5.1 Feature Engineering

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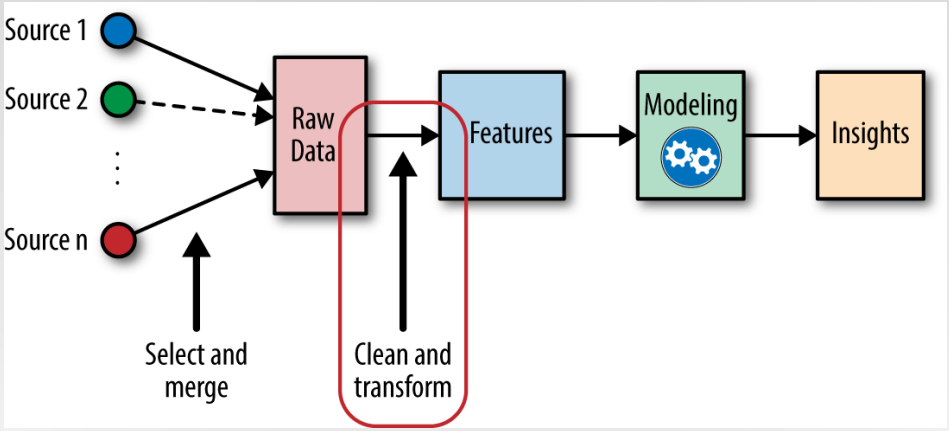
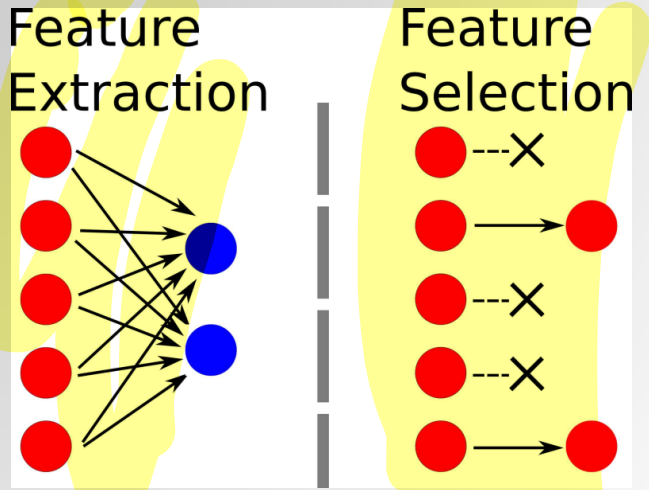
Feature Engineering

- The problem of transforming raw data into a dataset is called feature engineering.
- **Informative features**: those would allow the learning algorithm to build a model that does a good job of predicting labels of the data used for training.
  - Highly informative features are also called features with high **predictive power**.



Feature Selection vs Feature Extraction

- **Feature Selection**
  - Selecting subset of extracted features. This subset is relevant and contributes to minimizing the error rate of a trained model.
- **Feature Extraction**
  - Combining existing features to produce a more useful one.



Label Encoding

- Encode attributes and target labels with value between 0 and NumberOfClasses-1
  - Using ordered numbers as values is likely to confuse the learning algorithm
- Label Encoding can be helpful when the ordering of values of some categorical variable matters

...	quality	...
...	bad	...
...	bad	...
...	good	...
...	excellent	...

...	quality	...
...	0	...
...	0	...
...	1	...
...	2	...

One-Hot Encoding

Transforming categorical feature into several binary ones:

id	color
1	red
2	blue
3	green
4	blue

id	color_red	color_blue	color_green
1	1	0	0
2	0	1	0
3	0	0	1
4	0	1	0

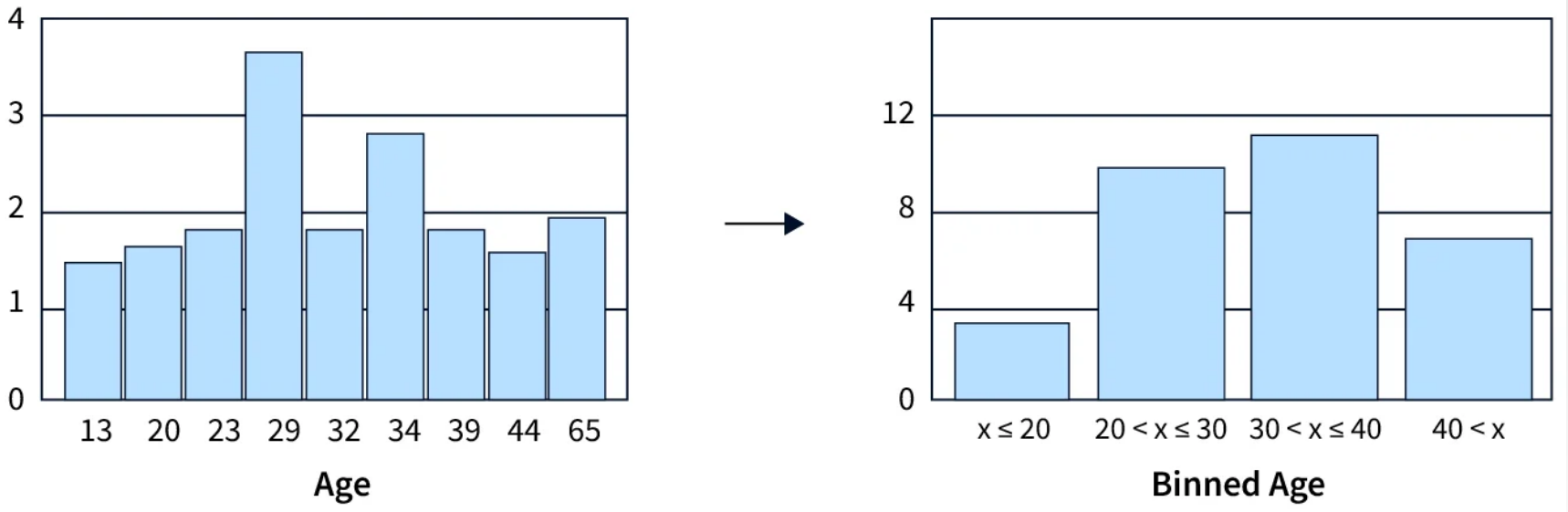
Binning

- Binning is the conversion of continuous values into categorical ones.
- Prevent overfitting.

Sex	Age
male	22
female	38
female	26
female	35
male	35
male	80
male	54
male	2
female	27
female	14
female	4
female	58

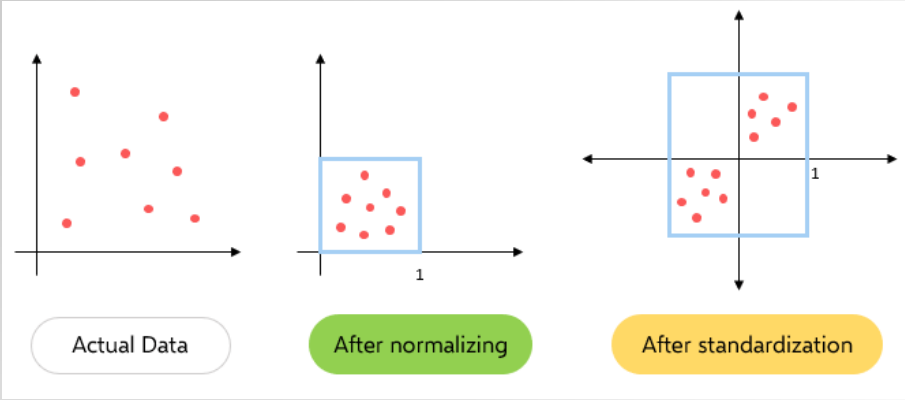
Sex	Age
male	Adult
female	Adult
female	Adult
female	Adult
male	Adult
male	Elderly
male	Adult
male	Toddler/baby
female	Adult
female	Child
female	Toddler/baby
female	Adult

Binning


4
3
2
1
0
13 20 23 29 32 34 39 44 65
Age
12
8
4
0
x ≤ 20
20 < x ≤ 30
30 < x ≤ 40
40 < x
Binned Age

Feature Scaling

- There are two common ways to get all attributes to have the same scale:
  - Normalization
  - Standardization

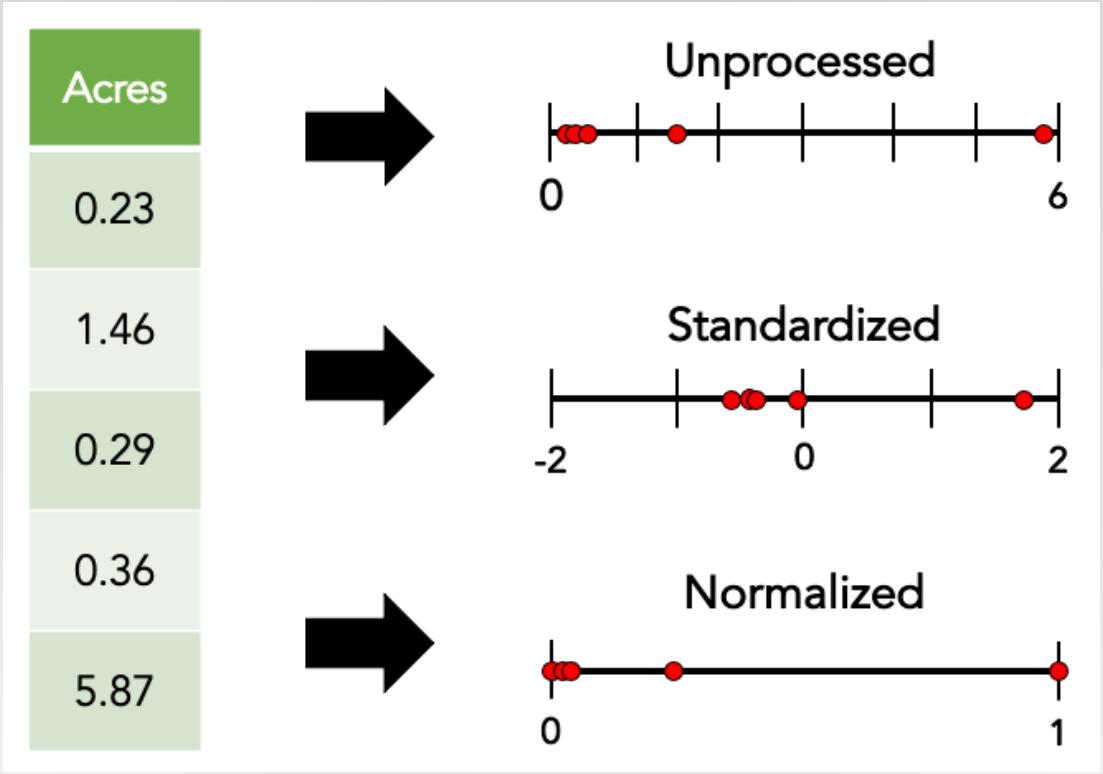


No Scaling Problem

Person_name	*Salary*	*Years_of_experience*	*Expected_Position_Level*
Ahmed	100000	10	**2**
Khaled	78000	7	**4**
Mohammed	32000	5	**8**
Ali	55000	6	**7**
Yousef	92000	8	**3**
Saleh	120000	15	**1**
Ayman	65750	7	**5**

The attributes *Salary* and *Years_of_experience* are on different scale and hence attribute *Salary* can take high priority over attribute *Years_of_experience* in the model.

Feature Scaling



Normalization

- Normalization (or min-max normalization) scale all values in a fixed range between **0 and 1**.

$$\bar{x}^{(j)} = \frac{x^{(j)} - min^{(j)}}{max^{(j)} - min^{(j)}}$$

- $min^{(j)}$: Minimum value of the feature j
- $max^{(j)}$: Maximum value of the feature j

...	cost	...
...	55000	...
...	70000	...
...	65000	...
...	43000	...

...	cost	...
...	0.4444	...
...	1	...
...	0.8148	...
...	0	...

Standardization

Rescale data to have

- **Standardization** (or z-score normalization) is the procedure during which the feature values are rescaled so that they have the properties of a standard normal distribution with $\mu = 0$ and $\sigma = 1$.

$$\hat{x}^{(j)} = \frac{x^{(j)} - \mu^{(j)}}{\sigma^{(j)}}$$

...	cost	...
...	55000	...
...	70000	...
...	65000	...
...	43000	...

...	cost	...
...	-0.314	...
...	1.137	...
...	0.653	...
...	-1.476	...

$\mu^{(j)}$: Mean value of the feature j

$\sigma^{(j)}$: Standard deviation from the mean value of the feature j

- Standardization is much **less** affected by **outliers**.

Dealing with Missing Features

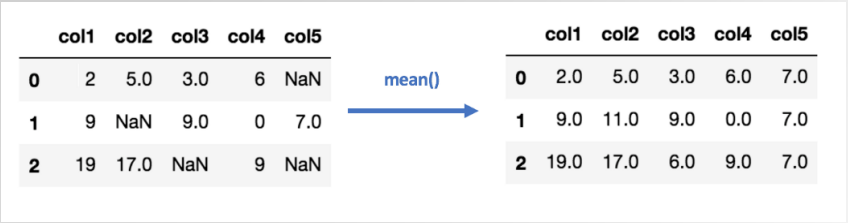
- Missing data are values that are not recorded in the dataset, represented by NaN.

- Different ways of dealing with missing features:
  1. Removing the examples with missing data from the dataset.
  2. Using a learning algorithm that can deal with missing feature values.
  3. Using a data imputation technique.

PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
1	0	3	male	22	1	0	A/5 21171	7.25		S
2	1	1	female	38	1	0	PC 17599	71.2833	C85	C
3	1	3	female	26	0	0	STON/O2. 3101282	7.925		S
4	1	1	female	35	1	0	113803	53.1	C123	S
5	0	3	male	35	0	0	373450	8.05		S
6	0	3	male		0	0	330877	8.4583		Q

Data Imputation Techniques

- Data Imputation Techniques are ways to deal with missing features by filling them with values such as:
  - Mean/Median Values
  - Most Frequent or Zero/Constant Values
  - Predicted value using a regression model



	col1	col2	col3	col4	col5
0	2	5.0	3.0	6	NaN
1	9	NaN	9.0	0	7.0
2	19	17.0	NaN	9	NaN

	col1	col2	col3	col4	col5
0	2.0	5.0	3.0	6.0	7.0
1	9.0	11.0	9.0	0.0	7.0
2	19.0	17.0	6.0	9.0	7.0

Python Example

- https://colab.research.google.com/drive/1YwvH-HLpmm4RDBrqOVX_UHQ66UskHwgS?usp=sharing