AIS477: S.T. in Artificial Intelligence

Lecture 4

DeepLearning.AI

DeepLearning.AI

Feature Engineering, Transformation and Selection

Welcome

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Feature Engineering

Introduction to Preprocessing

“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

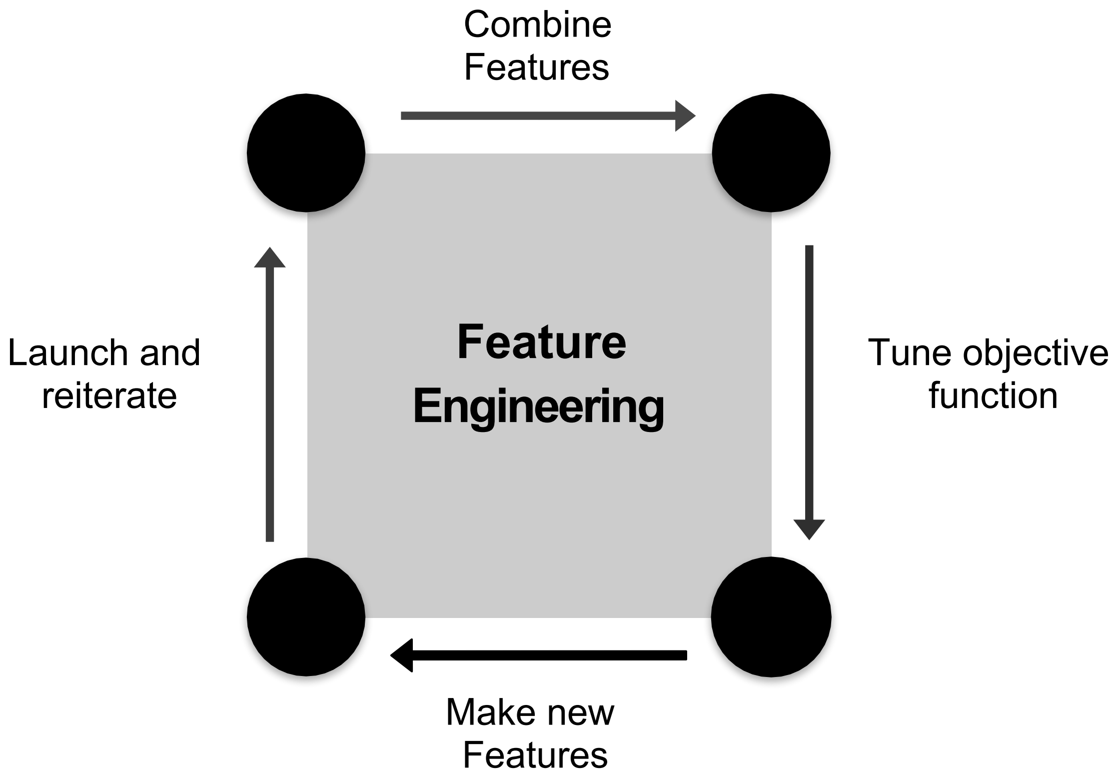
Outline

- Squeezing the most out of data
- The art of feature engineering
- Feature engineering process
- How feature engineering is done in a typical ML pipeline

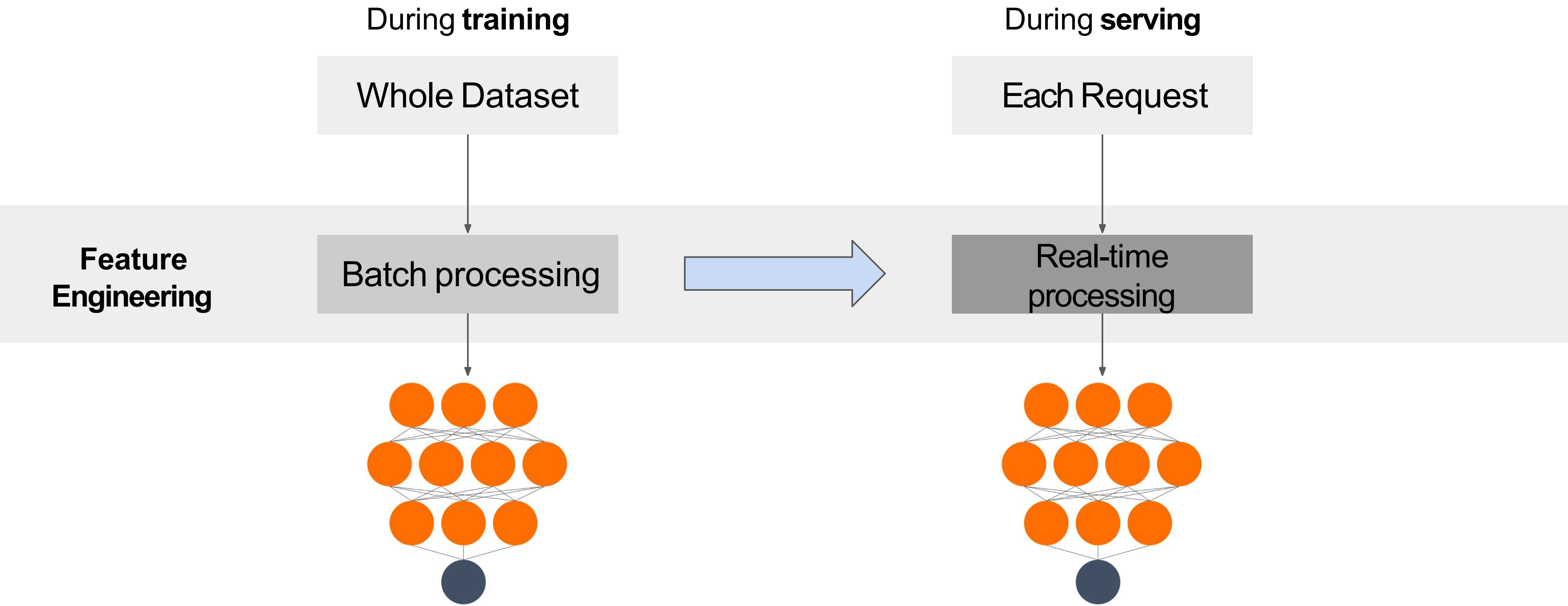
Squeezing the most out of data

- 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



Typical ML pipeline



Key points

- Feature engineering can be difficult and time consuming, but also very important to success
- Squeezing the most out of data through feature engineering enables models to learn better
- Concentrating predictive information in fewer features enables more efficient use of compute resources
- Feature engineering during training must also be applied correctly during serving

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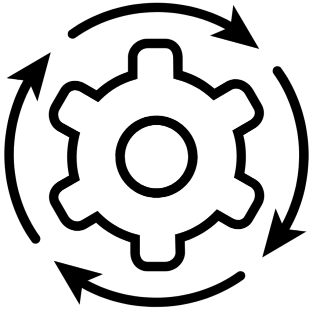
Feature Engineering

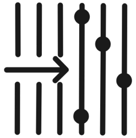
Preprocessing Operations

Outline

- Main preprocessing operations
- Mapping raw data into features
- Mapping numeric values
- Mapping categorical values
- Empirical knowledge of data



Main preprocessing operations

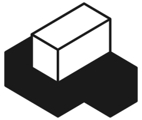


Data cleansing

Feature tuning

Representation transformation

Feature extraction



Feature construction

Mapping raw data into features

Raw Data

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

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,
...,
]
```

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, Canny filters, Sobel filters, photometric distortions

Key points

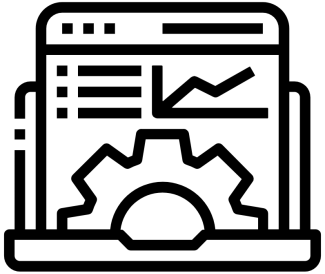
- Data preprocessing: transforms raw data into a clean and training-ready dataset
- Feature engineering maps:
  - Raw data into feature vectors
  - Integer values to floating-point values
  - Normalizes numerical values
  - Strings and categorical values to vectors of numeric values
  - Data from one space into a different space

Feature Engineering

Feature Engineering Techniques

Outline

- Feature Scaling
- Normalization and Standardization
- Bucketizing / Binning
- Other techniques



Feature engineering techniques

Numerical Range

- Scaling
- Normalizing
- Standardizing

Grouping

- Bucketizing
- Bag of words

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]

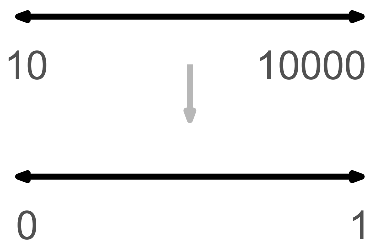
```
image = (image - 127.5) / 127.5
```

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

Normalization

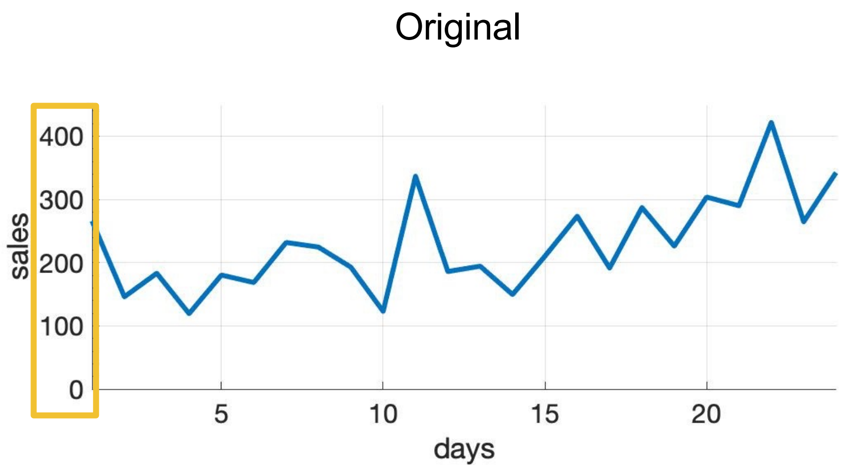
$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

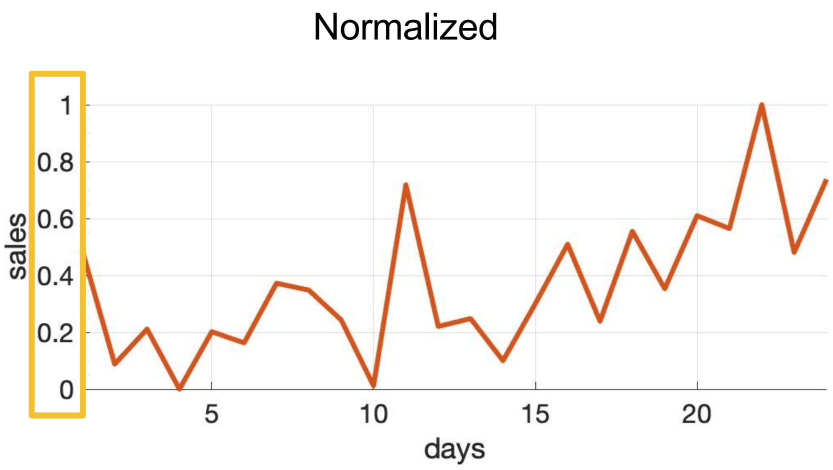
$$X_{\text{norm}} \in [0, 1]$$



Normalization works well for data that is not normally distributed

Normalization



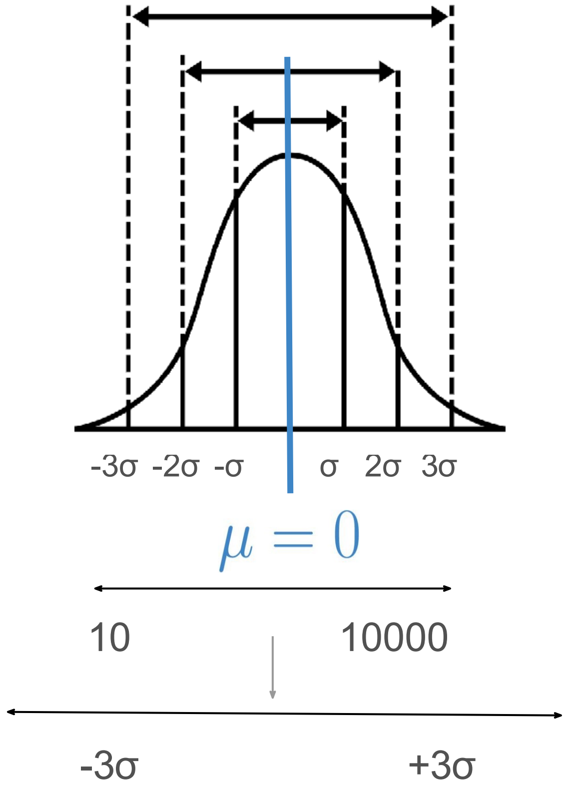


Standardization (z-score)

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

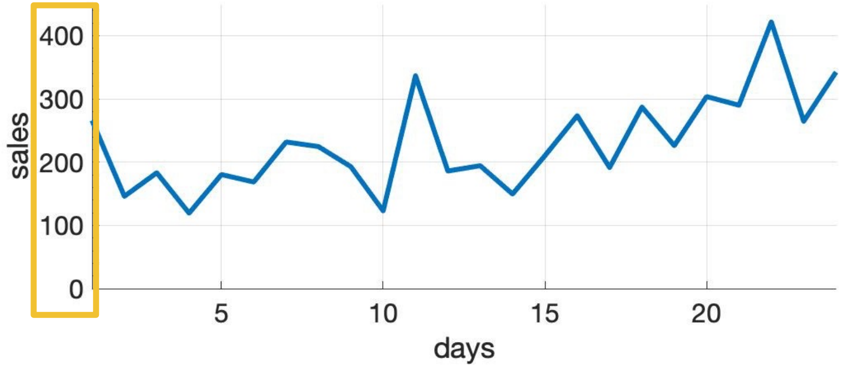
$$X_{\text{std}} = \frac{X - \mu}{\sigma}$$ (z-score)

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

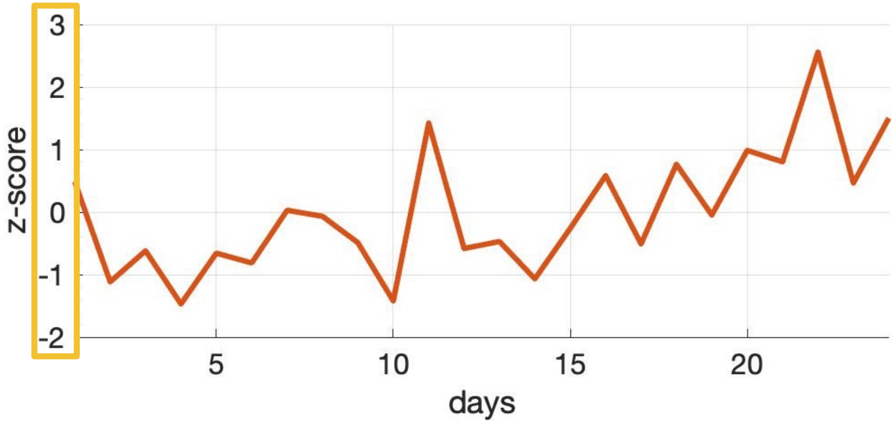


Standardization (z-score)

Original

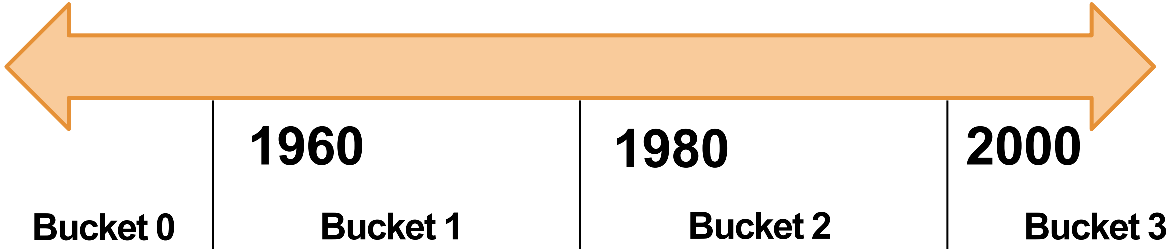


Standardized



Standardization works well for data that is normally distributed

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

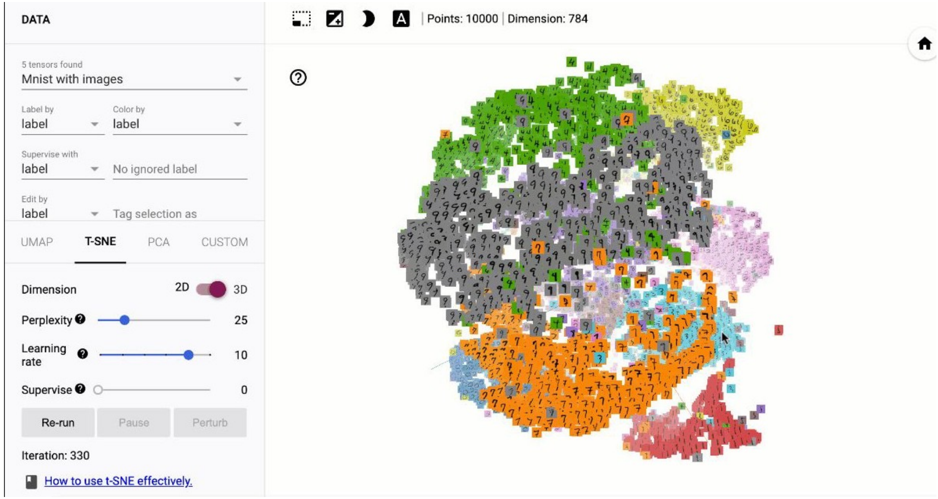
- Principal component analysis (PCA)
- t-Distributed stochastic neighbor embedding (t-SNE)
- Uniform manifold approximation and projection (UMAP)

Feature crossing

TensorFlow embedding projector

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

  @projector.tensorflow.org



Key points

- Feature engineering:
  - Prepares, tunes, transforms, extracts and constructs features.
- Feature engineering is key for model refinement
- Feature engineering helps with ML analysis

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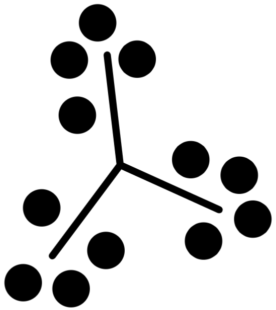
Feature Engineering

Feature Crosses

Outline

- Feature crosses
- Encoding features

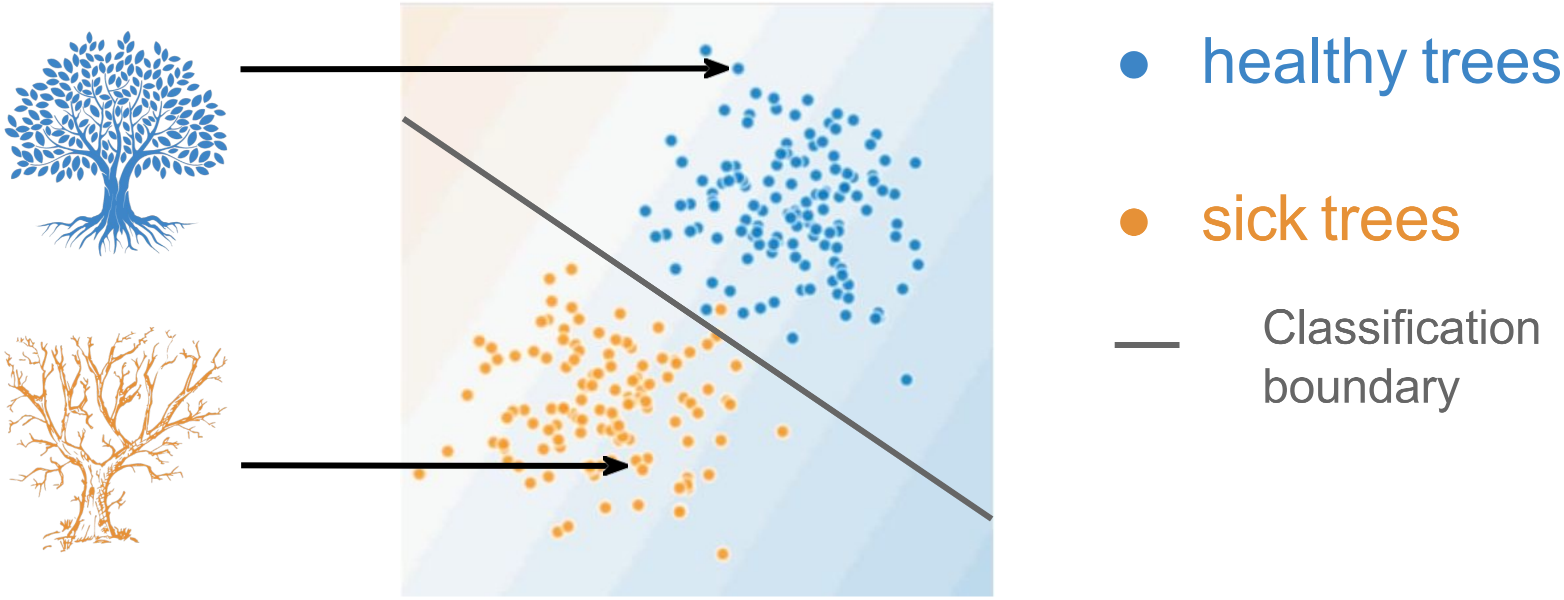


Feature crosses

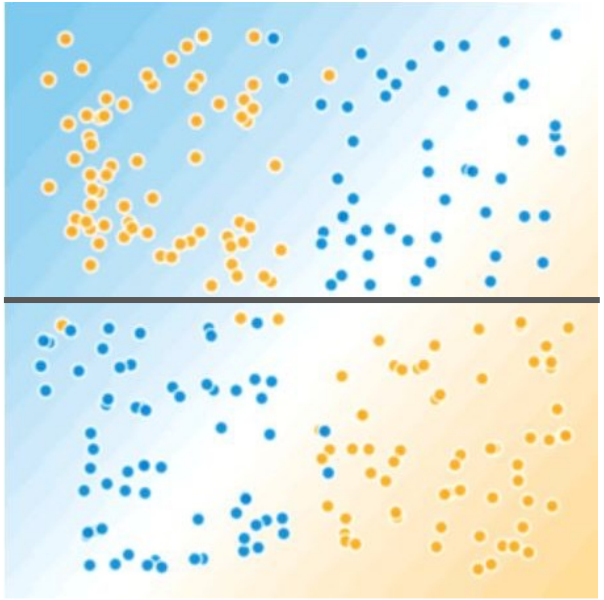
We can create many different kinds of feature crosses

- 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

Key points

- Feature crossing: synthetic feature encoding nonlinearity in feature space.
- Feature coding: transforming categorical to a continuous variable.

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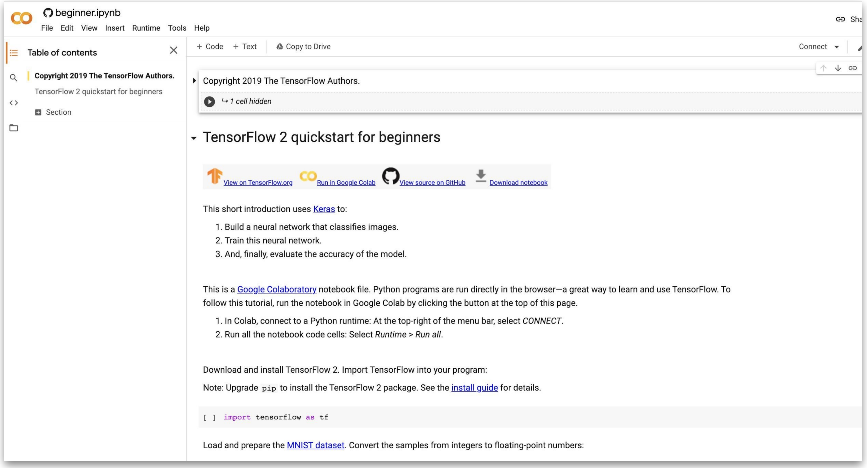
Feature Transformation At Scale

Preprocessing Data At Scale

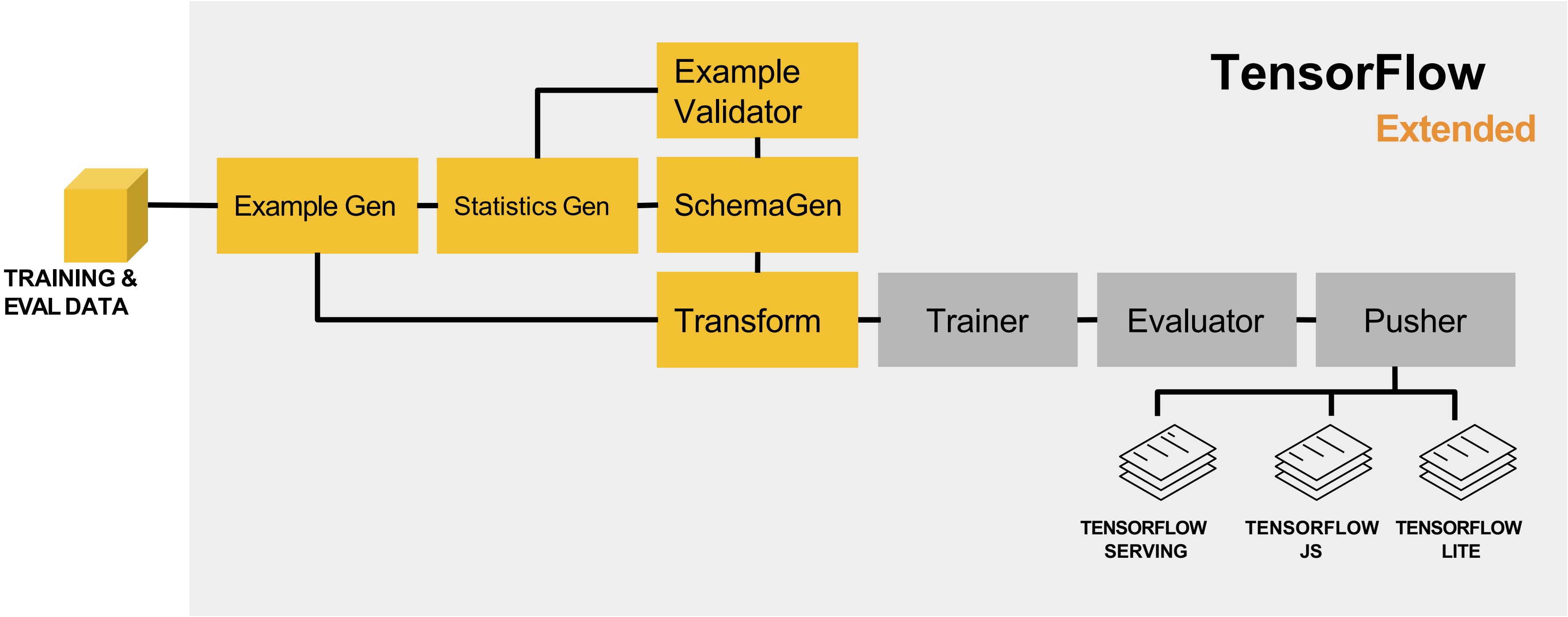
Probably not ideal



APACHE STORM™

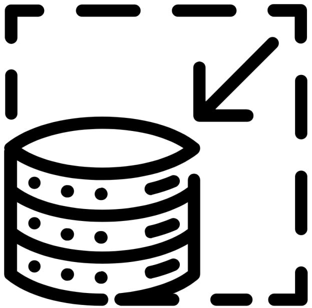
Python → Java

ML Pipeline


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

Outline

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



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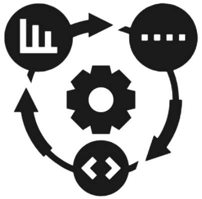
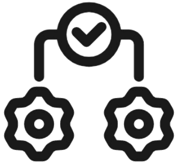
Preprocessing data at scale

Real-world models: terabytes of data



Large-scale data processing frameworks



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 per batch
- 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, …)

Key points

- Inconsistent data affects the accuracy of the results
- Need for scaled data processing frameworks to process large datasets in an efficient and distributed manner

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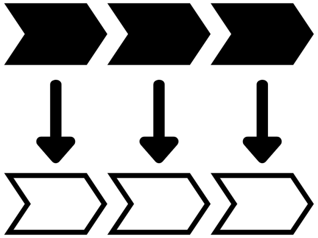
Preprocessing Data At Scale

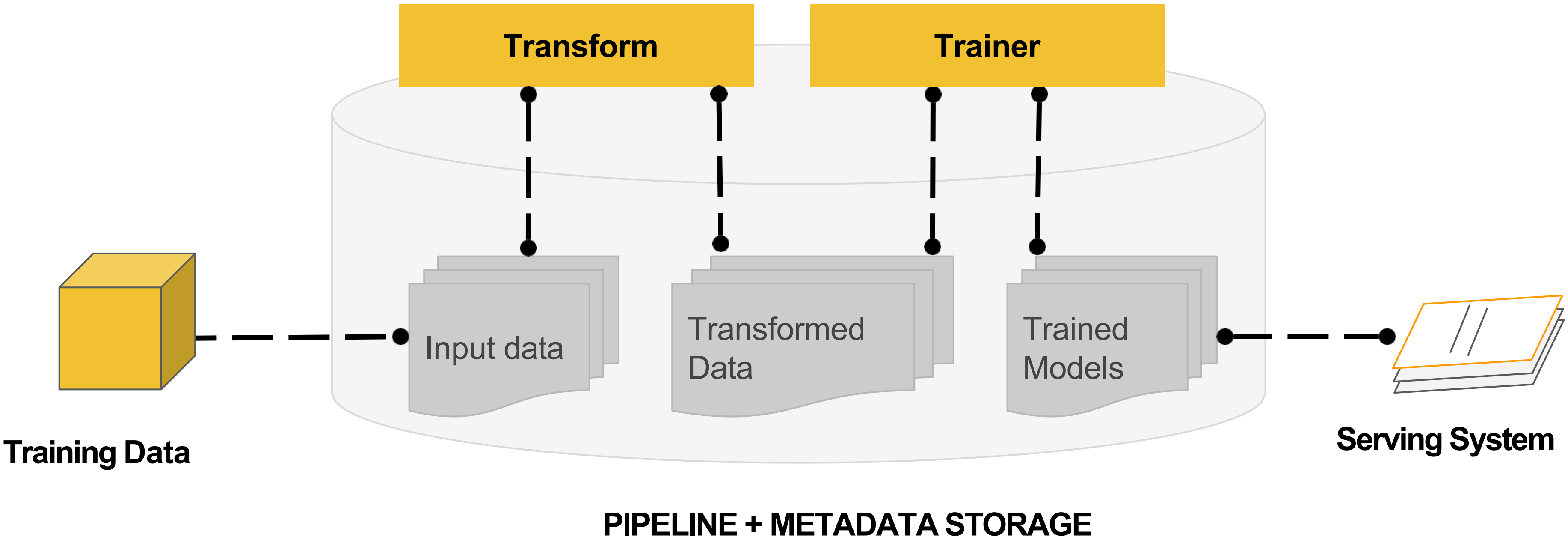
TensorFlow Transform

Outline

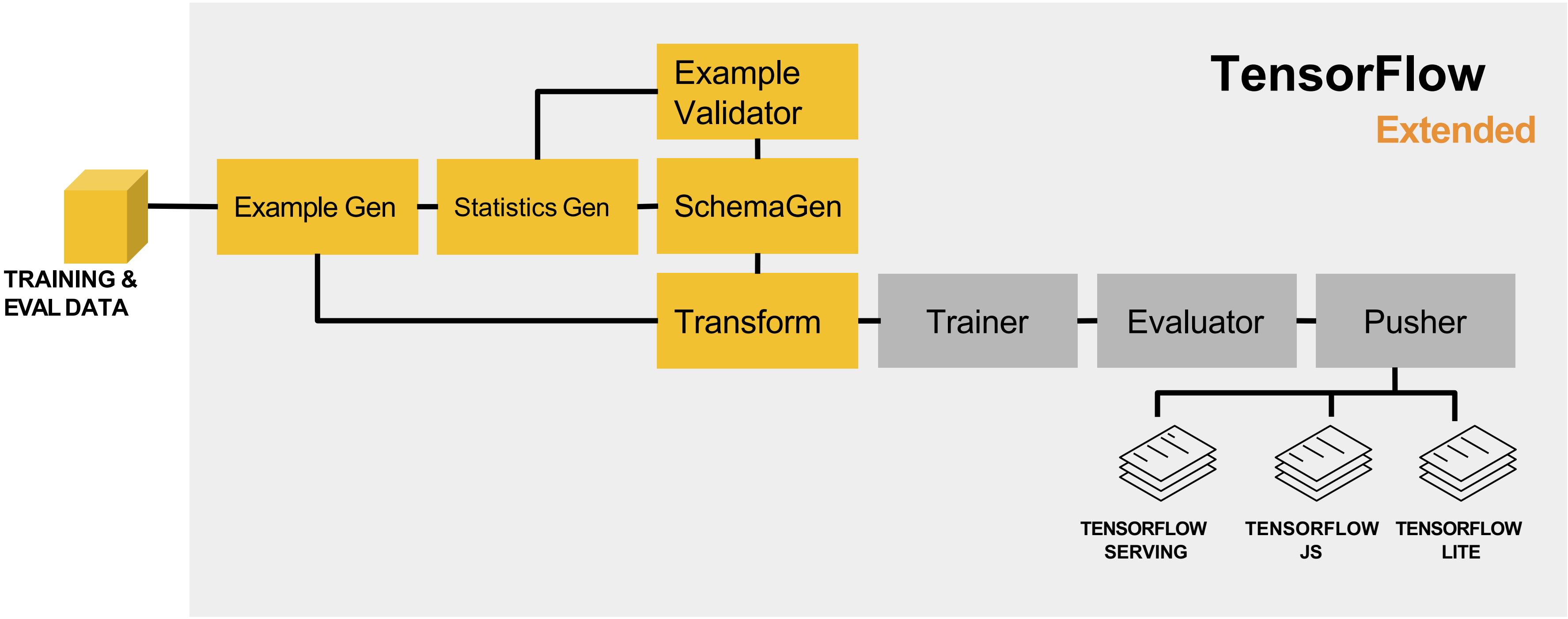
- Going deeper
- Benefits of using TensorFlow Transform
- Applies feature transformations
- tf.Transform Analyzers



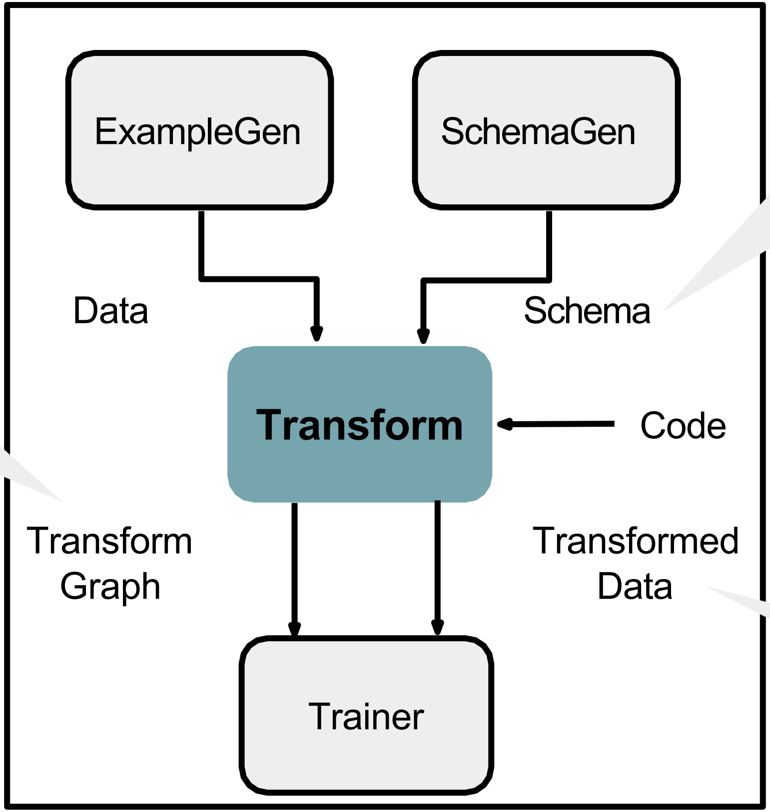
Enter tf.Transform



Inside TensorFlow Extended



tf.Transform layout

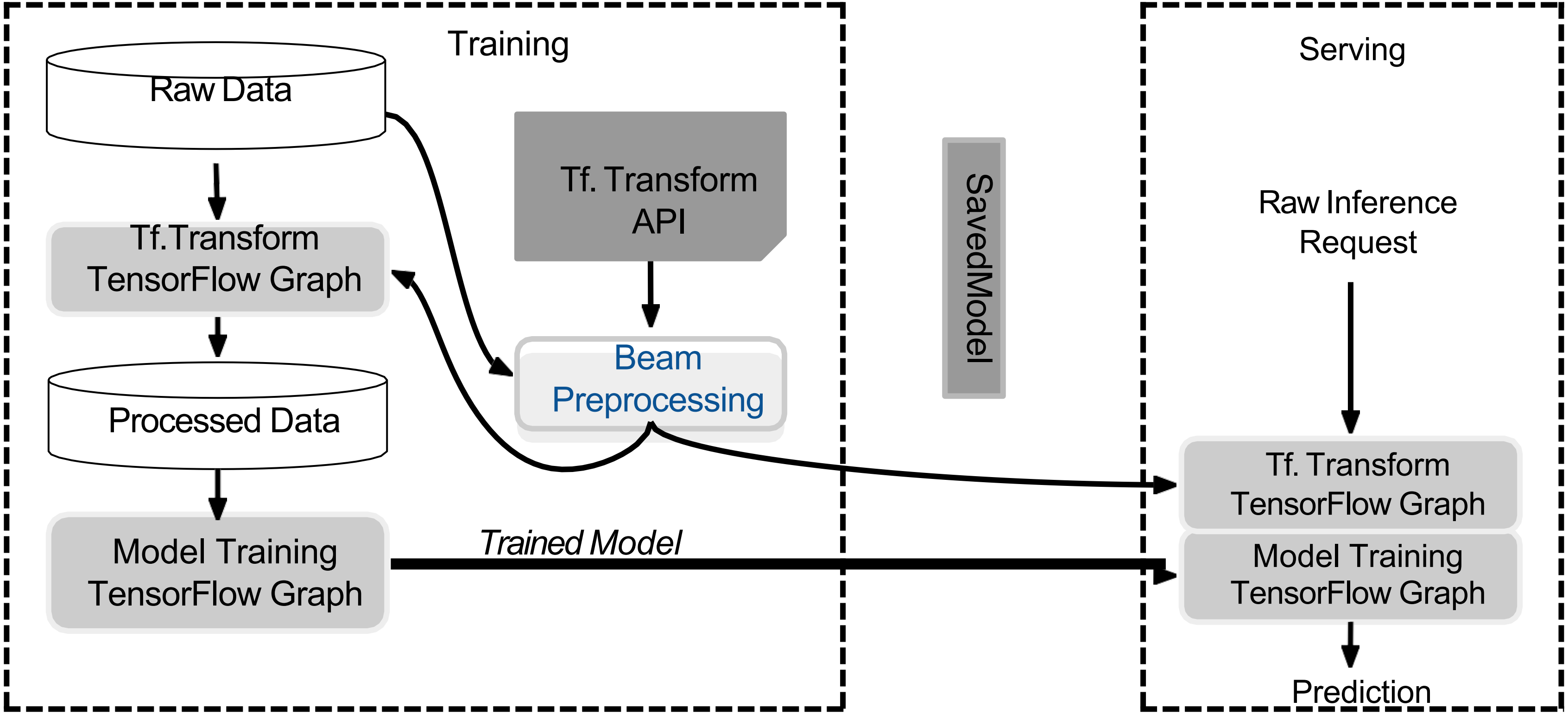


- User-provided **transform** (tf.Transform)
- **Schema** for parsing

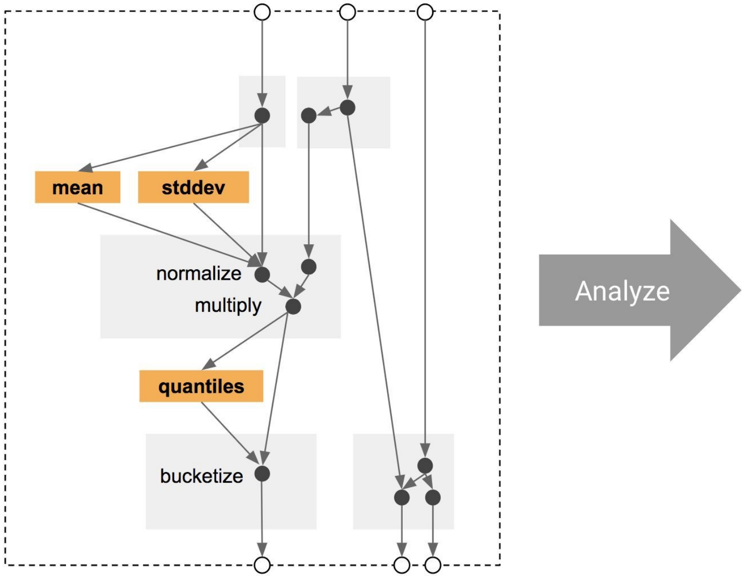
- Applied during **training**
- Embedded during **serving**

Performance optimizations

tf. Transform: Going deeper



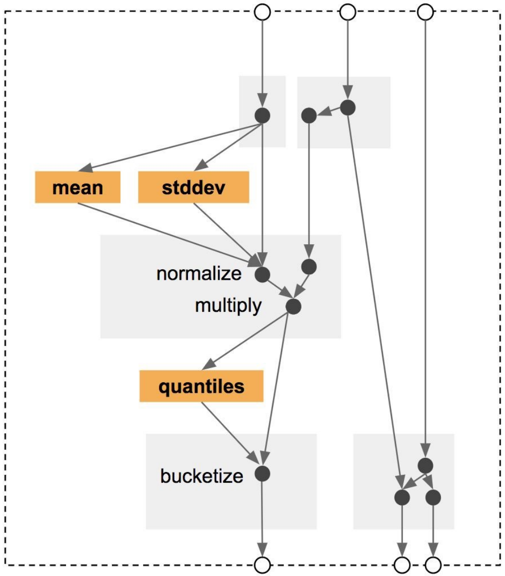
tf.Transform Analyzers

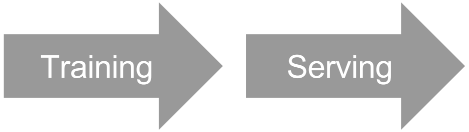


They behave like TensorFlow Ops, but run only once during training

For example:
tft.min *computes the minimum of a tensor over the training dataset*

How Transform applies feature transformations

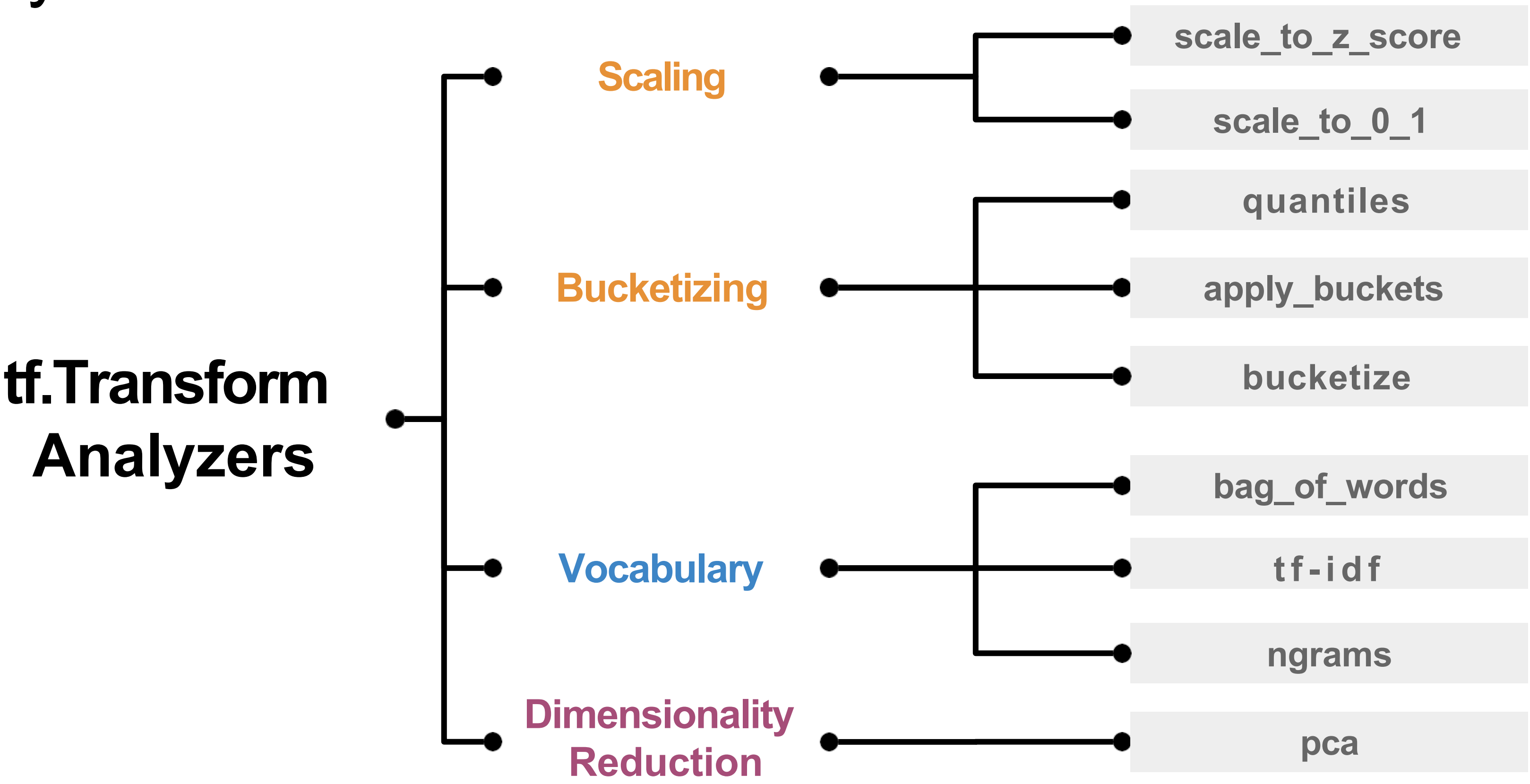




Benefits of using tf.Transform

- 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



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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
```

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Feature Transformation At Scale

Hello World with tf.Transform

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)
    }))
```

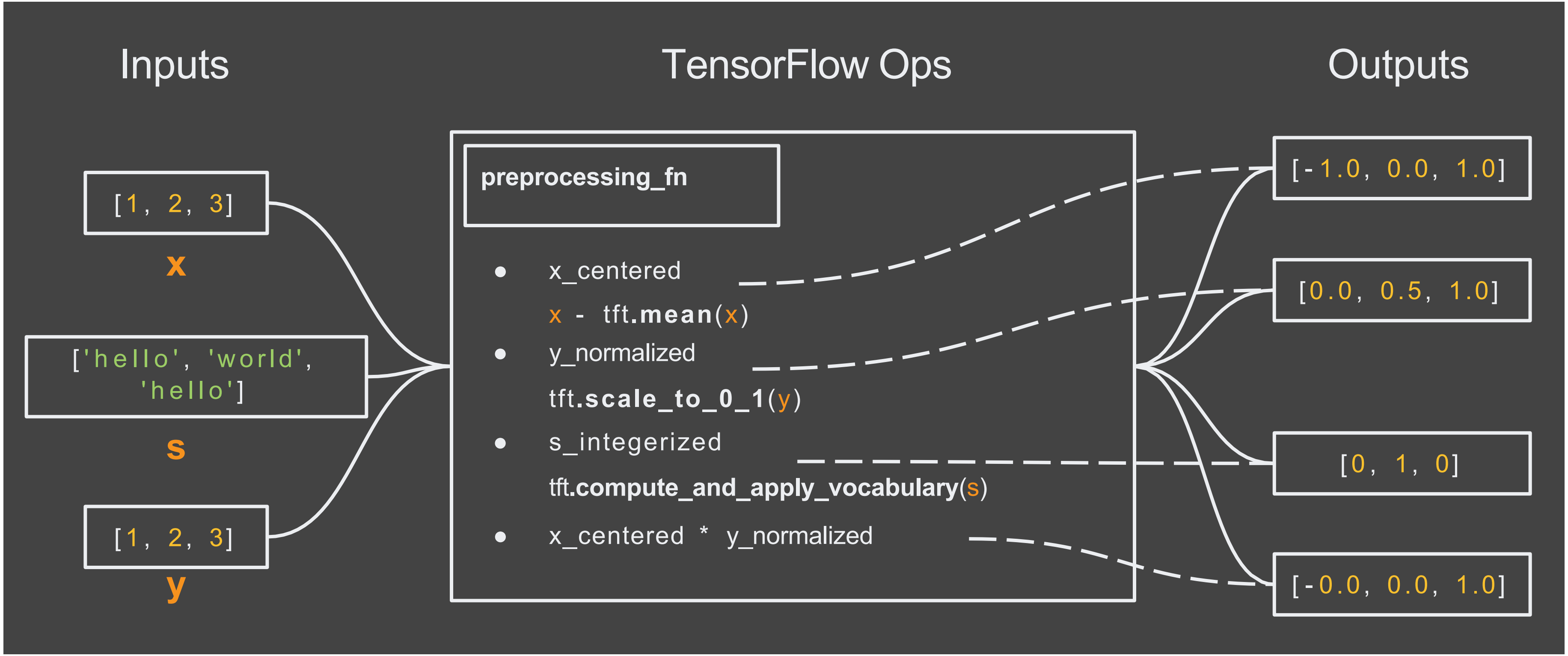
Preprocessing data (Transform)

```
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

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Feature Selection

Feature Spaces

Outline

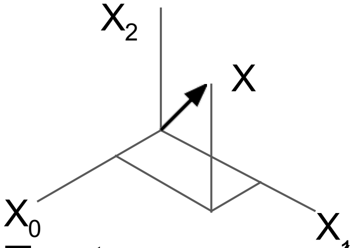
- Introduction to Feature Spaces
- Introduction to Feature Selection
- Filter Methods
- Wrapper Methods
- Embedded Methods

Feature space

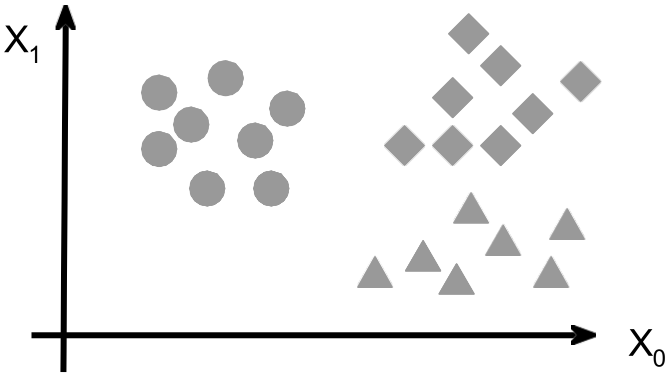
- N dimensional space defined by your N features
- Not including the target label

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

Feature vector



Feature space (3D)



Scatter plot (2D)

Feature space

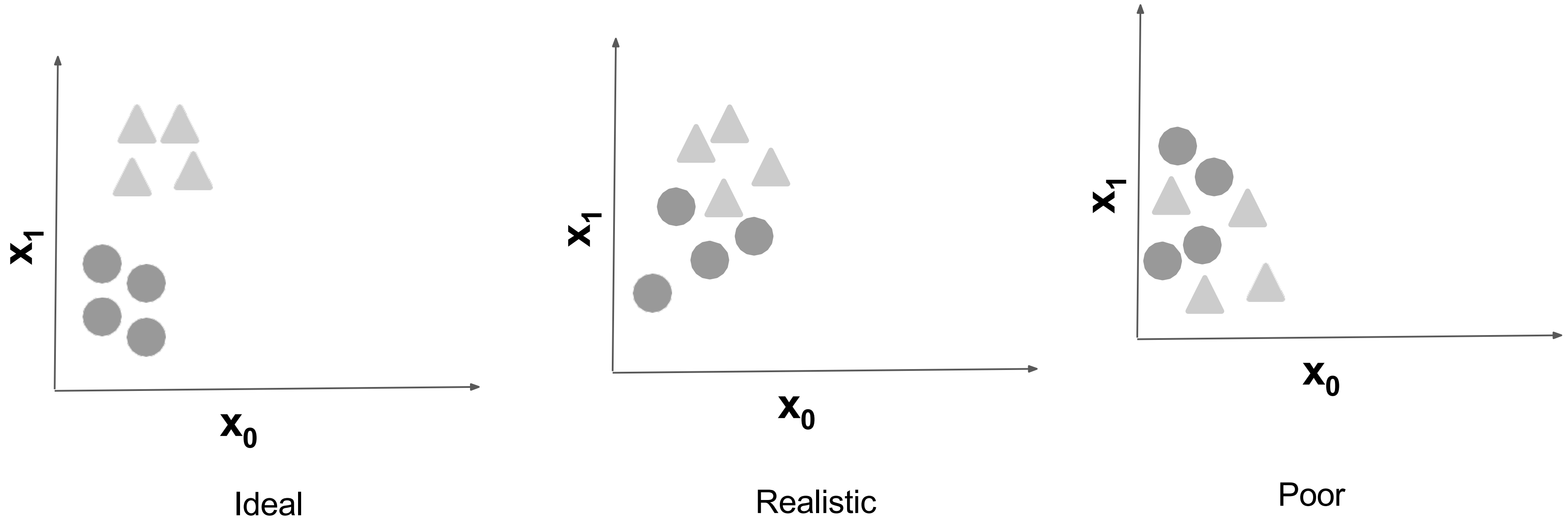
3D Feature Space

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

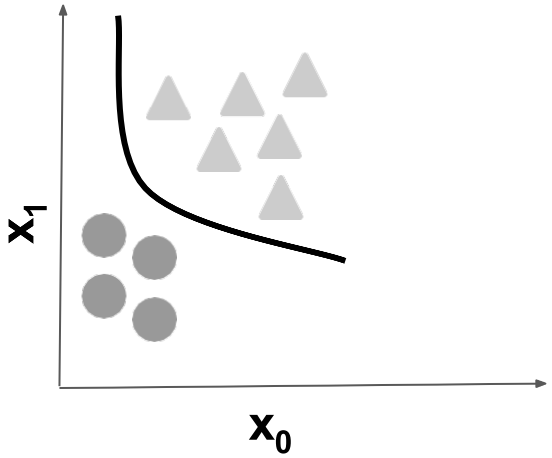
$Y = \mathbf{f}(X_0, X_1, X_2)$

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!

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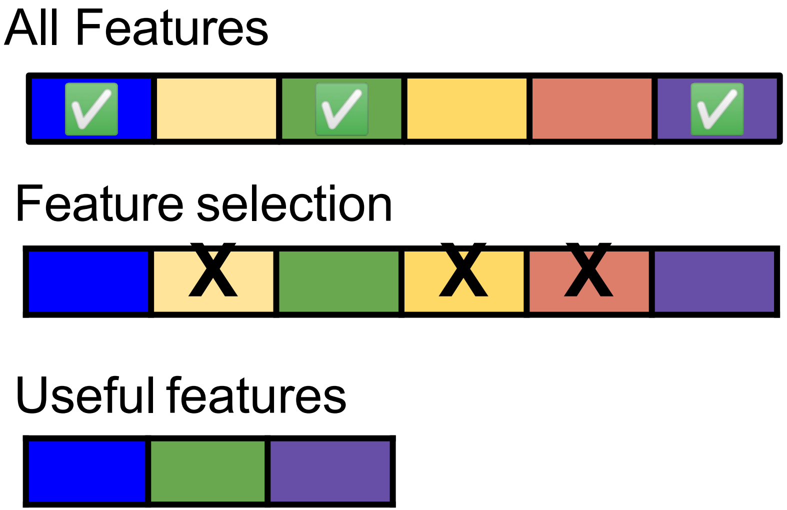
Feature Selection

Feature selection



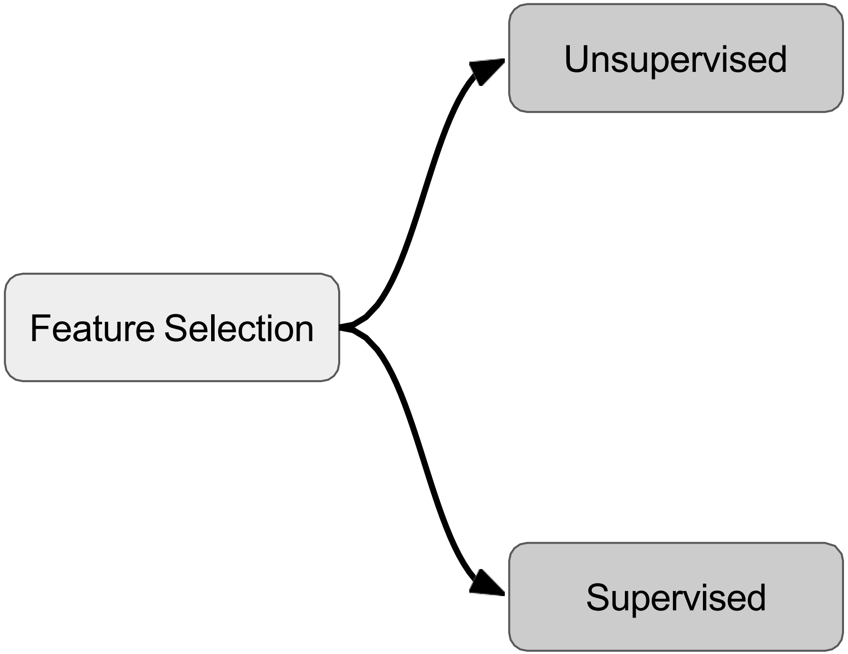
- Identify features that best represent the relationship
- Remove features that don't influence the outcome
- Reduce the size of the feature space
- Reduce the resource requirements and model complexity

Why is feature selection needed?

Reduce storage and I/O requirements

Minimize training and inference costs

Feature selection methods



Unsupervised feature selection

1. **Unsupervised**

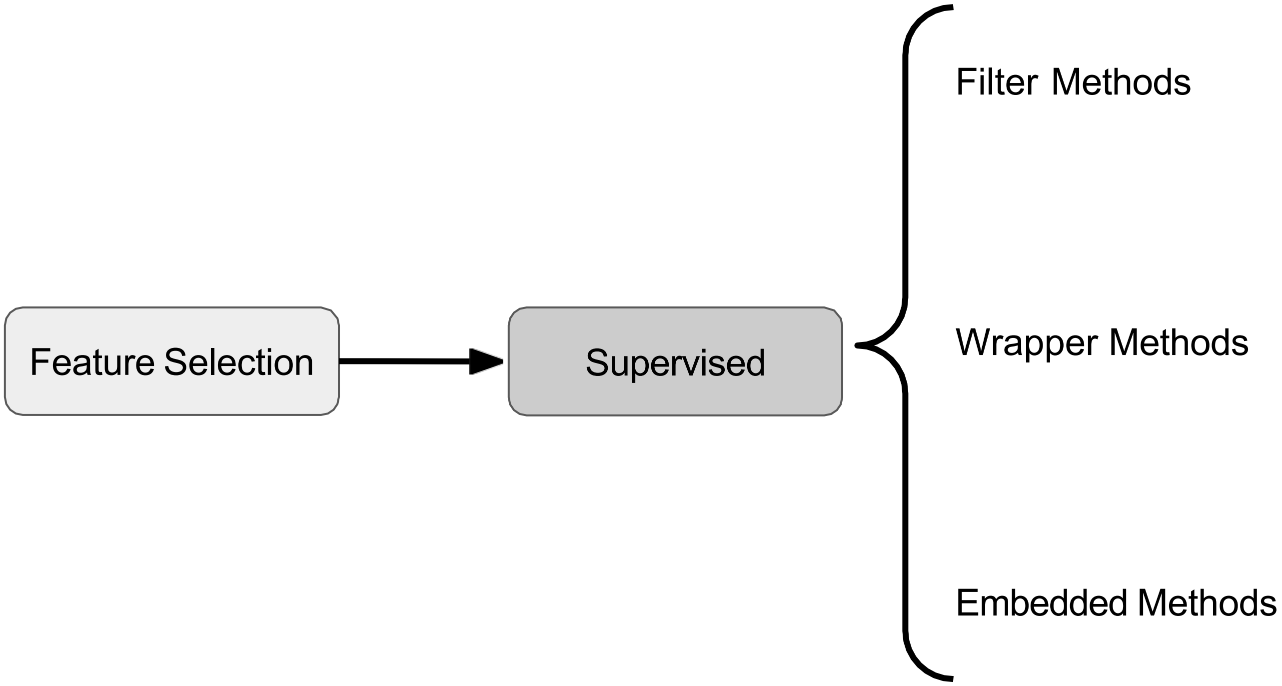
- Features-target variable relationship not considered
- Removes redundant features (correlation)

Supervised feature selection

2. Supervised

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

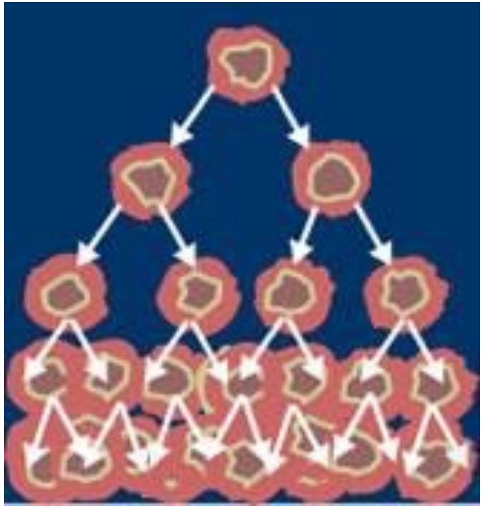
Supervised methods



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	compactness_mean	
842302	M	17.99	10.38	122.8	1001.0	0.1184	0.2776	
concavity_mean	concavepoints_mean	symmetry_mean	fractal_dimension_mean	radius_se	texture_se	perimeter_se	area_se	
0.3001	0.1471	0.2419	0.07871	1.095	0.9053	8.589	153.4	
smoothness_se	compactness_se	concavity_se	concavepoints_se	symmetry_se	fractal_dimension_se	radius-worst	texture_worst	
0.0064	0.049	0.054	0.016	0.03	0.006	25.38	17.33	
perimeter_worst	area_worst	smoothness_worst	compactness_worst	concavity_worst	concavepoints_worst	symmetry_worst	fractal_dimension_worst	Unnamed:32
184.6	2019.0	0.1622	0.6656	0.7119	0.2654	0.4601	0.1189	NaN

Irrelevant features

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

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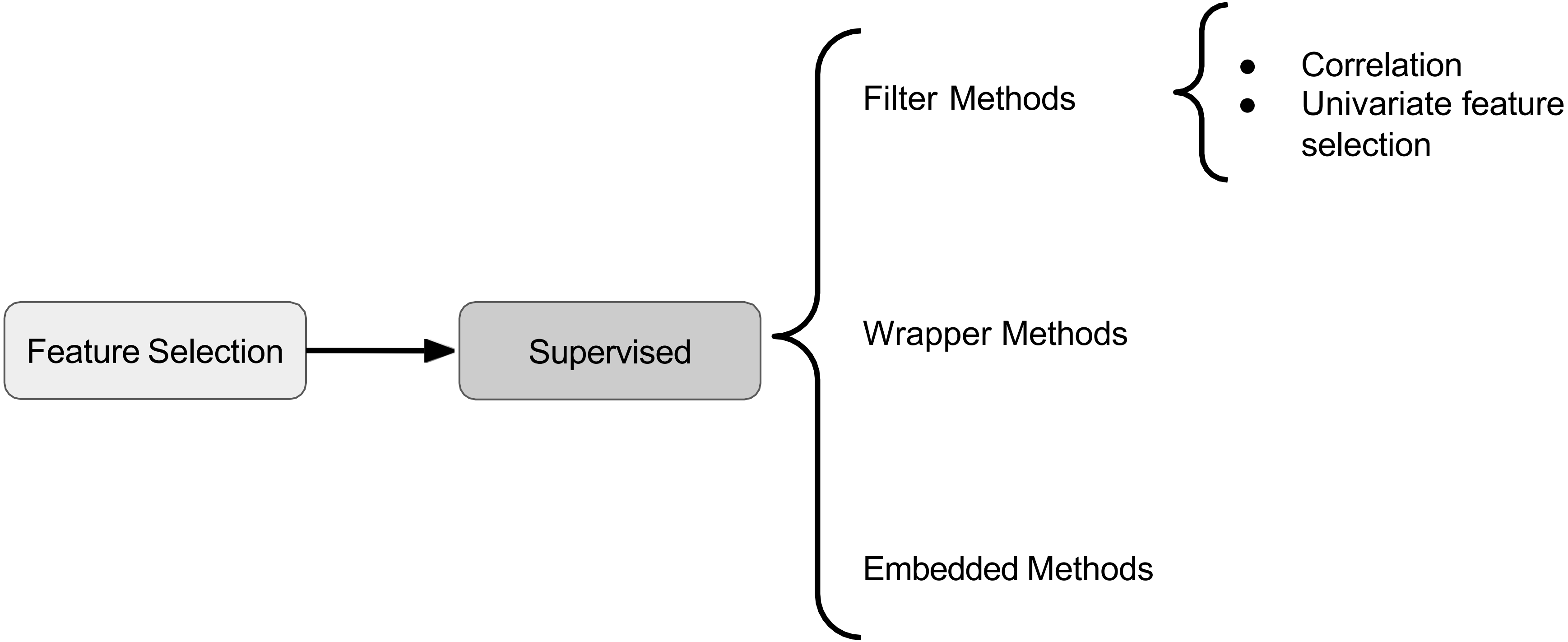
Feature Selection

Filter Methods

Filter methods



Filter methods

- Correlated features are usually redundant
    - Remove them!

Popular filter methods:

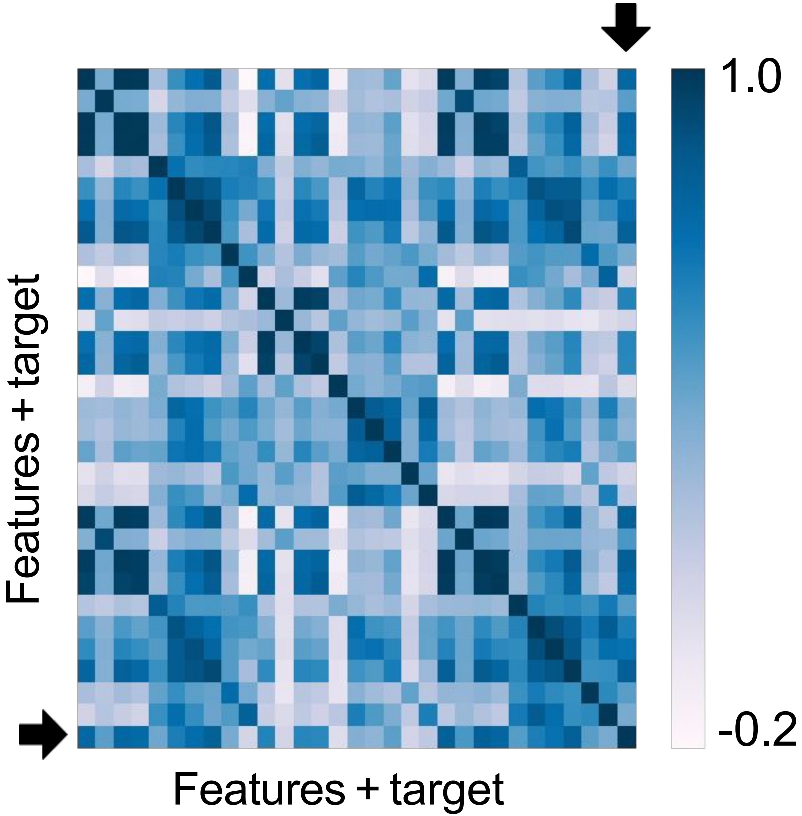
- Pearson Correlation
    - Between features, and between the features and the label
- Univariate Feature Selection

Filter methods

Set of All Features → Selecting the Best Subset → ML Model → Performance

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



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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

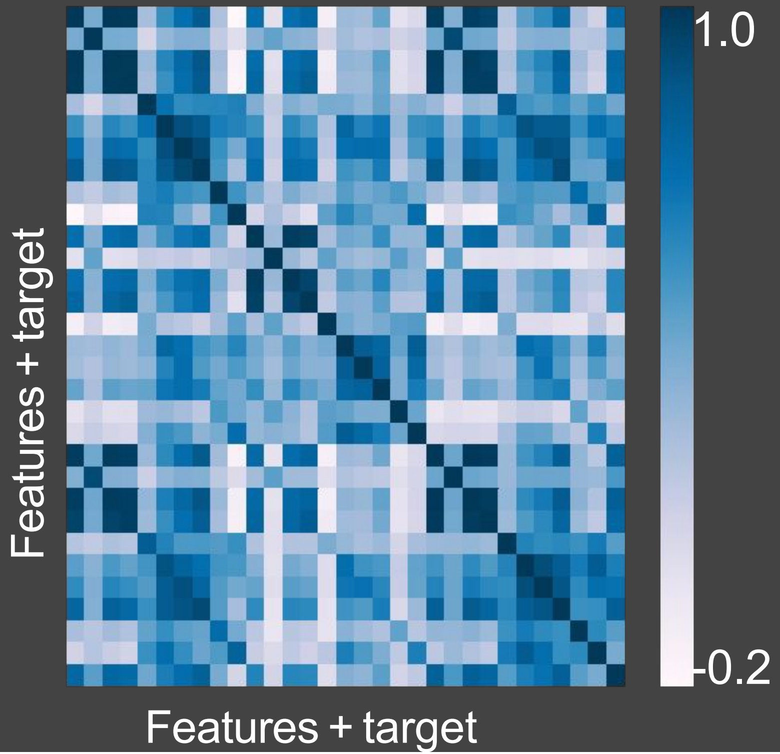
Other methods:

- 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**

Best Result

Univariate feature selection in SKLearn

SKLearn Univariate feature selection routines:

1. **SelectKBest**
2. SelectPercentile
3. 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
```

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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 (Chi^2)	**20**	**0.960317**	**0.95614**	**0.91111**	**0.97619**	**0.94252**

Best Result

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Feature Selection

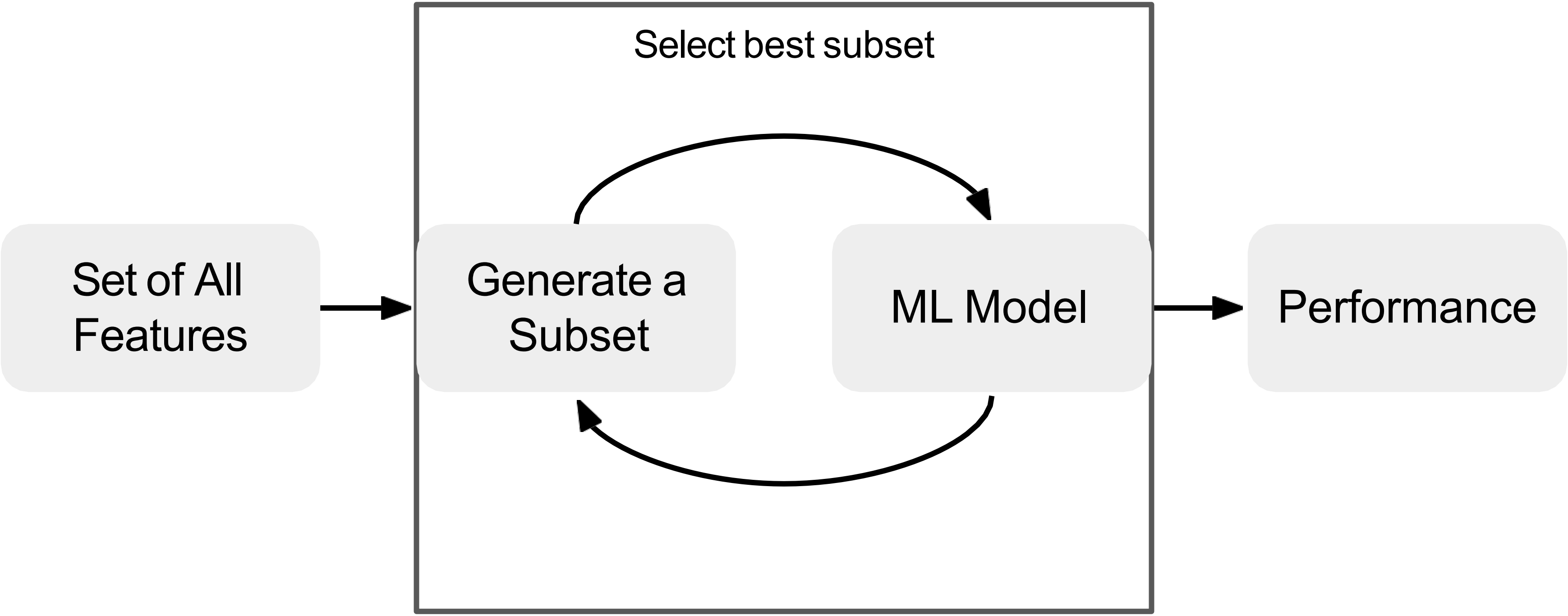
Wrapper Methods

Wrapper methods

Feature Selection → Supervised

- Filter Methods
  - Correlation
  - Univariate feature selection
- Wrapper Methods
  - Forward elimination
  - Backward elimination
  - Recursive feature elimination
- Embedded Methods

Wrapper methods



Wrapper methods

Popular wrapper methods

1. Forward Selection
2. Backward Selection
3. Recursive Feature Elimination

Forward selection

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

Backward elimination

1. Start with all features
2. Evaluate model performance when **removing** each of the included features, one at a time
3. Remove next feature that gives the best performance
4. Repeat until there is no improvement

Recursive feature elimination (RFE)

1. Select a model to use for evaluating feature importance
2. Select the desired number of features
3. Fit the model
4. Rank features by importance
5. Discard least important features
6. 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**

Best Result

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Feature Selection

Embedded Methods

Embedded methods

Feature Selection → Supervised

- Filter Methods
  - Correlation
  - Univariate feature selection
- Wrapper Methods
  - Forward elimination
  - Backward elimination
  - Recursive feature elimination
- Embedded Methods
  - L1 regularization
  - Feature importance

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., `RandomForestClassifier`)
- Feature importance is available as a property `feature_importances_`
- *We can then use* `SelectFromModel` *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
```

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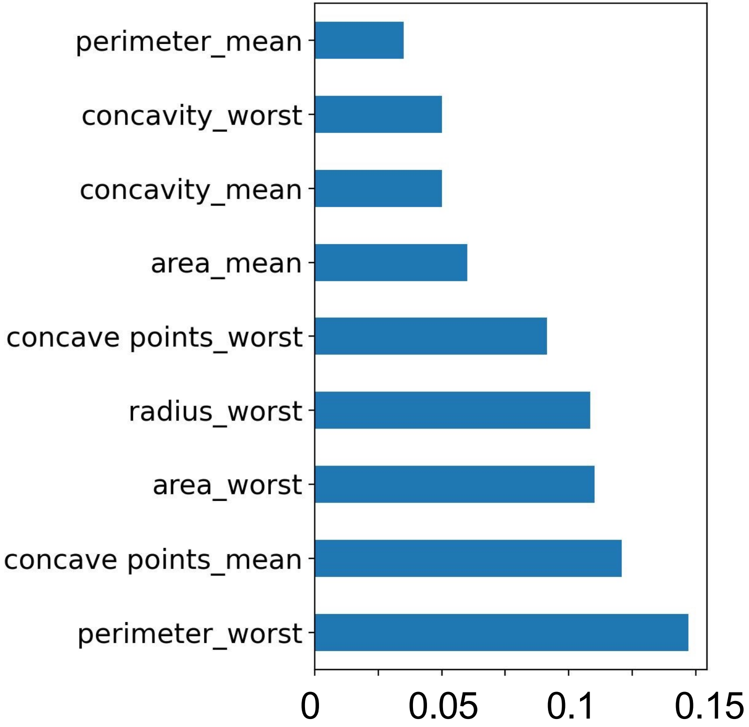
Feature importance plot



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

Best Result

Review

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