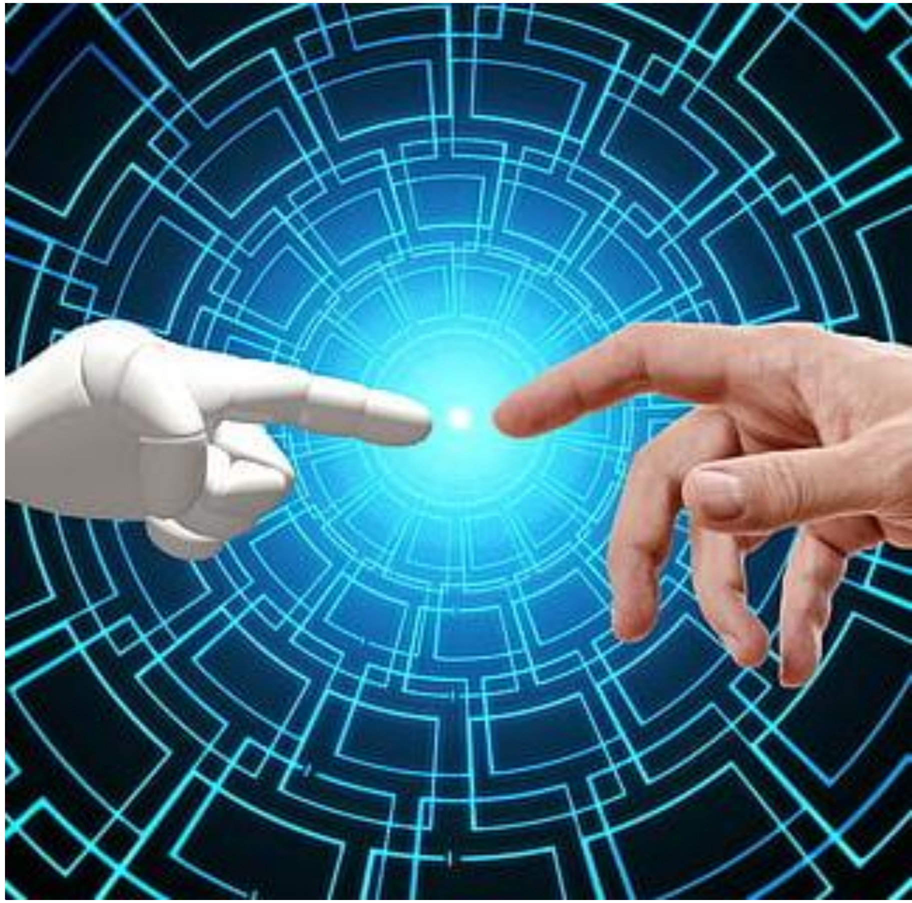
# Artificial Intelligence (AI) for Engineering



COS40007

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**Digital Innovation Lab**

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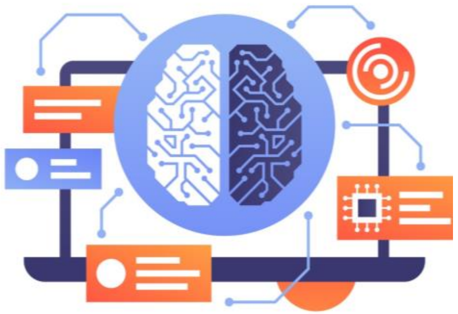

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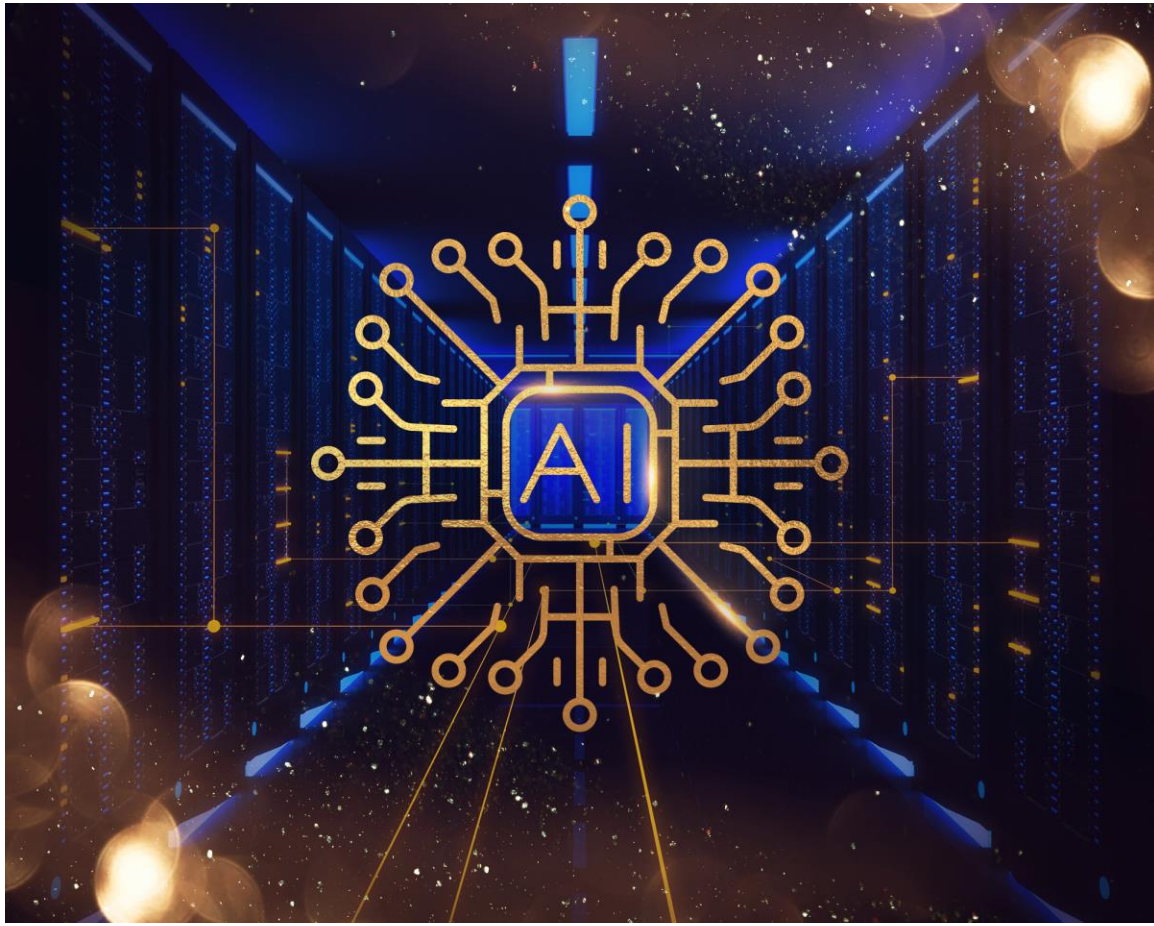
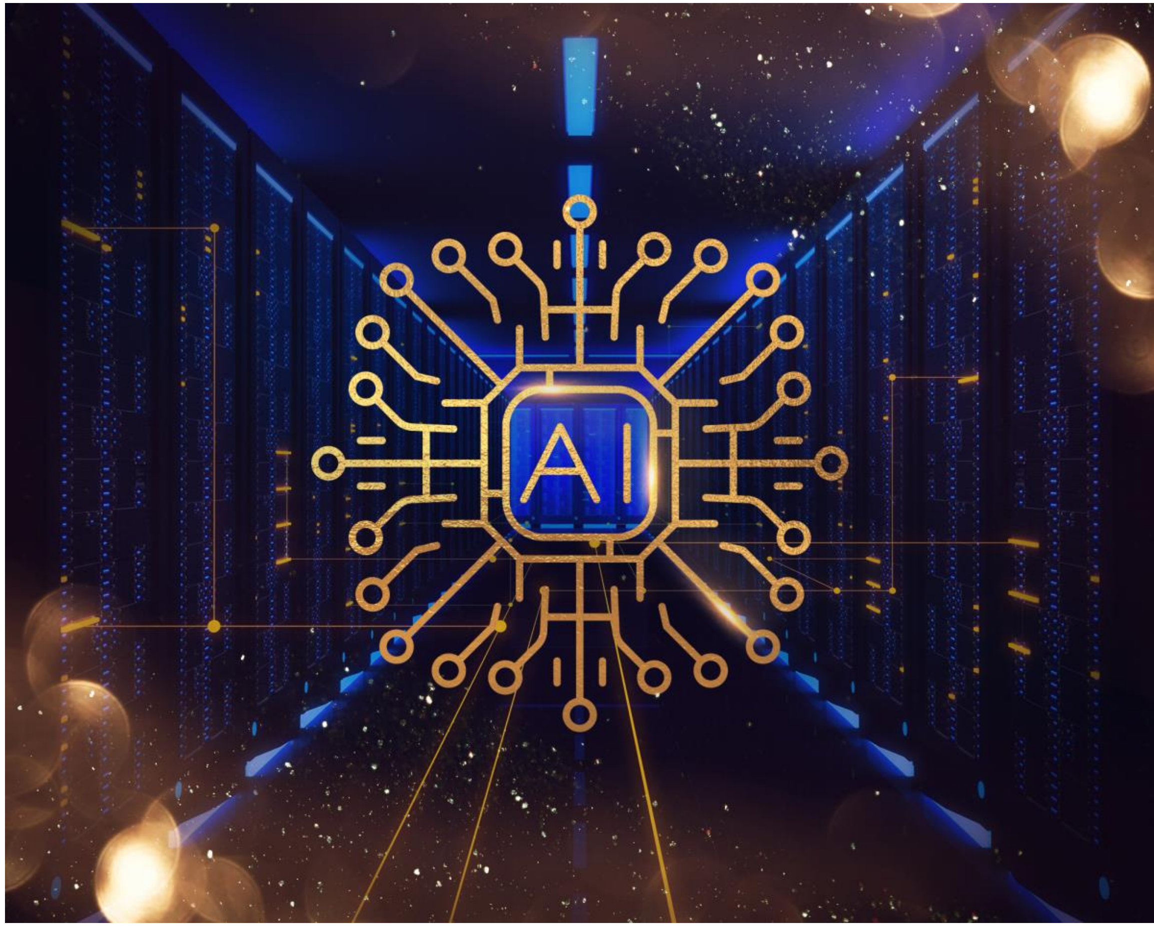
# Overview

- ❑Steps of Machine Learning
- ❑Data collection
- ❑Data cleaning and Feature Engineering
- ❑Model Training
- ❑Testing and Evaluation
- ❑Model improvement



# Required Reading

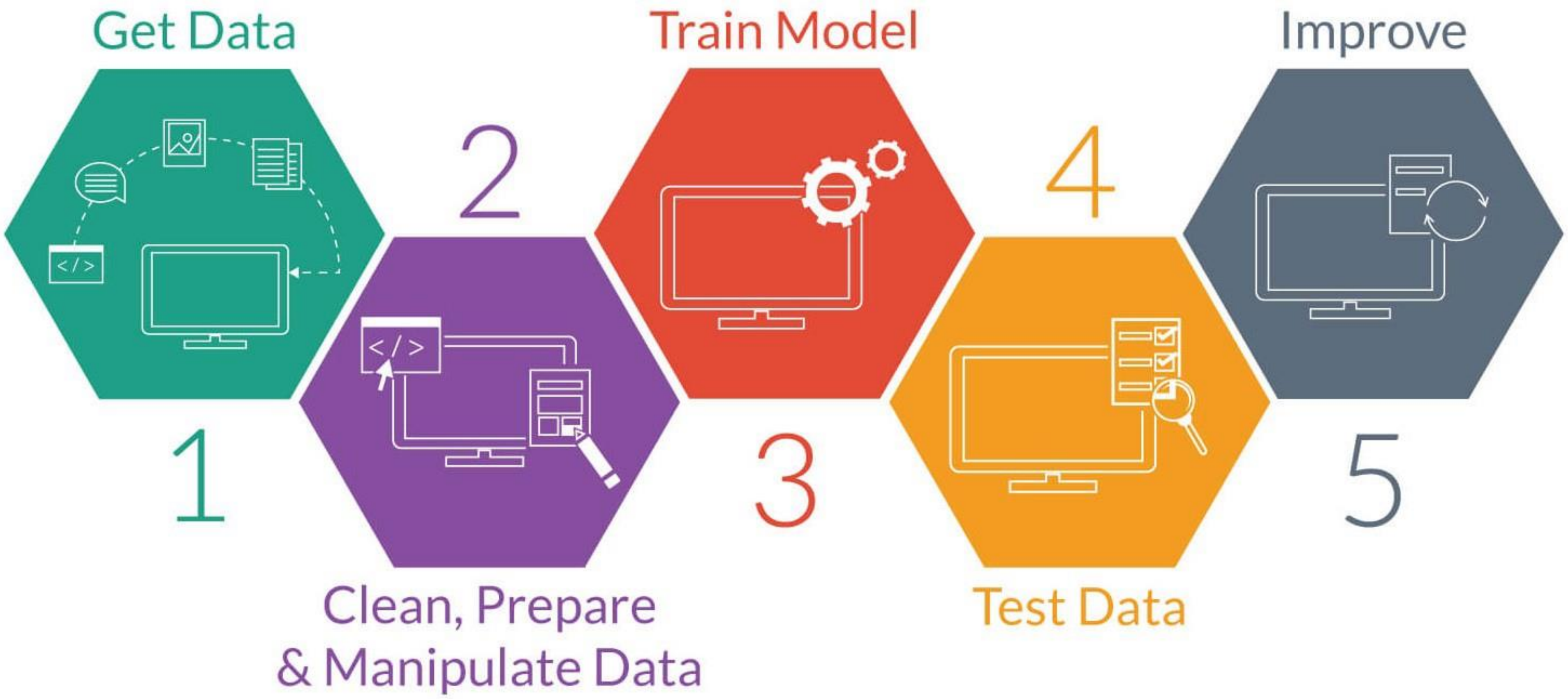
- Chapter 1 and  Chapter 4 of "Machine Learning with Pytorch and Scikit-Learn"
- A Reference Guide to Feature Engineering Methods



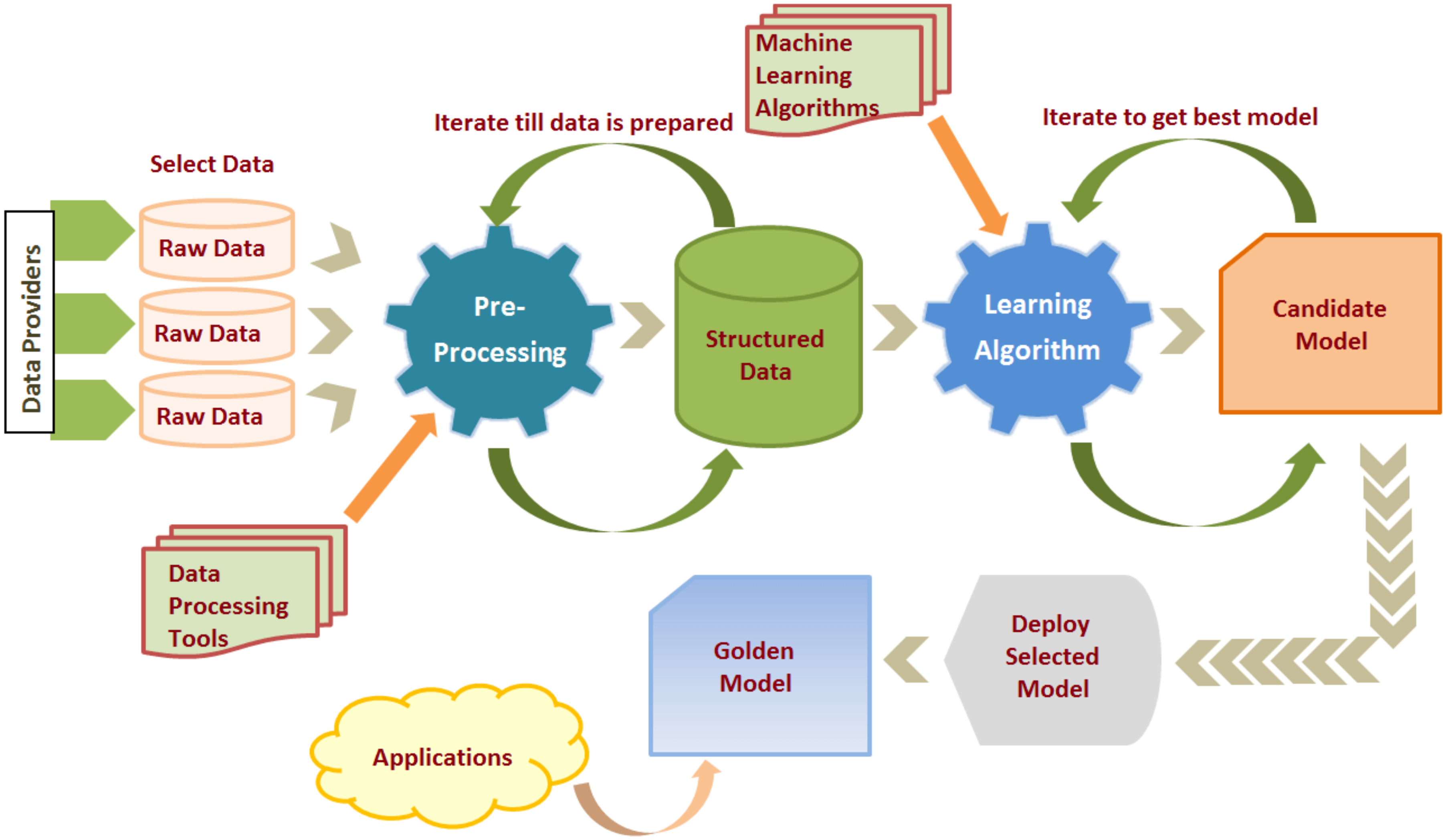
# At the end of this you should be able to

- Understand the steps you need to complete to develop machine learning models
- Understand how to perform data pre-processing
- Understand model training and development process

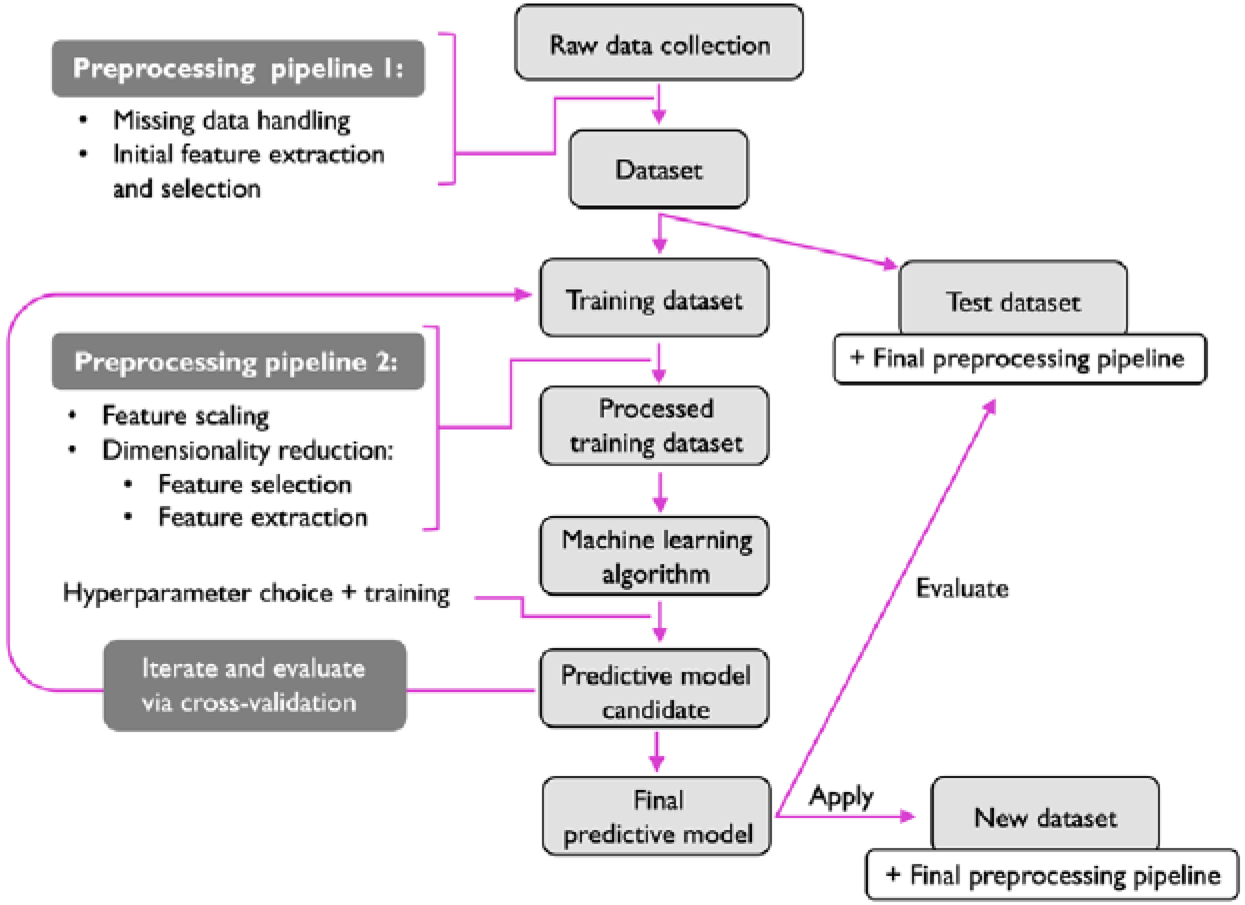
# Steps of Machine Learning



# How to use Machine Learning in applications ?



# Workflow for predictive modelling



# Data collection

- Raw data
- Database tables
- Data file dumps from machine, processes
- Continuous time series data from sensors
- Images
- Videos
- Text

Raw data rarely comes in the form and shape that is necessary for the optimal performance of a learning algorithm. Thus, the preprocessing of the data is one of the most crucial steps in any machine learning application

# Data preparation

- It is essential to have quality data that you can use to train your models
- If the data has small discrepancies or missing information, then it can have a great impact on your model's accuracy.
- Data preparation takes 80% of the total data engineering effort
- Real-world data may be noisy or impure. data preparation produces a narrower dataset than the source, which can boost data collection performance dramatically.

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# Example of Raw data

prediction of whether or not an object is a mine or a rock given the strength of sonar returns at different angles.

```
0.0200,0.0371,0.0428,0.0207,0.0954,0.0986,0.1539,0.1601,0.3109,0.2111,0.1609,0.1582,0.2238,0.0645,0.0660,0.227
3,0.3100,0.2999,0.5078,0.4797,0.5783,0.5071,0.4328,0.5550,0.6711,0.6415,0.7104,0.8080,0.6791,0.3857,0.1307,0.2
604,0.5121,0.7547,0.8537,0.8507,0.6692,0.6097,0.4943,0.2744,0.0510,0.2834,0.2825,0.4256,0.2641,0.1386,0.1051,0
.1343,0.0383,0.0324,0.0232,0.0027,0.0065,0.0159,0.0072,0.0167,0.0180,0.0084,0.0090,0.0032,R
0.0453,0.0523,0.0843,0.0689,0.1183,0.2583,0.2156,0.3481,0.3337,0.2872,0.4918,0.6552,0.6919,0.7797,0.7464,0.944
4,1.0000,0.8874,0.8024,0.7818,0.5212,0.4052,0.3957,0.3914,0.3250,0.3200,0.3271,0.2767,0.4423,0.2028,0.3788,0.2
947,0.1984,0.2341,0.1306,0.4182,0.3835,0.1057,0.1840,0.1970,0.1674,0.0583,0.1401,0.1628,0.0621,0.0203,0.0530,0
.0742,0.0409,0.0061,0.0125,0.0084,0.0089,0.0048,0.0094,0.0191,0.0140,0.0049,0.0052,0.0044,R
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045,0.1862,0.2709,0.4232,0.3043,0.6116,0.6756,0.5375,0.4719,0.4647,0.2587,0.2129,0.2222,0.2111,0.0176,0.1348,0
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.1576,0.0681,0.0294,0.0241,0.0121,0.0036,0.0150,0.0085,0.0073,0.0050,0.0044,0.0040,0.0117,R
0.0762,0.0666,0.0481,0.0394,0.0590,0.0649,0.1209,0.2467,0.3564,0.4459,0.4152,0.3952,0.4256,0.4135,0.4528,0.532
6,0.7306,0.6193,0.2032,0.4636,0.4148,0.4292,0.5730,0.5399,0.3161,0.2285,0.6995,1.0000,0.7262,0.4724,0.5103,0.5
459,0.2881,0.0981,0.1951,0.4181,0.4604,0.3217,0.2828,0.2430,0.1979,0.2444,0.1847,0.0841,0.0692,0.0528,0.0357,0
.0085,0.0230,0.0046,0.0156,0.0031,0.0054,0.0105,0.0110,0.0015,0.0072,0.0048,0.0107,0.0094,R
```

# Example of Raw data

## Time-series data for x,y,z acceleration from accelerometer sensor

| timestamp | x | y | z |
|---|---|---|---|
| 1502851906 | 0.371338 | 0.575684 | 0.69751 |
| 1502851906 | 0.21875 | 0.470215 | 0.672607 |
| 1502851906 | 0.161377 | 0.360107 | 0.707764 |
| 1502851906 | 0.164307 | 0.302734 | 0.666504 |
| 1502851906 | 0.243652 | 0.258545 | 0.632813 |
| 1502851906 | 0.326172 | 0.226074 | 0.577637 |
| 1502851906 | 0.358643 | 0.196045 | 0.577393 |
| 1502851906 | 0.428223 | 0.176025 | 0.656738 |
| 1502851906 | 0.460205 | 0.172363 | 0.603516 |
| 1502851906 | 0.47876 | 0.134521 | 0.559326 |
| 1502851906 | 0.411865 | 0.112793 | 0.531738 |
| 1502851906 | 0.384033 | 0.085938 | 0.487061 |
| 1502851906 | 0.404053 | 0.042236 | 0.435059 |
| 1502851906 | 0.428955 | -0.01685 | 0.387207 |
| 1502851906 | 0.175293 | -0.08179 | 0.121094 |
| 1502851906 | -0.12915 | -0.03638 | -0.00732 |
| 1502851906 | -0.39819 | -0.02417 | -0.04663 |

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# Example of Raw data

| Server time | Laptop time | Refrac date | Refrac time | Measured solids | Sample temperature | Certainty | Part | Scale | |
|---|---|---|---|---|---|---|---|---|---|
| 27/08/2019 3:46 | 27/08/2019 3:46 | 27/08/2011 | 00:53:30 | 65.5 | 20 | 26 | brd | bx | no |
| 27/08/2019 4:11 | 27/08/2019 4:11 | 27/08/2011 | 01:18:10 | 65 | 20 | 25 | brd | bx | no |
| 27/08/2019 4:40 | 27/08/2019 4:40 | 27/08/2011 | 01:46:55 | 66.2 | 20 | 25 | brd | bx | no |
| 27/08/2019 5:00 | 27/08/2019 5:00 | 27/08/2011 | 02:07:46 | 69 | 20 | 28 | brd | bx | no |
| 27/08/2019 5:01 | 27/08/2019 5:01 | 27/08/2011 | 02:08:47 | 68.6 | 20 | 27 | brd | bx | no |
| 27/08/2019 5:04 | 27/08/2019 5:04 | 27/08/2011 | 02:11:37 | 68.1 | 20 | 25 | brd | bx | no |
| 27/08/2019 5:21 | 27/08/2019 5:21 | 27/08/2011 | 02:27:58 | 67.4 | 20 | 22 | brd | bx | no |
| 27/08/2019 5:47 | 27/08/2019 5:47 | 27/08/2011 | 02:54:07 | 67.2 | 20 | 21 | brd | bx | no |
| 27/08/2019 5:51 | 27/08/2019 5:51 | 27/08/2011 | 02:58:20 | 41.3 | 20 | 28 | vegmite | bx | no |
| 27/08/2019 6:08 | 27/08/2019 6:08 | 27/08/2011 | 03:15:44 | 62.6 | 20 | 21 | vegmite | bx | no |
| 27/08/2019 6:12 | 27/08/2019 6:12 | 27/08/2011 | 03:19:41 | 62.3 | 20 | 21 | vegmite | bx | no |
| 27/08/2019 8:06 | 27/08/2019 8:06 | 27/08/2011 | 05:13:21 | 0 | 20 | 101 | vegmite | bx | no |
| 27/08/2019 8:45 | 27/08/2019 8:45 | 27/08/2011 | 05:51:53 | 66.3 | 20 | 22 | vegmite | bx | no |
| 27/08/2019 8:49 | 27/08/2019 8:49 | 27/08/2011 | 05:56:39 | 65.1 | 20 | 21 | vegmite | bx | no |
| 27/08/2019 9:42 | 27/08/2019 9:42 | 27/08/2011 | 06:49:34 | 63.9 | 20 | 23 | vegmite | bx | no |

# Example of Raw data

| RunId | RunDateTime | WorkOrderId | ProductId | RunType | QtyPlanned | QtyActual | QtyUofm | UserId | Notes | IsCompleted | IsCurrent |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 425 | 32:42.2 | WO451 | 2 | | 725.4 | 726 | KG | 1 | | 1 | 0 |
| 426 | 36:04.2 | WO451 | 3 | | 6.25 | 7.5 | KG | 1 | | 1 | 0 |
| 427 | 50:39.4 | WO451 | 4 | | 81.25 | 81.5 | KG | 1 | | 1 | 0 |
| 428 | 01:43.9 | WO451 | 24 | | 600 | 600 | KG | 1 | | 1 | 0 |
| 429 | 04:53.1 | WO451 | 16 | | 18 | 18 | KG | 1 | | 1 | 0 |
| 430 | 08:54.7 | WO451 | 24 | | 600 | 240 | KG | 1 | | 1 | 0 |
| 431 | 14:30.8 | WO451 | 7 | | 100 | 101.5 | KG | 1 | | 1 | 0 |
| 432 | 25:35.1 | WO451 | 24 | | 600 | 600 | KG | 1 | | 1 | 0 |
| 433 | 31:25.6 | WO451 | 19 | | 1 | 2.5 | KG | 1 | | 1 | 0 |
| 434 | 31:41.6 | WO451 | 24 | | 600 | 16 | KG | 1 | | 1 | 0 |
| 435 | 31:45.1 | WO451 | 24 | | 600 | 8 | KG | 1 | | 1 | 0 |
| 436 | 39:50.7 | WO451 | 18 | | 0.12 | 2.5 | KG | 1 | | 1 | 0 |
| 437 | 39:57.6 | WO451 | 24 | | 600 | 7 | KG | 1 | | 1 | 0 |
| 438 | 40:01.5 | WO451 | 20 | | 1 | 0 | KG | 1 | | 1 | 0 |
| 439 | 40:05.7 | WO451 | 24 | | 600 | 5 | KG | 1 | | 1 | 0 |
| 440 | 43:30.5 | WO451 | 21 | | 40 | 40.5 | KG | 1 | | 1 | 0 |
| 441 | 46:46.9 | WO451 | 24 | | 600 | 195 | KG | 1 | | 1 | 0 |
| 442 | 49:21.0 | WO451 | 2 | | 80.6 | 84 | KG | 1 | | 1 | 0 |
| 443 | | WO461 | 2 | | 805.5 | | KG | 1 | | 0 | 0 |
| 444 | | WO461 | 24 | | 600 | | KG | 1 | | 0 | 0 |
| 445 | | WO461 | 3 | | 11 | | KG | 1 | Increase stirrer | 0 | 0 |
| 446 | | WO461 | 24 | | 600 | | KG | 1 | | 0 | 0 |
| 447 | | WO461 | 4 | | 25 | | KG | 1 | | 0 | 0 |
| 448 | | WO461 | 24 | | 600 | | KG | 1 | | 0 | 0 |
| 449 | | WO461 | 8 | | 23.2 | | KG | 1 | Reduce stirrer | 0 | 0 |
| 450 | | WO461 | 24 | | 600 | | KG | 1 | | 0 | 0 |
| 451 | | WO461 | 7 | | 90 | | KG | 1 | | 0 | 0 |

| ProductId | ProductCode | ProductName | ProductType | BatchSize | Note |
|---|---|---|---|---|---|
| 1 | 1 | Assembly Stock | Manufactured | 1000 | |
| 2 | Water | Water | Raw Material | | |
| 3 | PC0041 | Pearl Caustic | Raw Material | | |
| 4 | PN0045 | Sodim Tripol | Raw Material | | |
| 5 | PD0011 | Fluorsceine | Raw Material | | |
| 6 | PD0032 | Tartrazine Yel | Raw Material | | |
| 7 | LC0040 | Product description | Raw Material | | |
| 8 | LN0114 | Product description | Raw Material | | |
| 9 | LF0019 | Lemon Fragrance | Raw Material | | |
| 10 | PC0042 | Sodium Meta | Raw Material | | |
| 11 | PC0002 | Product description | Raw Material | | |
| 12 | LN0010 | Butyl Glycoether | Raw Material | | |
| 13 | LN0070 | SLES 70% | Raw Material | | |
| 14 | LF0019 | Lemon Fragrance | Raw Material | | |
| 15 | LN0120 | Surfactant | Raw Material | | |
| 16 | LC0057 | Triethanolamine | Raw Material | | |
| 17 | LC0021 | Labs Acid | Raw Material | | |
| 18 | LD0163 | Product description | Raw Material | | |
| 19 | LC0013 | Acticide | Raw Material | | |
| 20 | LF0099 | Toasted Coconut | Raw Material | | |
| 21 | LN0005 | CDE 80 | Raw Material | | |
| 22 | 2 | T2000 | Manufactured | 1000 | |
| 23 | 3 | Bulldog Blue | Manufactured | 1000 | |
| 24 | Mixing | Manual Action | Recipe Action | | |
| 25 | 4 | Wash & Shine | Manufactured | 1000 | |
| 26 | PD0067 | CARMOISINE | Raw Material | | |
| 27 | LN0088 | Silicone Emul | Raw Material | | |

| LogId | WorkOrde | LogDateTime | SensorId | LogDescription | LogData |
|---|---|---|---|---|---|
| 19582 | WO451 | 09:33.8 | 2 | Current Value | 0 |
| 19583 | WO451 | 09:33.9 | 1 | Weight Value | 1 |
| 19584 | WO451 | 09:39.6 | 1 | Weight Value | 0.5 |
| 19585 | WO451 | 09:40.9 | 1 | Weight Value | 0 |
| 19586 | WO451 | 09:41.3 | 1 | Weight Value | 0.5 |
| 19587 | WO451 | 09:42.0 | 1 | Weight Value | 0 |
| 19588 | WO451 | 09:42.4 | 1 | Weight Value | 0.5 |
| 19589 | WO451 | 09:43.6 | 1 | Weight Value | 8.5 |
| 19590 | WO451 | 09:44.0 | 1 | Weight Value | 25 |
| 19591 | WO451 | 09:44.4 | 1 | Weight Value | 24 |
| 19592 | WO451 | 09:44.8 | 1 | Weight Value | 23.5 |
| 19593 | WO451 | 09:45.2 | 1 | Weight Value | 0.5 |
| 19594 | WO451 | 09:46.8 | 1 | Weight Value | 0 |
| 19595 | WO451 | 09:47.2 | 1 | Weight Value | 5.5 |
| 19596 | WO451 | 09:47.6 | 1 | Weight Value | 26.5 |
| 19597 | WO451 | 09:48.0 | 1 | Weight Value | 28 |
| 19598 | WO451 | 09:48.4 | 1 | Weight Value | 27 |
| 19599 | WO451 | 09:49.2 | 1 | Weight Value | 27.5 |

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# Data Pre-processing

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# Data cleaning

- Remove constant feature – does not have impact in the outcome
- Remove irrelevant feature – id values
- Remove duplicate features (across columns) and samples (across rows) – because this cause data imbalance and over-fitting during training
- Identify and remove outliers – as they fall well outside decision boundary and can skew your data
- Identify and remove highly correlated features - Some features may be highly correlated and therefore redundant to a certain degree (because they same information about the target variable)

# Data Imputation

- Detect missing features / incorrect or missing values
- Detecting missing features can be done by plotting the histogram of each feature
  - unusual outlier spikes indicate the use of special values,
  - a spike in the middle of the distribution is a sign that mean/median imputation has already been performed.
- To fix missing features
  - Sometime use mean / median / mode of the entire feature for imputation
  - For time-series data , impute using value repetition, or interpolation is good

# Data Imputation

- Categorical Imputation: Missing categorical variables are generally replaced by the most commonly occurring value in other records
- Numerical Imputation: Missing numerical values are generally replaced by the mean of the corresponding value in other records

# Discretization

- Discretization involves taking a set of data values and grouping sets of them together logically into bins
- Binning can apply to numerical values as well as to categorical data values.
- Grouping of equal intervals (e.g., from seconds to minute)
- Grouping based on equal frequencies
- Grouping based on sorting

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# Feature encoding

- Ordinal features (such as age) may have integer values, but they differ from numeric features
- Tree-based models can use label-encoding (i.e. fixed strings or integers denoting class membership) and don’t need further preprocessing.
- Non-tree methods require that categorical features be one-hot encoded (each category is converted to variable with value 0/1)

# Normalisation

- Scaling or normalisation is good for achieving low training loss in particular for non-tree based methods
- Numerical features can often benefit from transformations. Log transformation, np.log(1 + x), is a very strong transformation that is particularly helpful when a feature observes a power-law relationship

# Dimensionality Reduction

- dimensionality reduction techniques are useful for compressing the features onto a lower-dimensional subspace.
- Reducing the dimensionality of our feature space has the advantage that less storage space is required, and the learning algorithm can run much faster
- improve the predictive performance of a model if the dataset contains a large number of irrelevant features (or noise)

# Data Shuffling

- During preprocessing it's important to shuffle your dataset prior to splitting it into train/validation/test subsets.
- utilize the stratify on feature of sklearn.model_selection.train_test_split() to ensure there is consistent distribution of your minority targets across all your subsets.
- Help our machine learning algorithm not only performs well on the training dataset but also generalizes well to new data

# Feature Generation

- Mapping existing features into a new space, Example: Date-> day of the week
- Combining multiple features into a composite. Example: sum of 2 columns
- aggregating data to find patterns: Example: mean values of each minute in per second time-series data
- Merging auxiliary data

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# Train Model

- It is essential to compare at least a handful of different learning algorithms in order to train and select the best performing model
- Different techniques summarized as “cross-validation” can be used for validation during the training process
- In cross-validation, dataset is further divided into training and validation subsets in order to estimate the generalization performance of the model.

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# Train Model : Parameter Tuning

- We cannot expect that the default parameters of the different learning algorithms provided by software libraries are optimal for our specific problem task
- Frequent use of hyperparameter optimization techniques that help us to fine-tune the performance of our model
- We can think of those hyperparameters as parameters that are not learned from the data but represent the knobs of a model that we can turn to improve its performance

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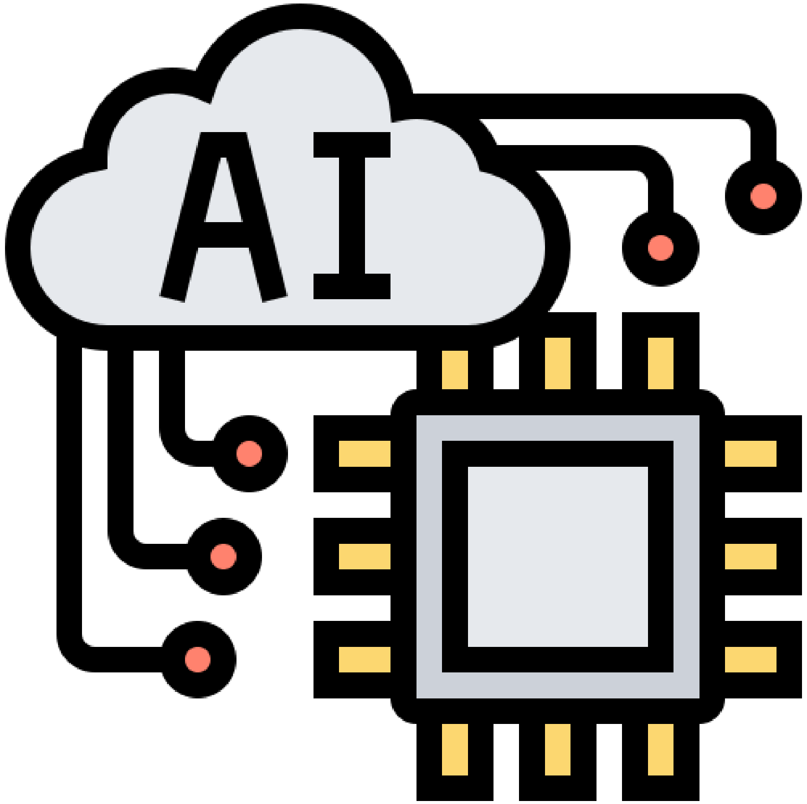
# Evaluating models

- After we have selected a model that has been fitted on the training dataset, we can use the test dataset to estimate how well it performs on this unseen data
- If we are satisfied with its performance, we can now use this model to predict new, future data.
- Data must be in pre-processed format for test dataset also.
- One commonly used metric for evaluation is accuracy, which is defined as the proportion of correctly classified instances

# Learn, Practice and Enjoy the AI journey

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