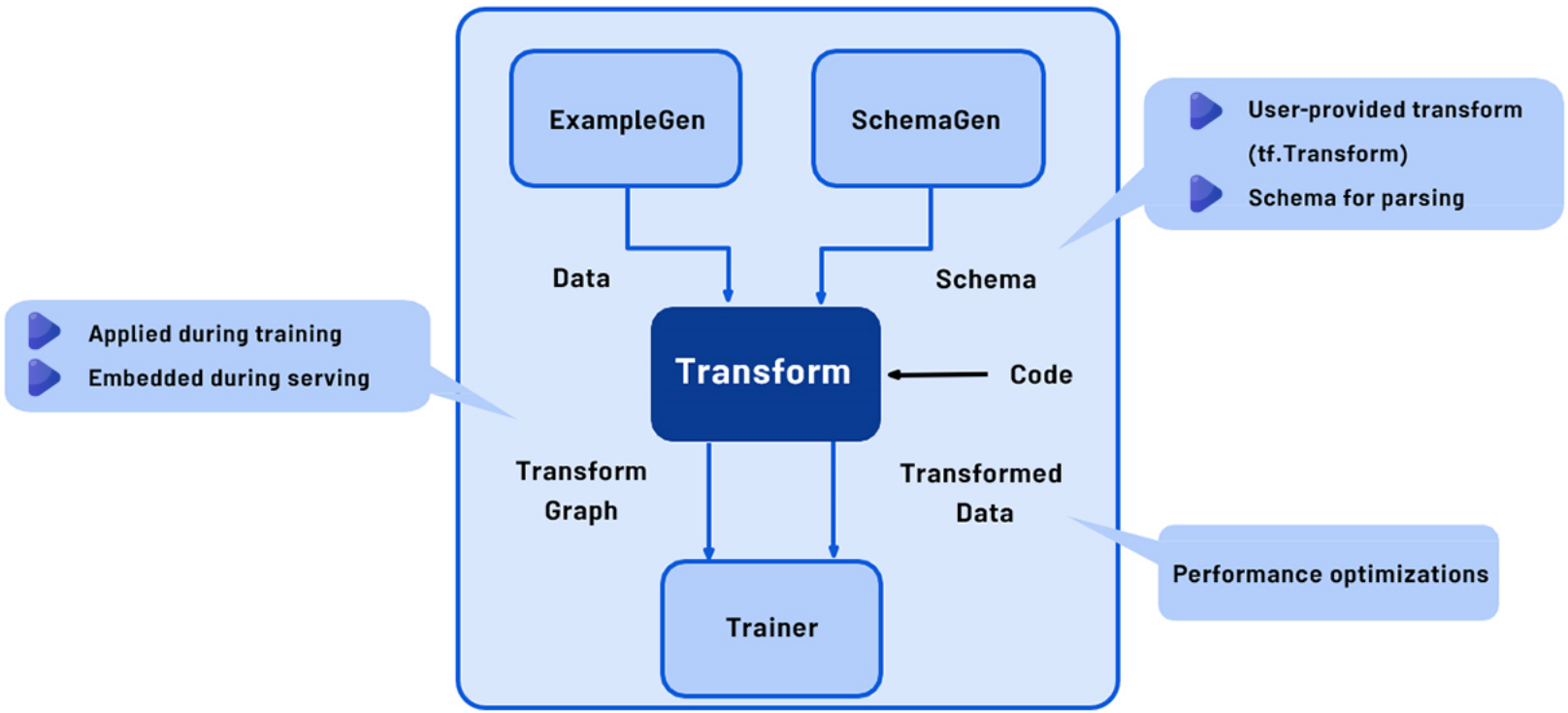
Enter tf.Transform



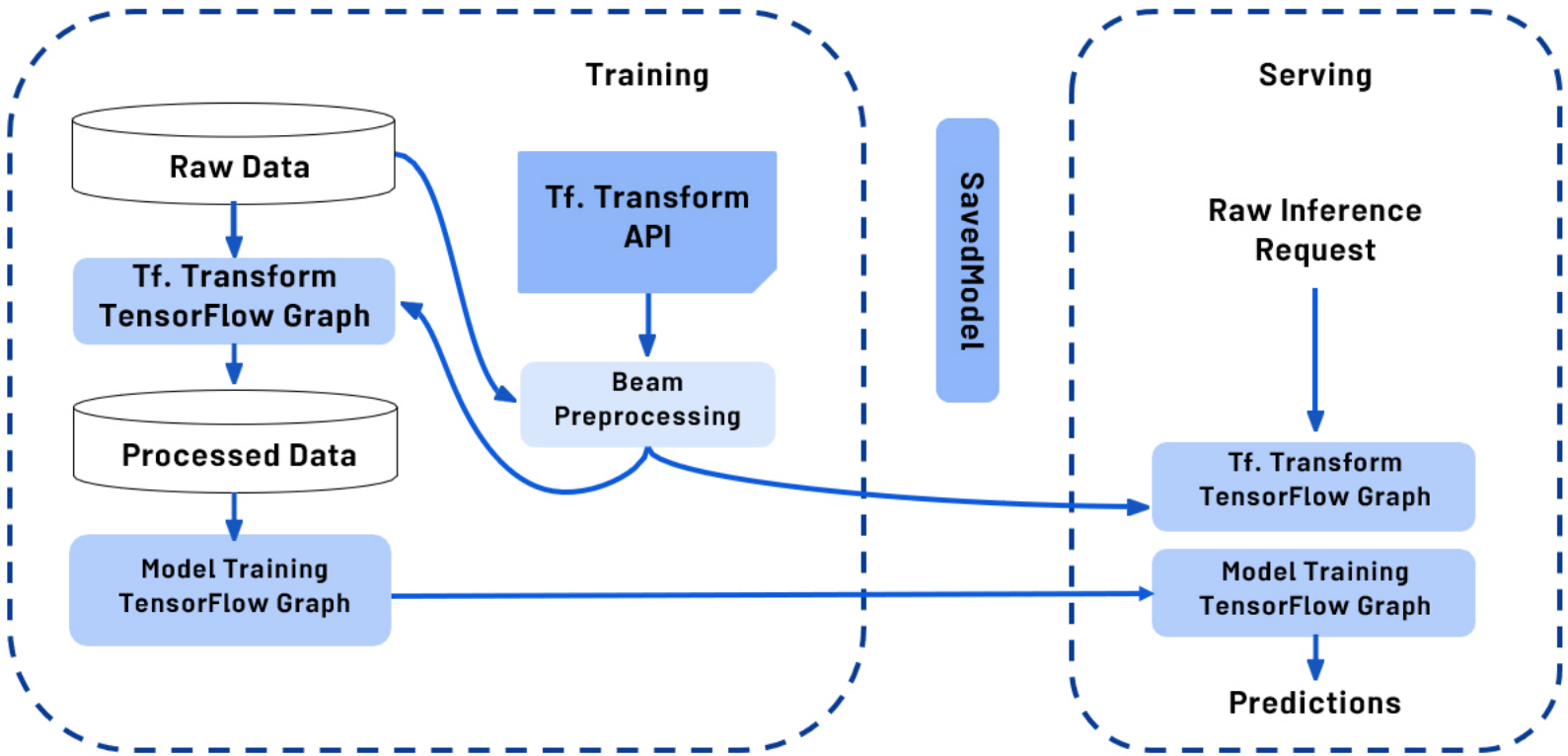
Inside TensorFlow Extended



tf.Transform layout

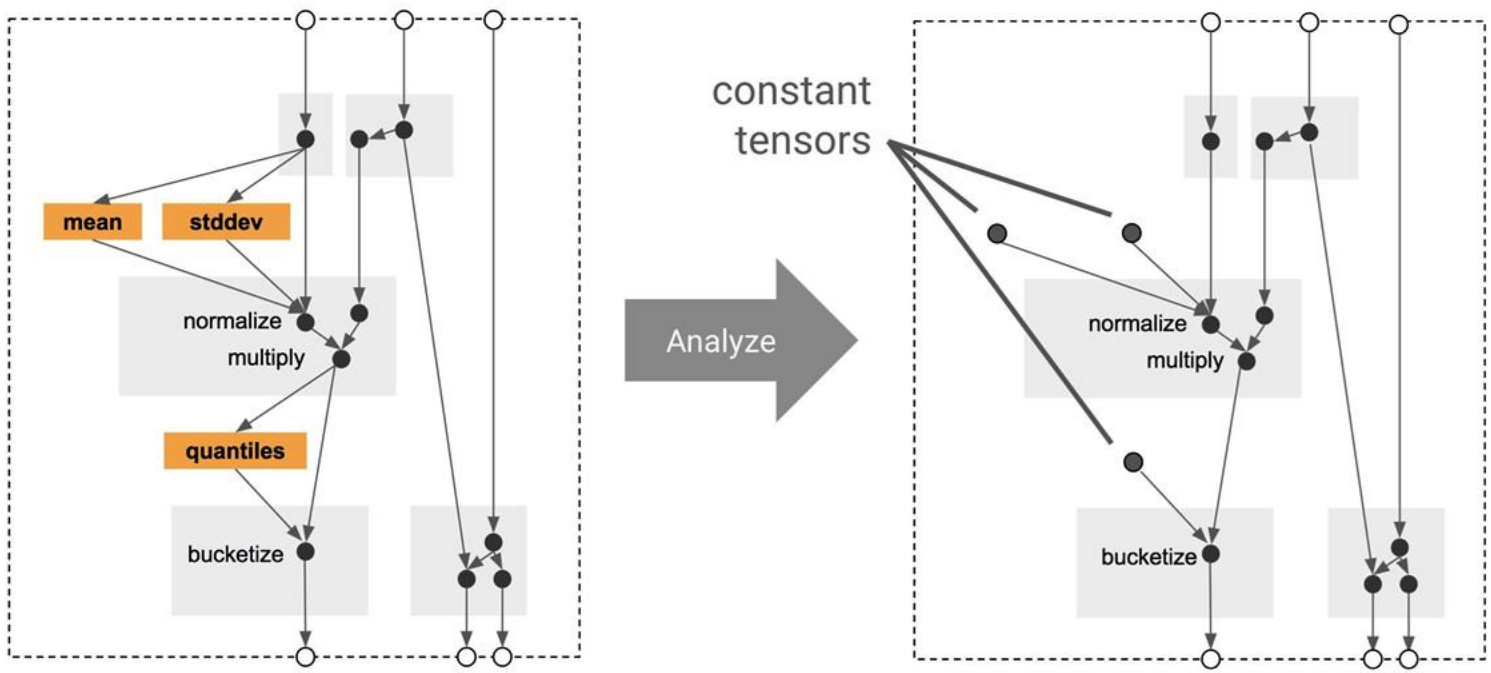


tf. Transform: Going deeper

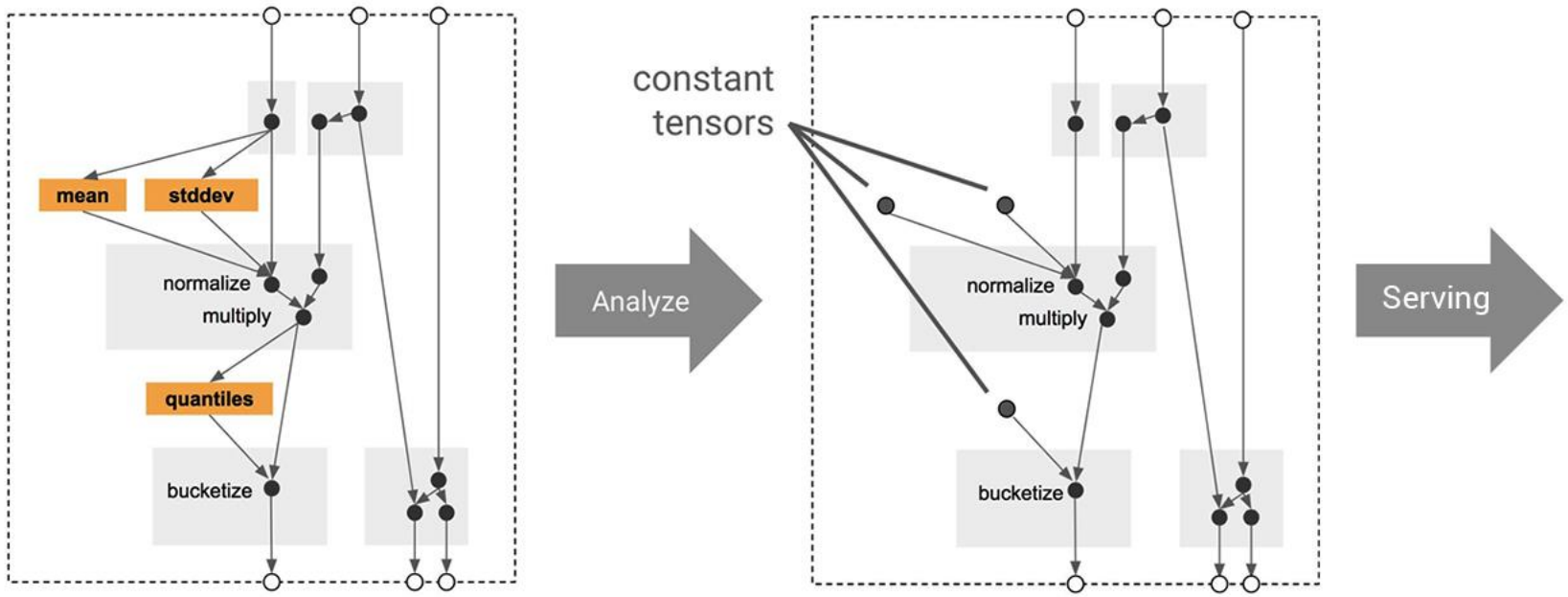


tf.Transform Analyzers

- They behave like TensorFlow Ops, but run only once during training
- For example:
  - tft.min computes the minimum of a tensor over the training dataset



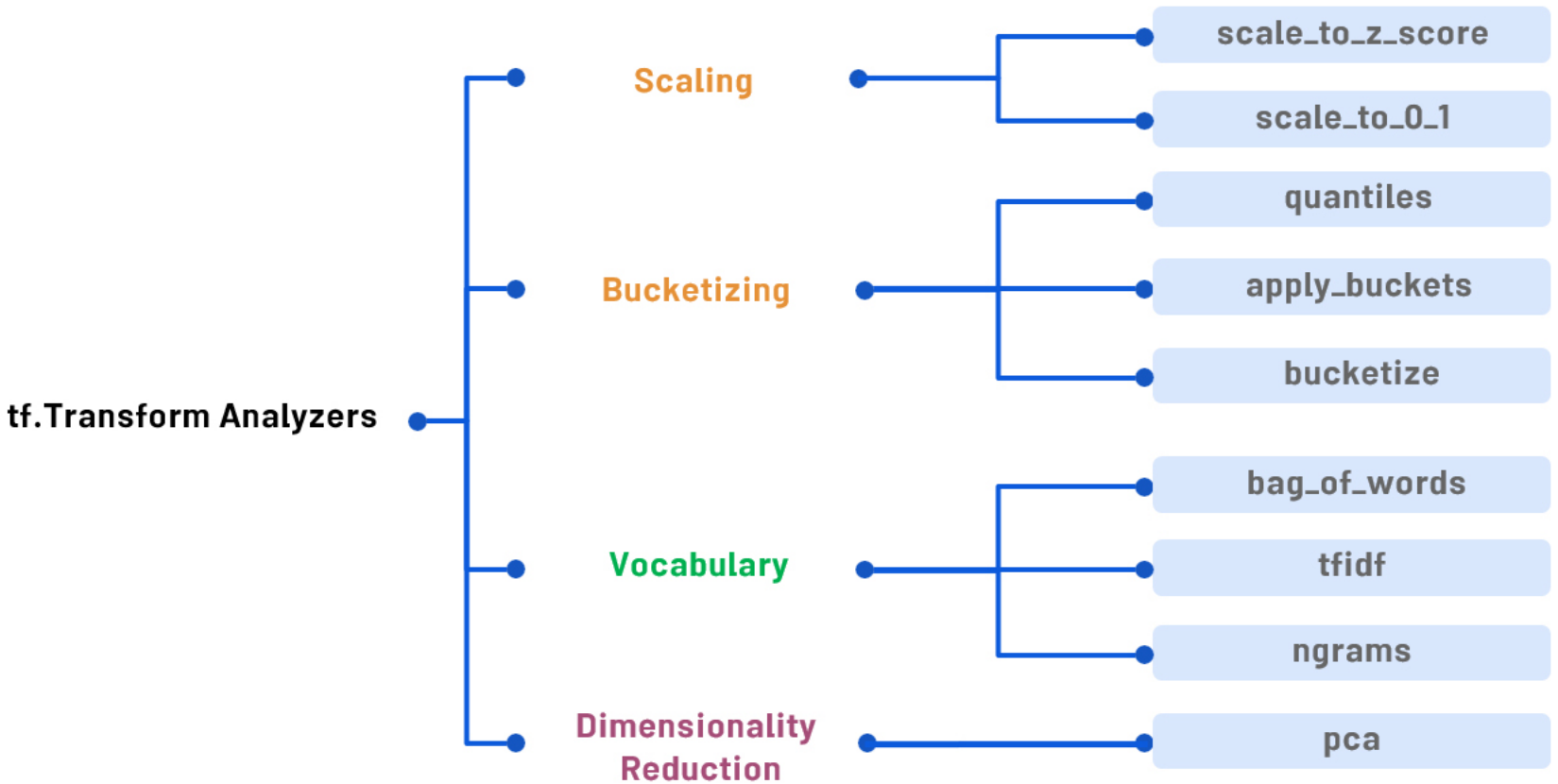
How Transform applies feature transformations



Benefits of using tf.Transform

- Emitted tf.Graph holds all necessary constants and transformations
- Focus on data preprocessing only at training time
- Works in-line during both training and serving
- No need for preprocessing code at serving time
- Consistently applied transformations irrespective of deployment platform

Analyzers framework



tf.Transform preprocessing_fn

```
def preprocessing_fn(inputs):
    ...

for key in DENSE_FLOAT_FEATURE_KEYS:
    outputs[key] = tft.scale_to_z_score(inputs[key])

for key in VOCAB_FEATURE_KEYS:
    outputs[key] = tft.vocabulary(inputs[key],
    vocab_filename=key)

for key in BUCKET_FEATURE_KEYS:
  outputs[key] = tft.bucketize(inputs[key], FEATURE_BUCKET_COUNT)
```

Commonly used imports

```
import tensorflow as tf
import apache_beam as beam
import apache_beam.io.iobase

import tensorflow_transform as tft
import tensorflow_transform.beam as tft_beam
```

Hello world with tf.Transform

1 — 2 — 3 — Analyze — tf.Transform — 4

Data

Collect raw data

Define metadata

Prepare metadata for the dataset using DatasetMetadata

Transform

Define the preprocessing function with tf.Transform analyzers

Constant graph

Generate a constant graph with the required transformations

Collect raw samples (Data)

```
[
    {'x': 1, 'y': 1, 's': 'hello'},
    {'x': 2, 'y': 2, 's': 'world'},
    {'x': 3, 'y': 3, 's': 'hello'}
]
```

Inspect data and prepare metadata (Data)

```
from tensorflow_transform.tf_metadata import (
    dataset_metadata, dataset_schema)

raw_data_metadata = dataset_metadata.DatasetMetadata(
    dataset_schema.from_feature_spec({

    'y': tf.io.FixedLenFeature([], tf.float32),
        'x': tf.io.FixedLenFeature([], tf.float32),
        's': tf.io.FixedLenFeature([], tf.string)
    }))
```

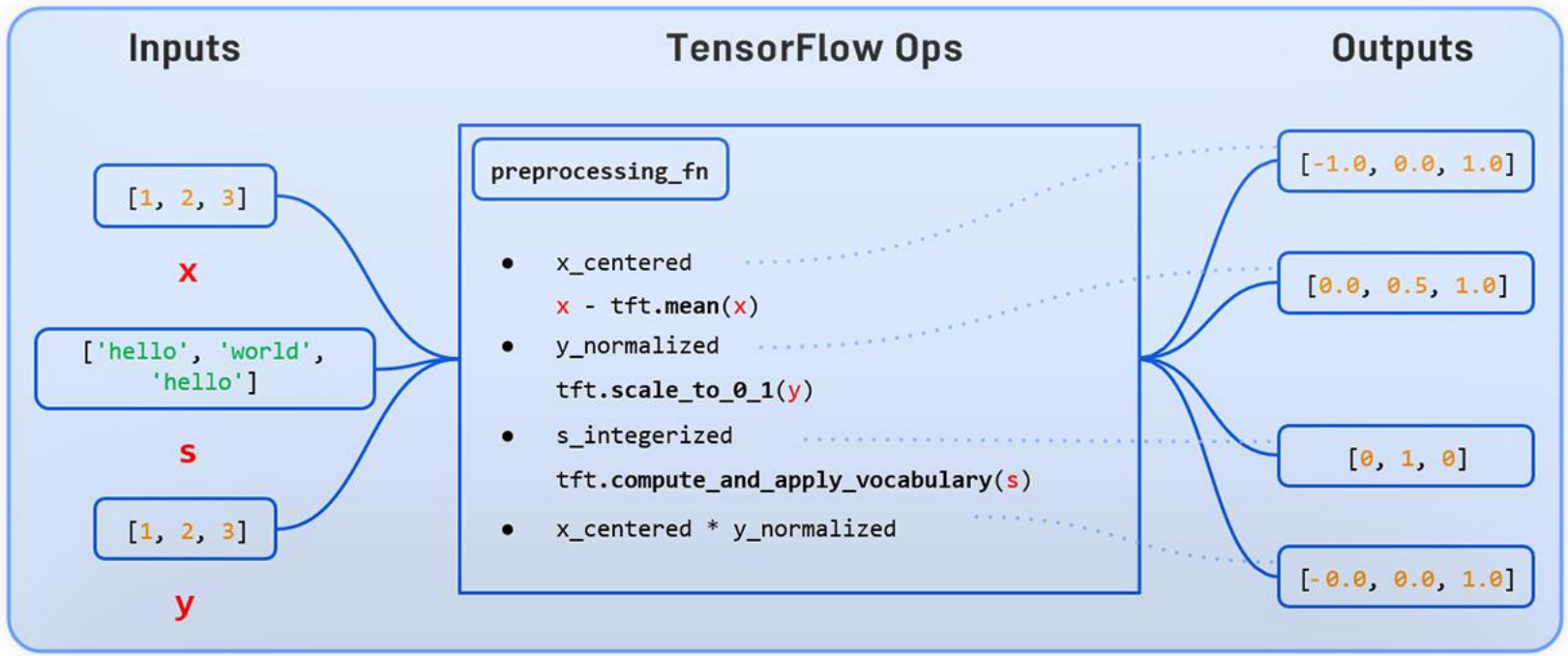
Preprocessing data (Transform)

```
def preprocessing_fn(inputs):
"""Preprocess input columns into transformed columns."""
    x, y, s = inputs['x'], inputs['y'], inputs['s']
    x_centered = x - tft.mean(x)
    y_normalized = tft.scale_to_0_1(y)
    s_integerized = tft.compute_and_apply_vocabulary(s)
    x_centered_times_y_normalized = (x_centered * y_normalized)
```

Preprocessing data (Transform)

```
return {
   'x_centered': x_centered,
   'y_normalized': y_normalized,
   's_integerized': s_integerized,
   'x_centered_times_y_normalized': x_centered_times_y_normalized,
 }
```

Tensors in... tensors out



Running the pipeline

```
def main():
with
  tft_beam.Context(temp_dir=tempfile.mkdtemp()):
  transformed_dataset, transform_fn = (
      (raw_data, raw_data_metadata) |
          tft_beam.AnalyzeAndTransformDataset(preprocessing_fn))
```

Running the pipeline

```
transformed_data, transformed_metadata =
transformed_dataset


print('\nRaw data:\n{}\n'.format(pprint.pformat(raw_data)))
print('Transformed data:\n{}'.format(pprint.pformat(transformed_data)))


if ____name_____ == '_____main_____':
main()
```

Before transforming with tf.Transform

```
# Raw data:

[{'s': 'hello', 'x': 1, 'y':
1},

 {'s': 'world', 'x': 2, 'y':
 2},

 {'s': 'hello', 'x': 3, 'y':
 3}]
```

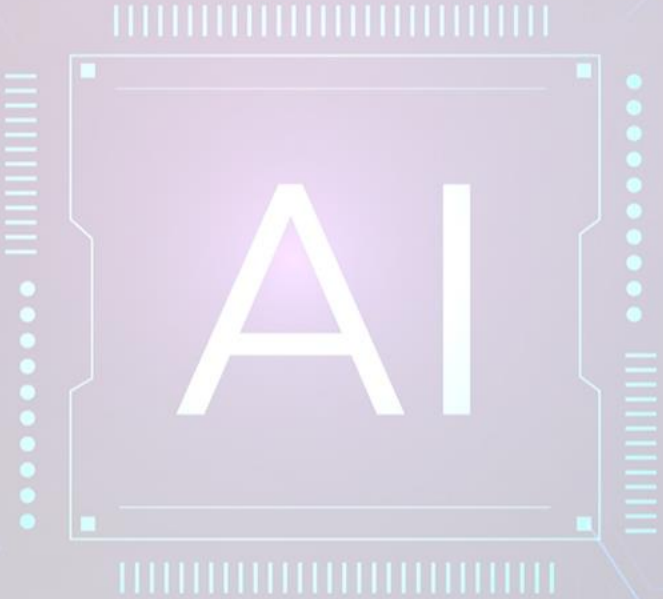
After transforming with tf.Transform

```
# After transform
[{'s_integerized': 0,
  'x_centered': -1.0,
  'x_centered_times_y_normalized': -0.0,
  'y_normalized': 0.0},
 {'s_integerized': 1,
  'x_centered': 0.0,
  'x_centered_times_y_normalized': 0.0,
  'y_normalized': 0.5},
 {'s_integerized': 0,
  'x_centered': 1.0,
  'x_centered_times_y_normalized': 1.0,
  'y_normalized': 1.0}]
```

Key Points

- tf.Transform allows the pre-processing of input data and creating features
- tf.Transform allows defining pre-processing pipelines and their execution using large-scale data processing frameworks
- In a TFX pipeline, the Transform component implements feature engineering using TensorFlow Transform

Feature spaces

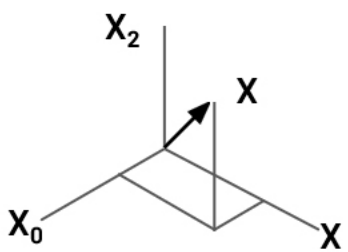


Feature space

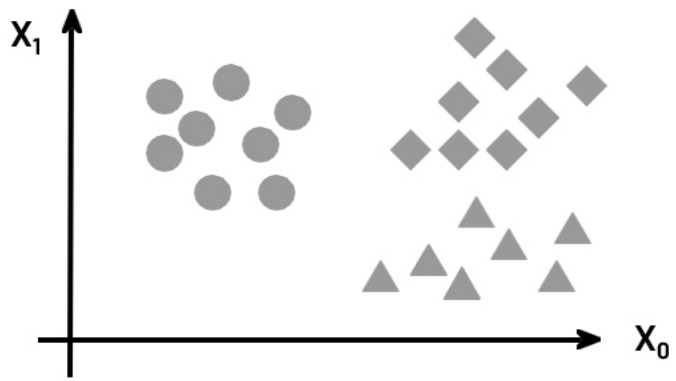
- N dimensional space defined by your N features
- Not including the target label

$$X = \begin{bmatrix} X_0 \\ X_1 \\ \vdots \\ X_d \end{bmatrix}$$

Feature vector



Feature space (3D)



Scatter plot (2D)

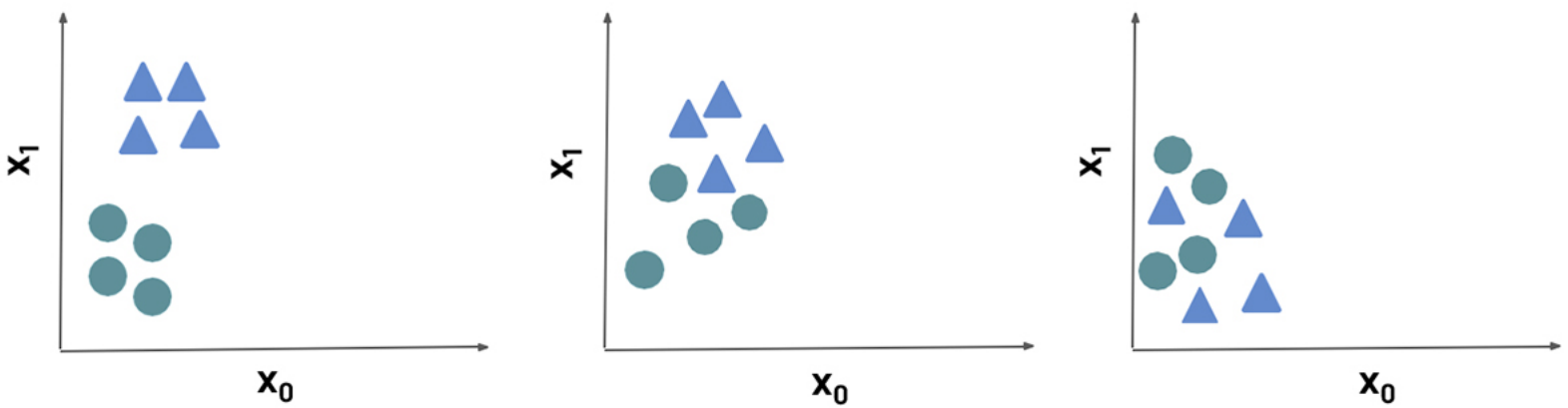
Feature space

3D Feature Space

No. of Rooms X_0	Area X_1	Locality X_2	Price Y
5	1200 sq. ft	New York	$40,000
6	1800 sq. ft	Texas	$30,000

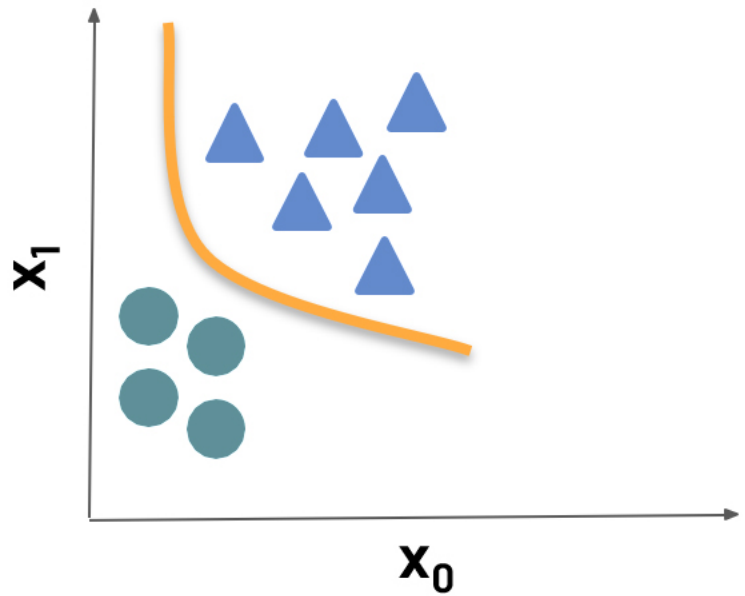
- $Y = f(X_0, X_1, X_2)$
- f is your ML model acting on feature space X_0, X_1, X_2

2D Feature space - Classification



Drawing decision boundary

- Model learns decision boundary
- Boundary used to classify data points

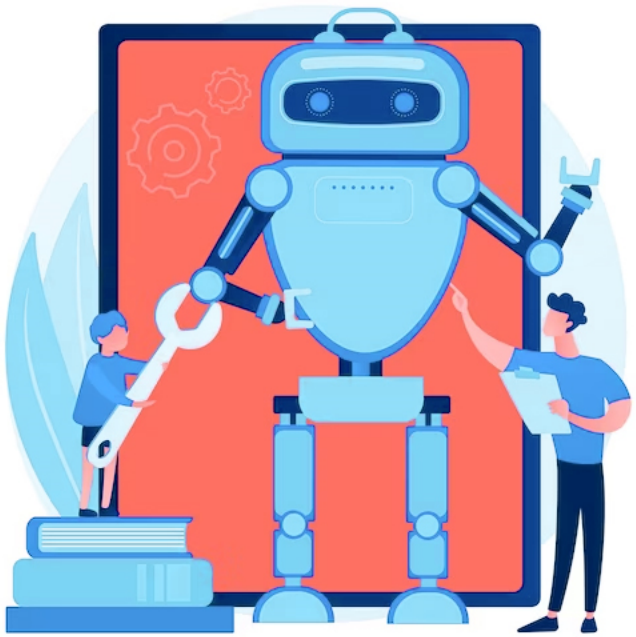


Feature space coverage

- **Train/Eval datasets representative of the serving dataset**
  - Same numerical ranges
  - Same classes
  - Similar characteristics for image data
  - Similar vocabulary, syntax, and semantics for NLP data

Ensure feature space coverage

- Data affected by: seasonality, trend, drift.
- Serving data: new values in features and labels.
- Continuous monitoring, key for success!



Feature selection

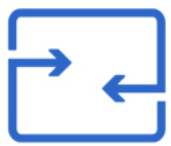
- Identify features that best represent the relationship
- Remove features that don't influence the outcome
- Reduce the size of the feature space
- Reduce the resource requirements and model complexity

All Features

Feature selection

Useful features

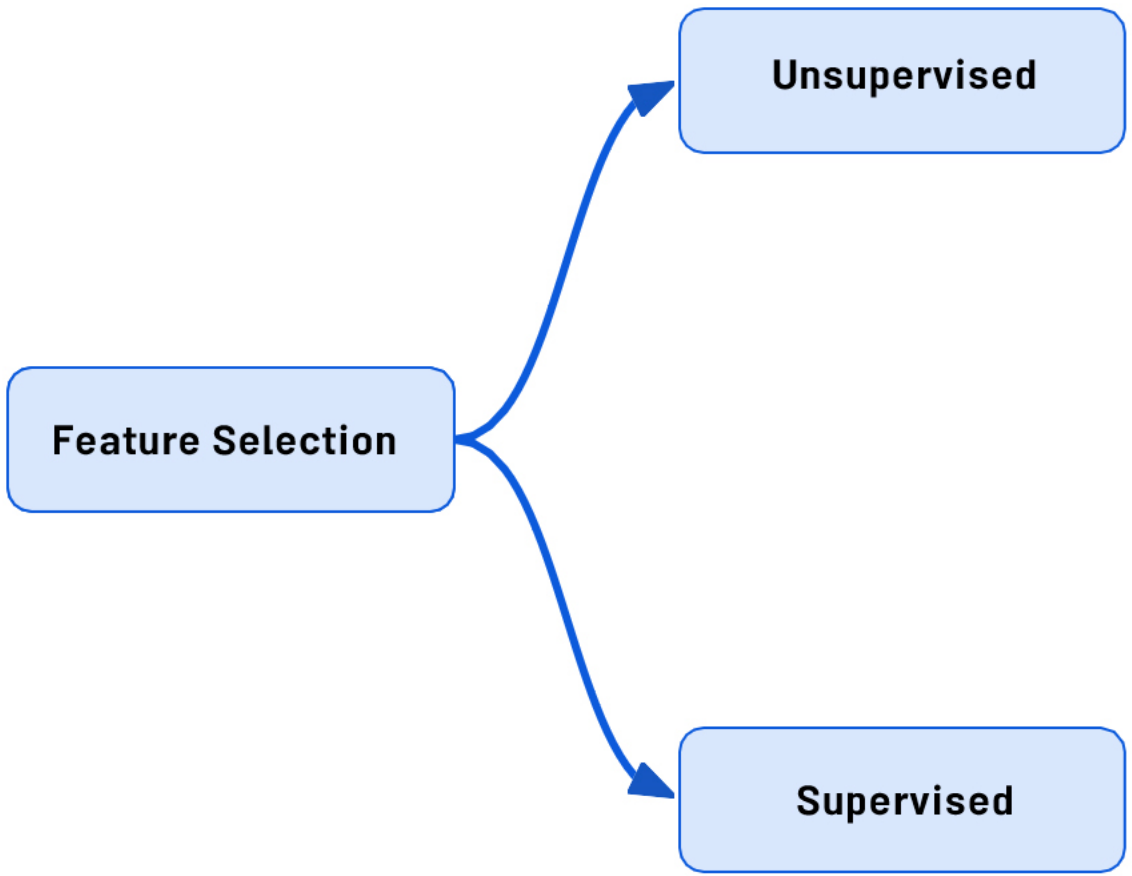
Why is feature selection needed?



Reduce storage and I/O requirements

Minimize training and inference costs

Feature selection methods



Feature selection

1. Unsupervised

- Features-target variable relationship not considered
- Removes redundant features (correlation)

Feature selection

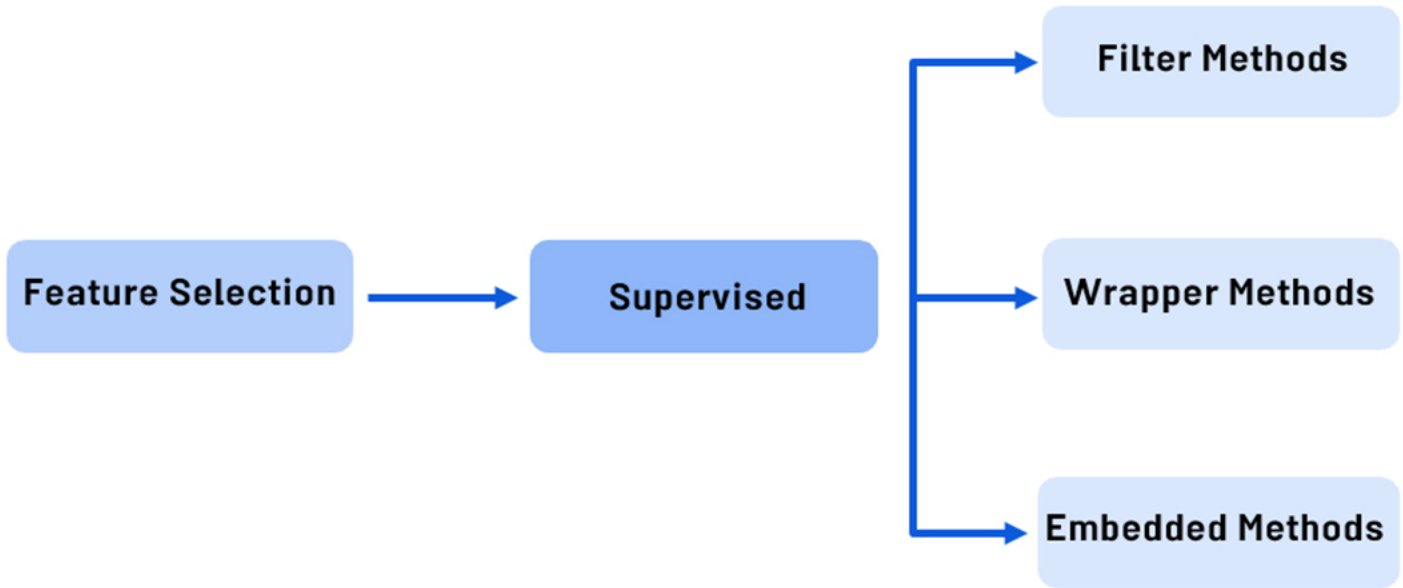
1. Unsupervised

- Features-target variable relationship not considered
- Removes redundant features (correlation)

2. Supervised

- Uses features-target variable relationship
- Selects those contributing the most

Supervised methods



Practical example

- Feature selection techniques on Breast Cancer Dataset (Diagnostic)
- Predicting whether tumour is benign or malignant.

Feature list

id	diagnosis	radius-mean	Texture_mean	perimeter_ mean	area_mean	smoothness _mean	compactnes s_mean
842302	M	17.99	10.38	122.8	1001.0	0.1184	0.2776

concavity_m ean	concavepoin ts_mean	symmetry_ mean	fractal_dime nsion_mean	radius_se	texture_se	perimeter_s e	area_se
0.3001	0.1471	0.2419	0.07871	1.095	0.9053	8.589	153.4
smoothness _se	compactnes s_se	concavity_se	concavepoint s_se	symmetry_ se	fractal_dime nsion_se	radius-wors t	texture_wor st

Irrelevant features

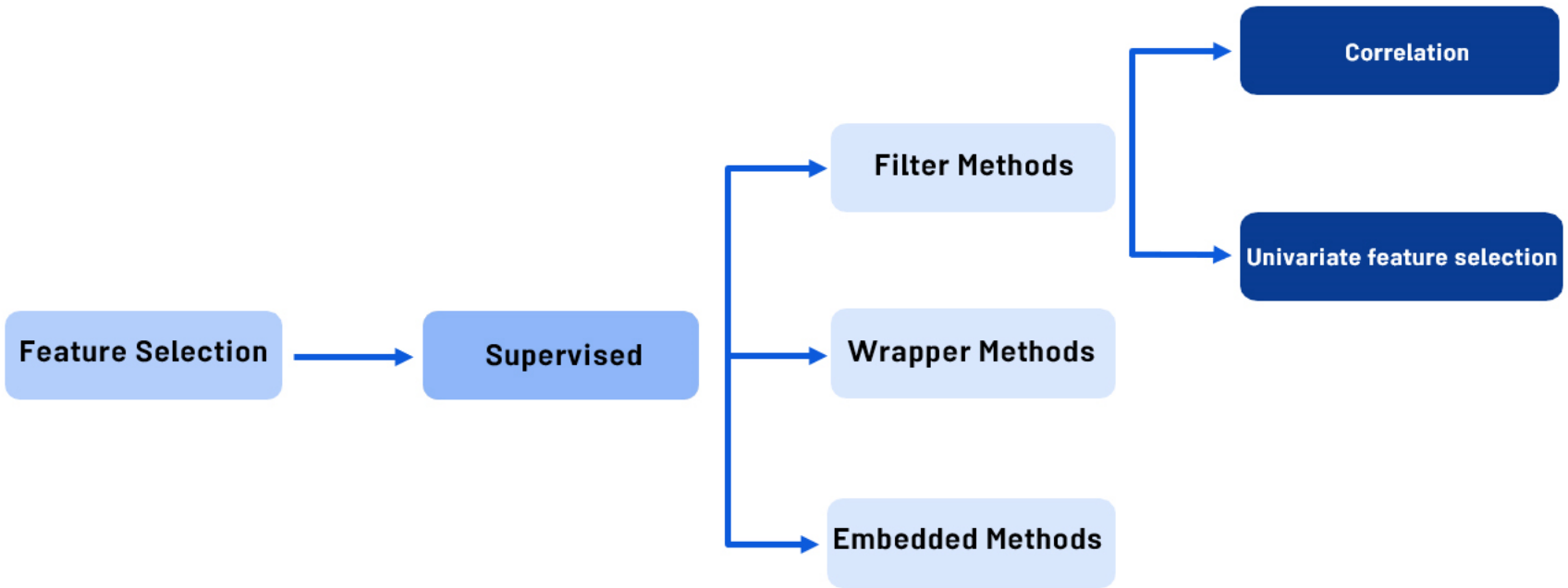
0.0064	0.049	0.054	0.016	0.03	0.006	25.38	17.33	
perimeter_w orst	area_worst	smoothness _worst	compactness _worst	concavity_ worst	concavepoin ts_worst	symmetry_ worst	fractal_dime nsion_worst	Unnamed:3 2
184.6	2019.0	0.1622	0.6656	0.7119	0.2654	0.4601	0.1189	NaN

Performance evaluation

- We train a RandomForestClassifier model in sklearn.ensemble on selected features
- Metrics (sklearn.metrics):

Method	Feature Count	Accuracy	AUROC	Precision	Recall	F1 Score
All Features	30	0.967262	0.964912	0.931818	0.97619	0.953488

Filter methods



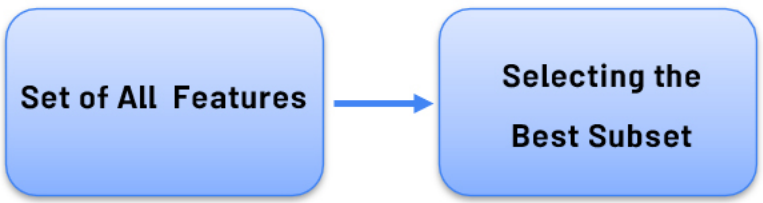
Filter methods

- Correlated features are usually redundant
  - Remove them!
- Popular filter methods:
- Pearson Correlation
  - Between features, and between the features and the label
- Univariate Feature Selection

Filter methods

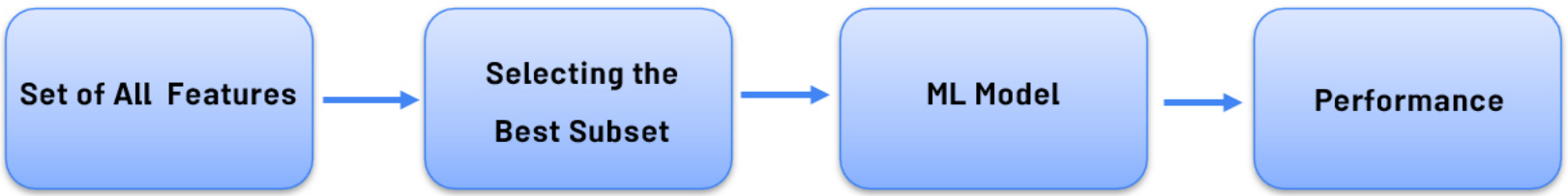
Set of All Features

Filter methods



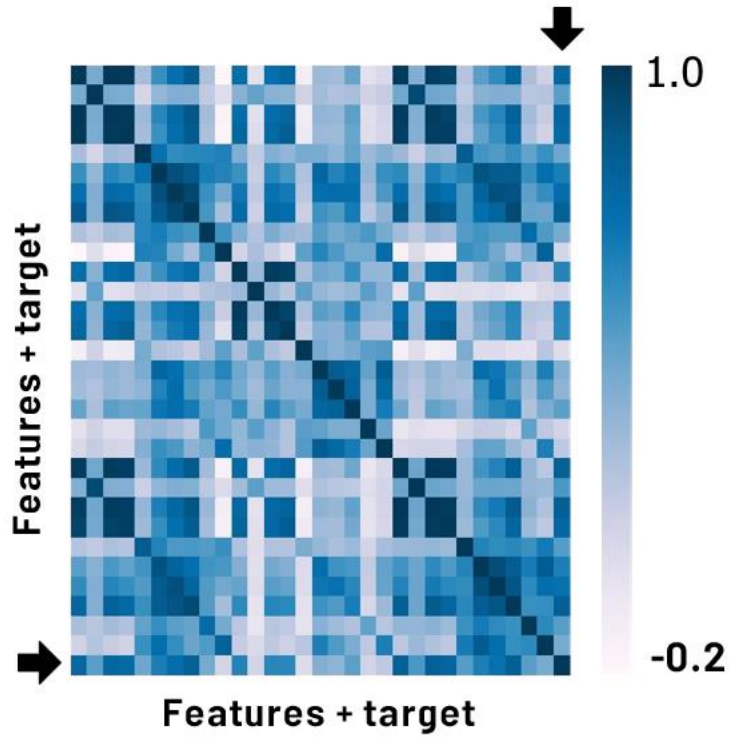
Filter methods

Filter methods



Correlation matrix

- Shows how features are related:
  - To each other (Bad)
  - And with target variable (Good)
- Falls in the range [-1, 1]
  - 1 High positive correlation
  - -1 High negative correlation



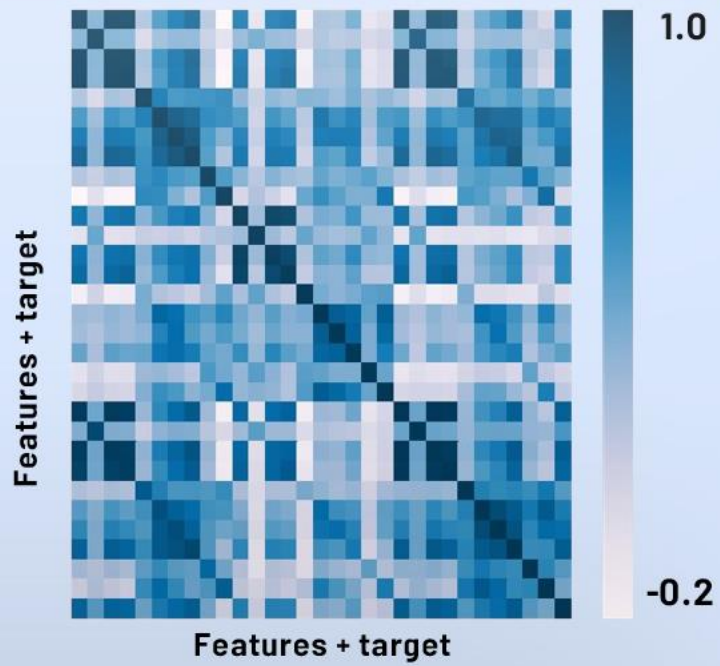
Feature comparison statistical tests

- Pearson's correlation: Linear relationships
- Kendall Tau Rank Correlation Coefficient:
  - Monotonic relationships & small sample size
- Spearman's Rank Correlation Coefficient:
  - Monotonic relationships
- Other methods:
  - Mutual information
  - F-Test
  - Chi-Squared test

Determine correlation

```
# Pearson’s correlation by default
cor = df.corr()


plt.figure(figsize=(20,20))
# Seaborn
sns.heatmap(cor, annot=True, cmap=plt.cm.PuBu)
plt.show()
```



Selecting features

```
cor_target = abs(cor["diagnosis_int"])

# Selecting highly correlated features as potential features to eliminate
relevant_features = cor_target[cor_target>0.2]
```

Performance table

Method	Feature Count	Accuracy	AUROC	Precision	Recall	F1 Score
All Features	30	0.967262	0.964912	0.931818	0.97619	0.953488
Correlation	21	0.974206	0.973684	0.953488	0.97619	0.964706

Univariate feature selection in SKLearn

- **SKLearn Univariate feature selection routines:**
  - SelectKBest
  - SelectPercentile
  - GenericUnivariateSelect
- **Statistical tests available:**
  - Regression: f_regression, mutual_info_regression
  - Classification: chi2, f_classif, mutual_info_classif

SelectKBest implementation

```
def univariate_selection():

  X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
                                                      test_size = 0.2,stratify=Y, random_state = 123)

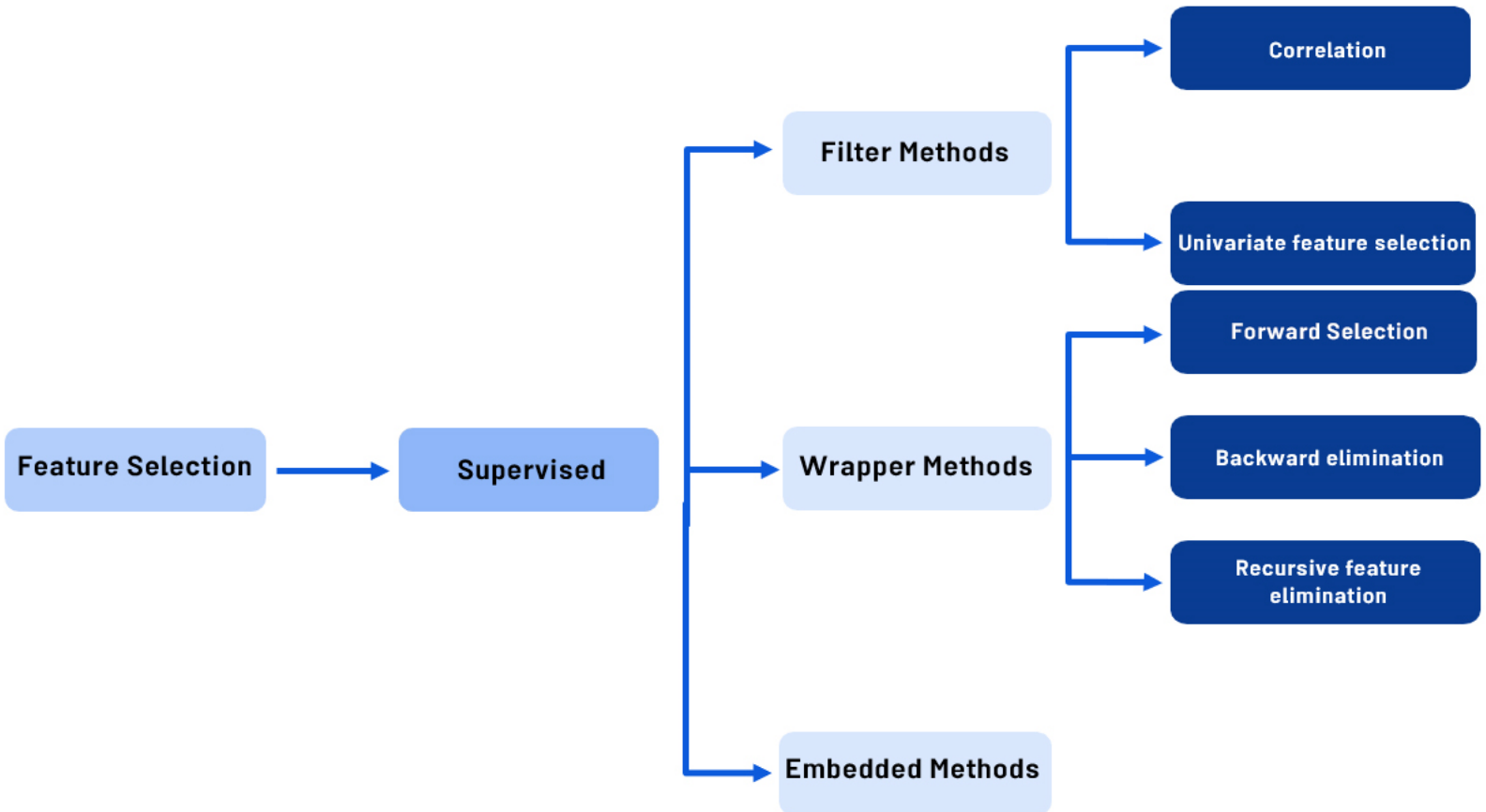
  X_train_scaled = StandardScaler().fit_transform(X_train)
  X_test_scaled = StandardScaler().fit_transform(X_test)

  min_max_scaler = MinMaxScaler()
  Scaled_X = min_max_scaler.fit_transform(X_train_scaled)
  selector = SelectKBest(chi2, k=20) # Use Chi-Squared test
  X_new = selector.fit_transform(Scaled_X, Y_train)  feature_idx
  = selector.get_support()
  feature_names = df.drop("diagnosis_int",axis = 1 ).columns[feature_idx]
  return feature_names
```

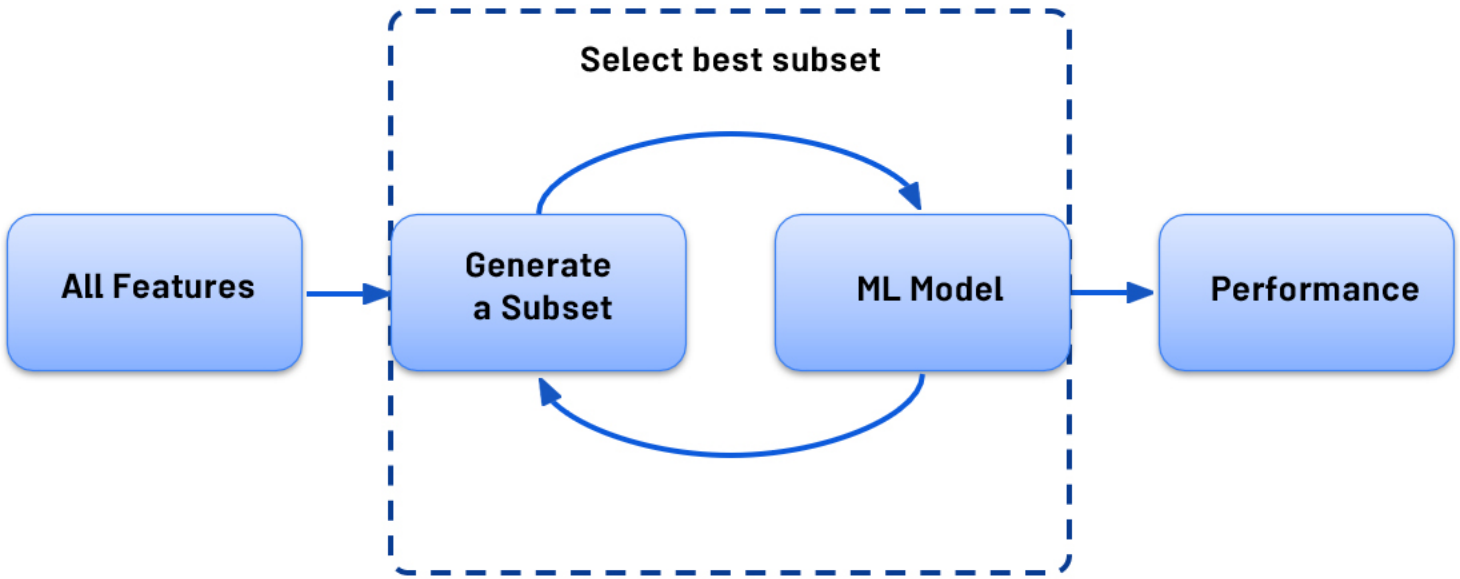
Performance table

Method	Feature Count	Accuracy	AUROC	Precision	Recall	F1 Score
All Features	30	0.967262	0.964912	0.931818	0.97619	0.953488
Correlation	21	0.974206	0.973684	0.953488	0.97619	0.964706
Univariate (Chi²)	20	0.960317	0.95614	0.91111	0.97619	0.94252

Wrapper methods



Wrapper methods



Wrapper methods

- **Popular wrapper methods**
  - Forward Selection
  - Backward elimination
  - Recursive Feature Elimination

Forward selection

- Iterative, greedy method
- Starts with 1 feature
- Evaluate model performance when adding each of the additional features, one at a time
- Add next feature that gives the best performance
- Repeat until there is no improvement

Backward elimination

- Start with all features
- Evaluate model performance when removing each of the included features, one at a time
- Remove next feature that gives the best per-formance
- Repeat until there is no improvemen

Recursive feature elimination (RFE)

- Select a model to use for evaluating feature importance
- Select the desired number of features
- Fit the model
- Rank features by importance
- Discard least important features
- Repeat until the desired number of features remains

Recursive feature elimination

```
def run_rfe():
  X_train, X_test, y_train, y_test = train_test_split(X,Y, test_size = 0.2, random_state = 0)
  X_train_scaled = StandardScaler().fit_transform(X_train)
  X_test_scaled = StandardScaler().fit_transform(X_test)


  model = RandomForestClassifier(criterion='entropy', random_state=47)
  rfe = RFE(model,20)
  rfe = rfe.fit(X_train_scaled, y_train)
  feature_names = df.drop("diagnosis_int",axis = 1
  ).columns[rfe.get_support()]  return feature_names

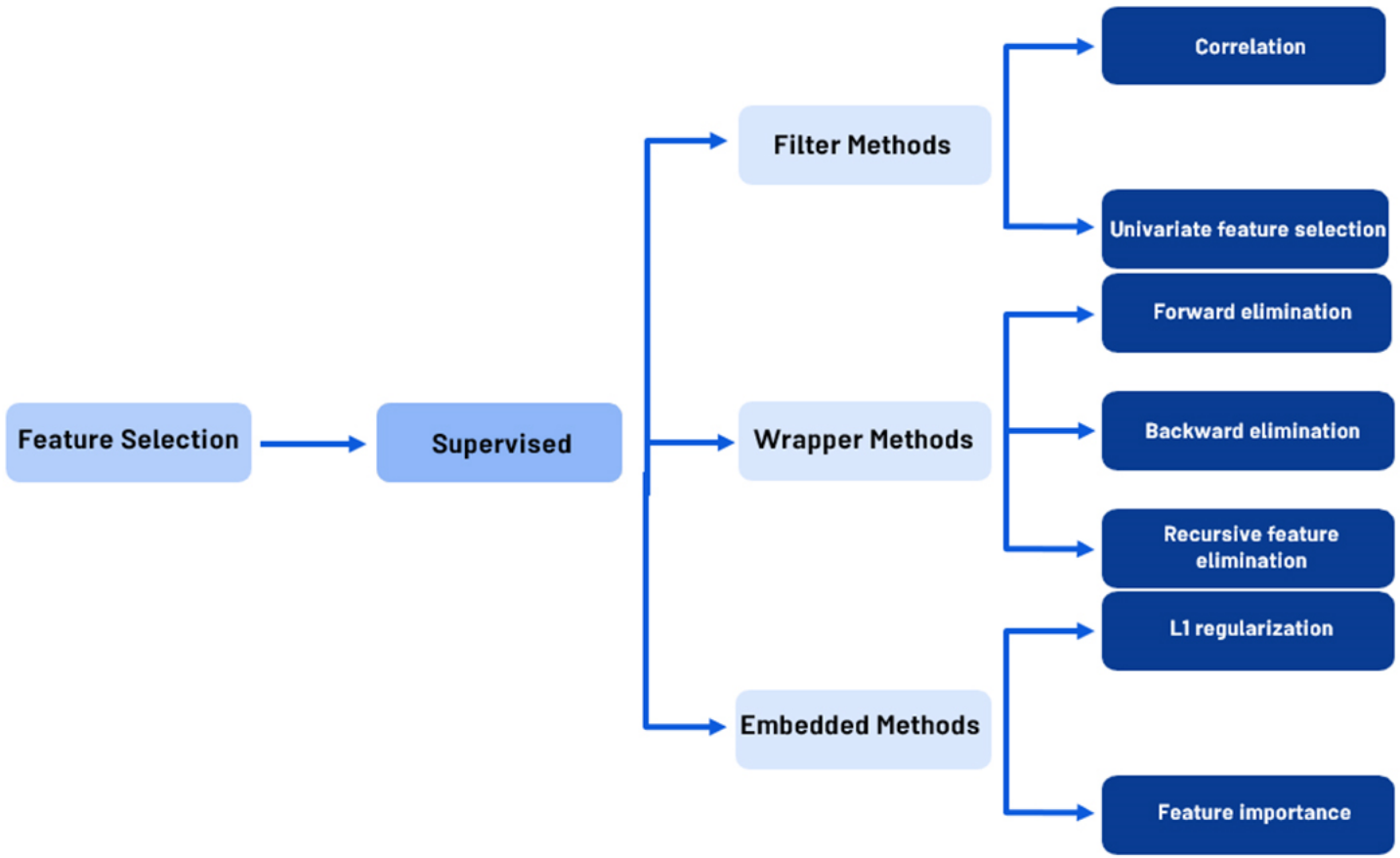
rfe_feature_names = run_rfe()


rfe_eval_df = evaluate_model_on_features(df[rfe_feature_names], Y)
rfe_eval_df.head()
```

Performance table

Method	Feature Count	Accuracy	AUROC	Precision	Recall	F1 Score
All Features	30	0.96726	0.96491	0.931818	0.97619	0.953488
Correlation	21	0.97420	0.97368	0.9534883	0.97619	0.964705
Univariate (Chi^2)	20	0.96031	0.95614	0.91111	0.97619	0.94252
Recursive Feature Elimination	20	0.97420	0.97368	0.953488	0.97619	0.964706

Embedded methods



Feature importance

- Assigns scores for each feature in data
- Discard features scored lower by feature importance

Feature importance with SKLearn

- Feature Importance class is in-built in Tree Based Models (eg., RandomForest Classifier)
- Feature importance is available as a property feature_importances_
- We can then use Select From Model to select features from the trained model based on assigned feature importances.

Extracting feature importance

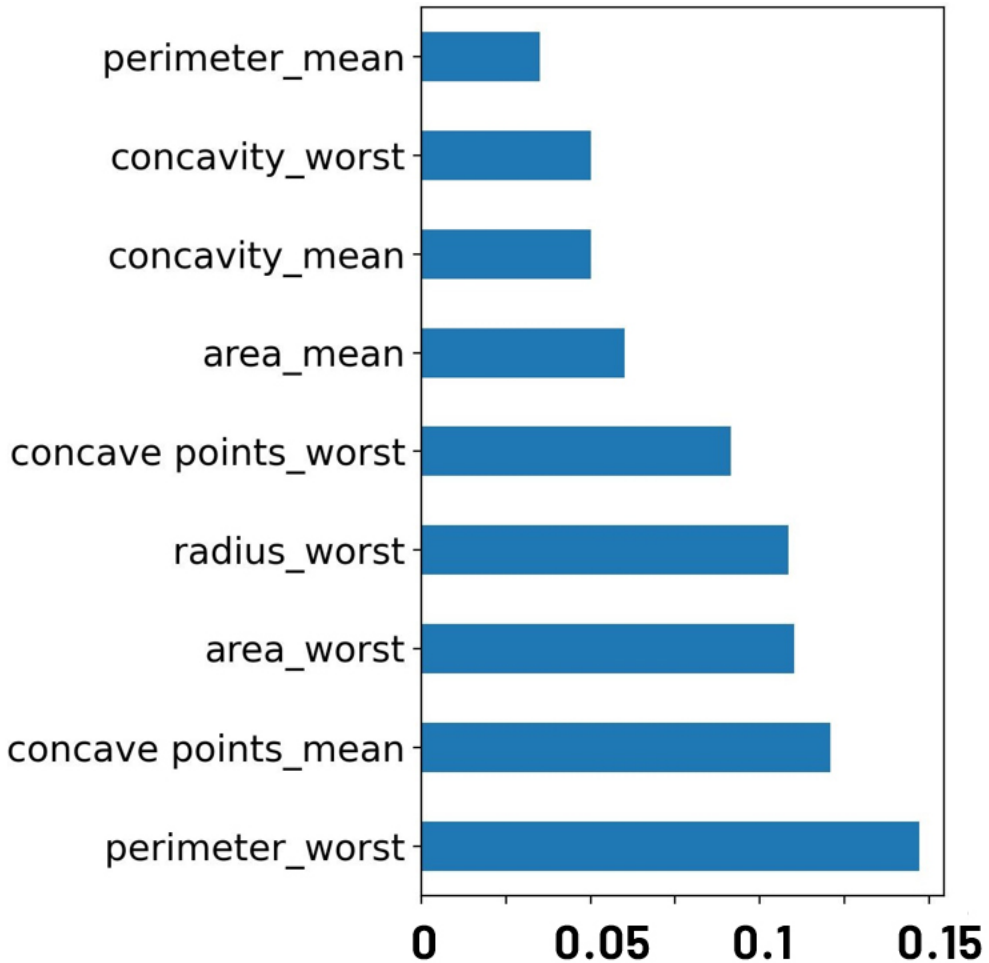
```
def feature_importances_from_tree_based_model_():

  X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2,
                                                      stratify=Y, random_state = 123)
  model = RandomForestClassifier()
  model = model.fit(X_train,Y_train)

  feat_importances = pd.Series(model.feature_importances_, index=X.columns)
  feat_importances.nlargest(10).plot(kind='barh')
  plt.show()

  return model
```

Feature importance plot



Select features based on importance

```
def select_features_from_model(model):


    model = SelectFromModel(model, prefit=True, threshold=0.012)

    feature_idx = model.get_support()
    feature_names = df.drop("diagnosis_int",1 ).columns[feature_idx]
    return feature_names
```

Tying together and evaluation

```
# Calculate and plot feature importances
model = feature_importances_from_tree_based_model_()

# Select features based on feature importances
feature_imp_feature_names = select_features_from_model(model)
```

Performance table

Method	Feature Count	Accuracy	ROC	Precision	Recall	F1 Score
All Features	30	0.96726	0.964912	0.931818	0.9761900	0.953488
Correlation	21	0.97420	0.973684	0.953488	0.9761904	0.964705
Univariate Feature Selection	20	0.96031	0.95614	0.91111	0.97619	0.94252
Recursive Feature Elimination	20	0.9742	0.973684	0.953488	0.97619	0.964706
Feature Importance	14	0.96726	0.96491	0.931818	0.97619	0.953488

Review

- Intro to Preprocessing
- Feature Engineering
- Preprocessing Data at Scale
  - TensorFlow Transform
- Feature Spaces
- Feature Selection
  - Filter Methods
  - Wrapper Methods
  - Embedded Methods