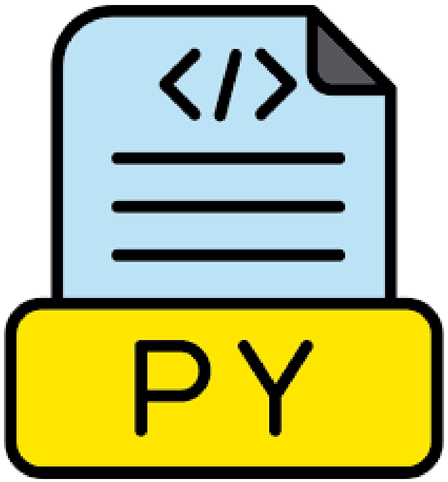
Fouille de Données

Data Mining

Classification - Partie 3

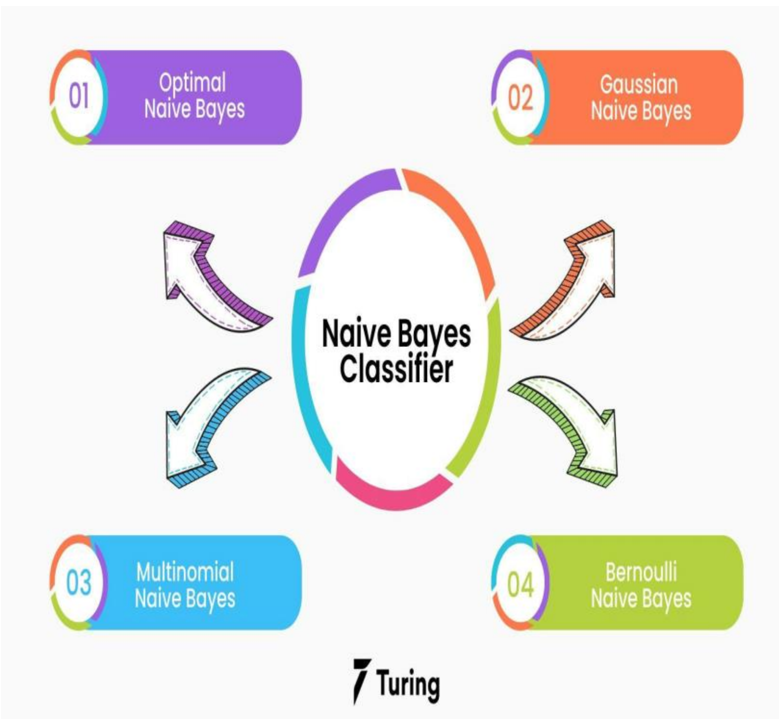
La classification naïve bayésienne

- **Série TP 4 – Naive Bayes with Scikit Learn**



La classification naïve bayésienne

- **Série TP 4 – Naive Bayes with Scikit Learn**



https://scikit-learn.org/stable/modules/naive_bayes.html

La classification naïve bayésienne

- **Série TP 4 – Naive Bayes with Scikit Learn**

1.9.1. Gaussian Naive Bayes

1.9.2. Multinomial Naive Bayes

1.9.3. Complement Naive Bayes

1.9.4. Bernoulli Naive Bayes

1.9.5. Categorical Naive Bayes

https://scikit-learn.org/stable/modules/naive_bayes.html

La classification naïve bayésienne

- **Série TP 4 – Naive Bayes with Scikit Learn**

$$P(y \mid x_1, \dots, x_n) \propto P(y) \prod_{i=1}^{n} P(x_i \mid y)$$

$$\Downarrow$$

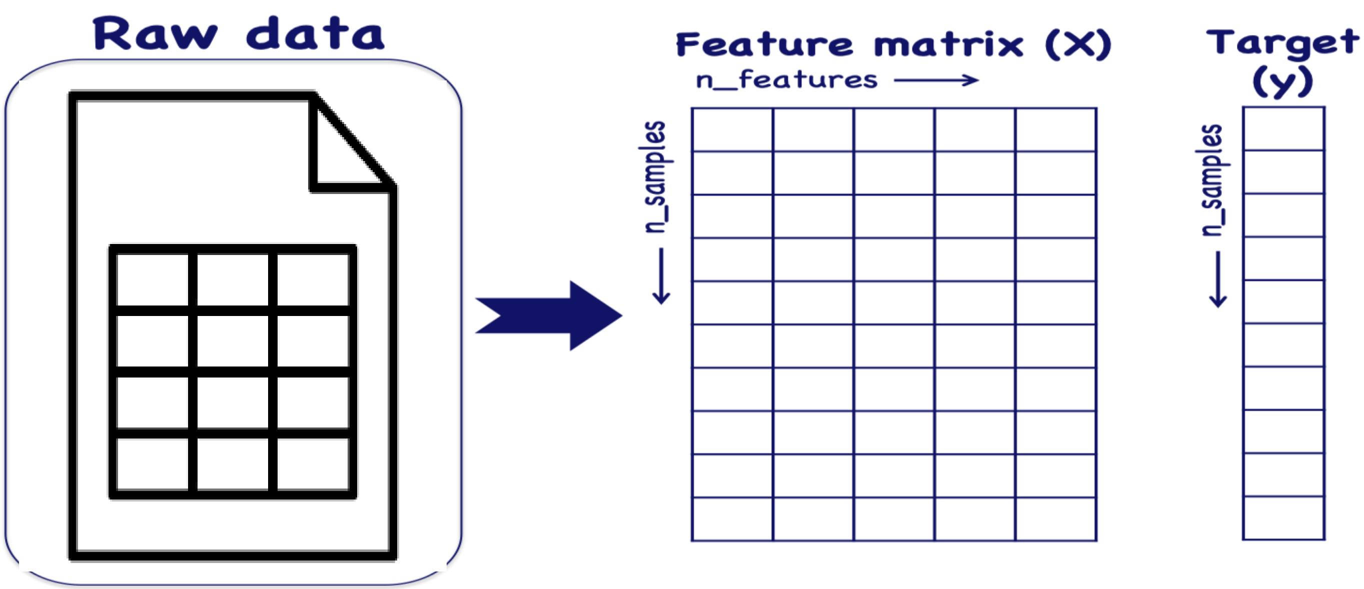
$$\hat{y} = \arg\max_y P(y) \prod_{i=1}^{n} P(x_i \mid y),$$

https://scikit-learn.org/stable/modules/naive_bayes.html

La classification naïve bayésienne

- **sklearn.naive_bayes.CategoricalNB** implements the categorical naive Bayes algorithm for categorically distributed data.

- Takes as **input** two arrays: an **array X** of shape (n_samples, n_features) holding the **training samples**, and an **array Y** of integer values, shape (n_samples,), holding the **class labels** for the training samples.



La classification naïve bayésienne

- **sklearn.naive_bayes.CategoricalNB**

$$\underbrace{P(c \mid x)}_{\text{Posterior Probability}} = \frac{\overbrace{P(x \mid c)}^{\text{Likelihood}}\,\overbrace{P(c)}^{\text{Class Prior Probability}}}{\underbrace{P(x)}_{\text{Predictor Prior Probability}}}$$

$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

La classification naïve bayésienne

- **sklearn.naive_bayes.CategoricalNB**

$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

Probability calculation

The probability of category t in feature i given class c is estimated as:

$$P(x_i = t \mid y = c \,;\, \alpha) = \frac{N_{tic} + \alpha}{N_c + \alpha n_i},$$

where $N_{tic} = |\{j \in J \mid x_{ij} = t, y_j = c\}|$ is the number of times category t appears in the samples x_i, which belong to class c, $N_c = |\{j \in J \mid y_j = c\}|$ is the number of samples with class c, α is a smoothing parameter and n_i is the number of available categories of feature i.

La classification naïve bayésienne

- **sklearn.naive_bayes.CategoricalNB**

In `CategoricalNB`, for each feature X_j with possible categorical values x_j, the conditional probability of a value given a class y is estimated as:

$$P(X_j = x_j \mid Y = y) = \frac{N_{y,x_j} + \alpha}{N_y + \alpha \cdot n_j}$$

where:

- N_{y,x_j} = number of samples with class y having feature $X_j = x_j$
- N_y = total number of samples with class y
- n_j = number of possible categories for feature X_j
- α = smoothing parameter (default = 1.0)

La classification naïve bayésienne

- **sklearn.naive_bayes.CategoricalNB**

Whether	Play
Sunny	No
Sunny	No
Overcast	Yes
Rainy	Yes
Rainy	Yes
Rainy	No
Overcast	Yes
Sunny	No
Sunny	Yes
Rainy	Yes
Sunny	Yes
Overcast	Yes
Overcast	Yes
Rainy	No

- Prédire la classe quand le **Weather** = Overcast :

P(Yes | Overcast) = P(Overcast | Yes) * P(Yes)

P(Overcast |Yes) = 4 / 9

La classification naïve bayésienne

- **sklearn.naive_bayes.CategoricalNB**

Whether	Play
Sunny	No
Sunny	No
Overcast	Yes
Rainy	Yes
Rainy	Yes
Rainy	No
Overcast	Yes
Sunny	No
Sunny	Yes
Rainy	Yes
Sunny	Yes
Overcast	Yes
Overcast	Yes
Rainy	No

- Prédire la classe quand le **Weather** = Overcast :

P(Yes | Overcast) = P(Overcast | Yes) * P(Yes)

P(Overcast |Yes) = 4 / 9

$$P(X_j = x_j \mid Y = y) = \frac{N_{y,x_j}}{N_y}$$

La classification naïve bayésienne

- **sklearn.naive_bayes.CategoricalNB**

Whether	Play
Sunny	No
Sunny	No
Overcast	Yes
Rainy	Yes
Rainy	Yes
Rainy	No
Overcast	Yes
Sunny	No
Sunny	Yes
Rainy	Yes
Sunny	Yes
Overcast	Yes
Overcast	Yes
Rainy	No

- Prédire la classe quand le **Weather** = Overcast :

P(Yes | Overcast) = P(Overcast | Yes) * P(Yes)

P(Overcast |Yes) = 4 / 9

Problem - If a certain category never appears in training for a given class :

- its probability becomes **zero,**
- which makes the whole product of probabilities for that class **zero** during prediction.

La classification naïve bayésienne

- **sklearn.naive_bayes.CategoricalNB**

Whether	Play
Sunny	No
Sunny	No
Overcast	Yes
Rainy	Yes
Rainy	Yes
Rainy	No
Overcast	Yes
Sunny	No
Sunny	Yes
Rainy	Yes
Sunny	Yes
Overcast	Yes
Overcast	Yes
Rainy	No

- Prédire la classe quand le **Weather** = Overcast :

P(Yes | Overcast) = P(Overcast | Yes) * P(Yes)

P(Overcast |Yes) = 4 / 9

Solution – Smoothing (Lissage) : It adds a small constant (α) to each count.

$$P(X_j = x_j \mid Y = y) = \frac{N_{y,x_j} + \alpha}{N_y + \alpha \cdot n_j}$$

La classification naïve bayésienne

sklearn.naive_bayes.CategoricalNB

- CategoricalNB in scikit-learn uses **additive** (Laplace) **smoothing** when estimating conditional probabilities.
- This is controlled by the parameter alpha.
- It adds a small constant (α) to each count. Ensures **no zero probabilities**, and improves generalization on unseen category combinations.
- alpha=**1.0** → **Laplace** smoothing & alpha **> 1** is called **Lidstone** smoothing. Defaut = 1.
- alpha=0.0 → no smoothing.

La classification naïve bayésienne

sklearn.naive_bayes.CategoricalNB

✅ In summary

Concept	In `CategoricalNB`
Type of smoothing	Additive (Laplace / Lidstone)
Parameter	`alpha`
Default	`alpha=1.0`
Purpose	Avoid zero probabilities for unseen categories

La classification naïve bayésienne

1. Import necessary modules
2. Load & explore the dataset
3. Split the DataFrame into features (X) and target/class (y)
4. Create training and test sets
5. Encode categorical data as numbers : LabelEncoding
6. Train the model
7. Predict and Evaluate : Accuracy & Confusion matrix

La classification naïve bayésienne

sklearn.naive_bayes.CategoricalNB

Import necessary modules : scikit-learn package

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB, CategoricalNB
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
```

La classification naïve bayésienne

sklearn.naive_bayes.CategoricalNB

Load & explore the dataset : Exercice 2 - Série TD 2

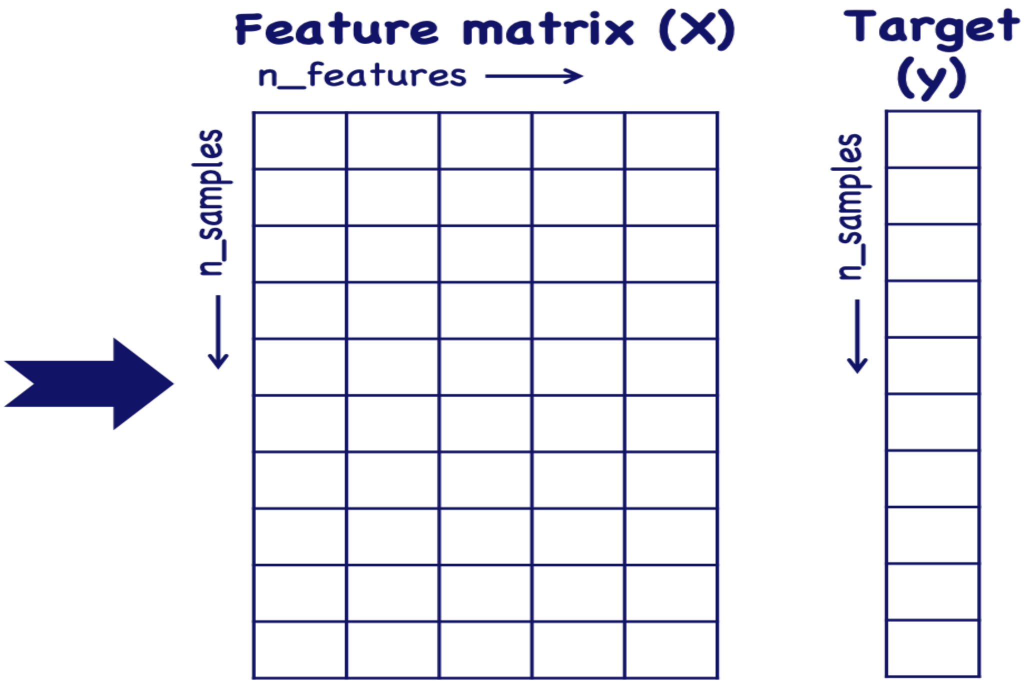
```
lst_data = [
    ['jeune', 'f', 'v', 'faible'],
    ['jeune', 'v', 'v', 'eleve'],
    ['adulte', 'f', 'f', 'faible'],
    ['senior', 'v', 'f', 'eleve'],
    ['senior', 'f', 'v', 'moyen'],
    ['jeune', 'f', 'f', 'faible'],
    ['adulte', 'v', 'f', 'moyen'],
    ['adulte', 'v', 'v', 'moyen'],
    ['senior', 'f', 'f', 'faible'],
    ['senior', 'v', 'v', 'eleve'],
]
```

```
df = pd.DataFrame(lst_data, columns=['age', 'S1', 'S2', 'risque'])
```

La classification naïve bayésienne

sklearn.naive_bayes.CategoricalNB

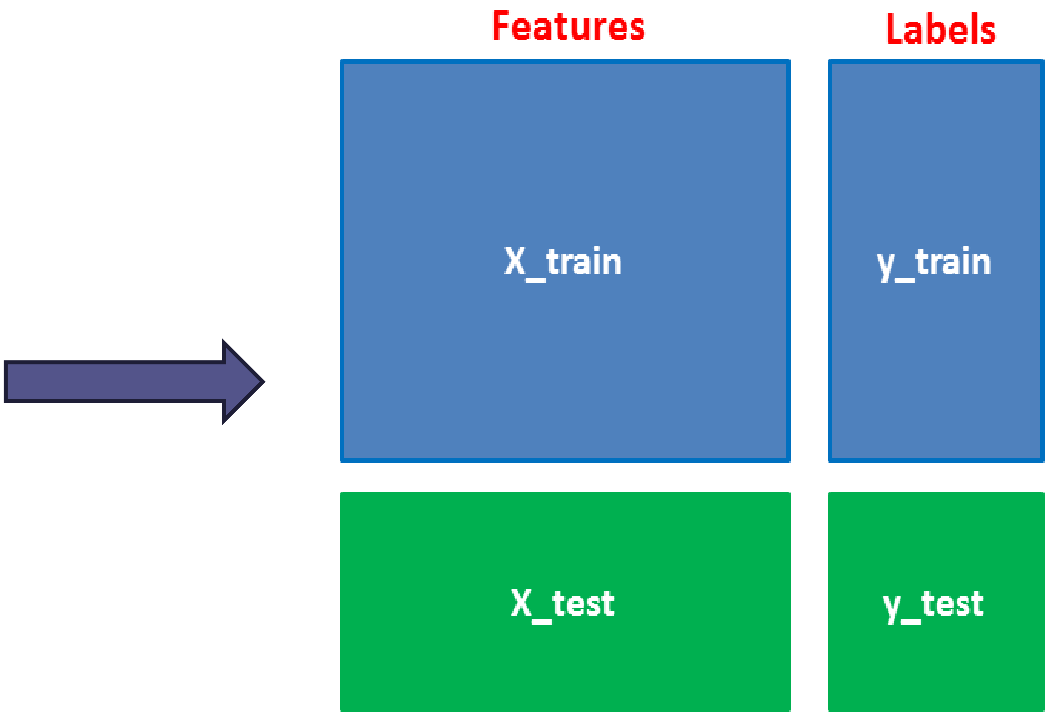
	age	S1	S2	risque
0	jeune	f	v	faible
1	jeune	v	v	eleve
2	adulte	f	f	faible
3	senior	v	f	eleve
4	senior	f	v	moyen
5	jeune	f	f	faible
6	adulte	v	f	moyen
7	adulte	v	v	moyen
8	senior	f	f	faible
9	senior	v	v	eleve



La classification naïve bayésienne

sklearn.naive_bayes.CategoricalNB

	age	S1	S2	risque
0	jeune	f	v	faible
1	jeune	v	v	eleve
2	adulte	f	f	faible
3	senior	v	f	eleve
4	senior	f	v	moyen
5	jeune	f	f	faible
6	adulte	v	f	moyen
7	adulte	v	v	moyen
8	senior	f	f	faible
9	senior	v	v	eleve



La classification naïve bayésienne

```
x = df[['age', 'S1', 'S2’]]

y = df['risque’]
```

La classification naïve bayésienne

```
X = df[['age', 'S1', 'S2']]

y = df['risque']
```

```
X_train, X_test, y_train, y_test    =

      train_test_split( X,  y,
                           test_size = 0.3,
                           random_state = 42 )
```

La classification naïve bayésienne

1. Import necessary modules
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5. Encode categorical data as numbers : LabelEncoding
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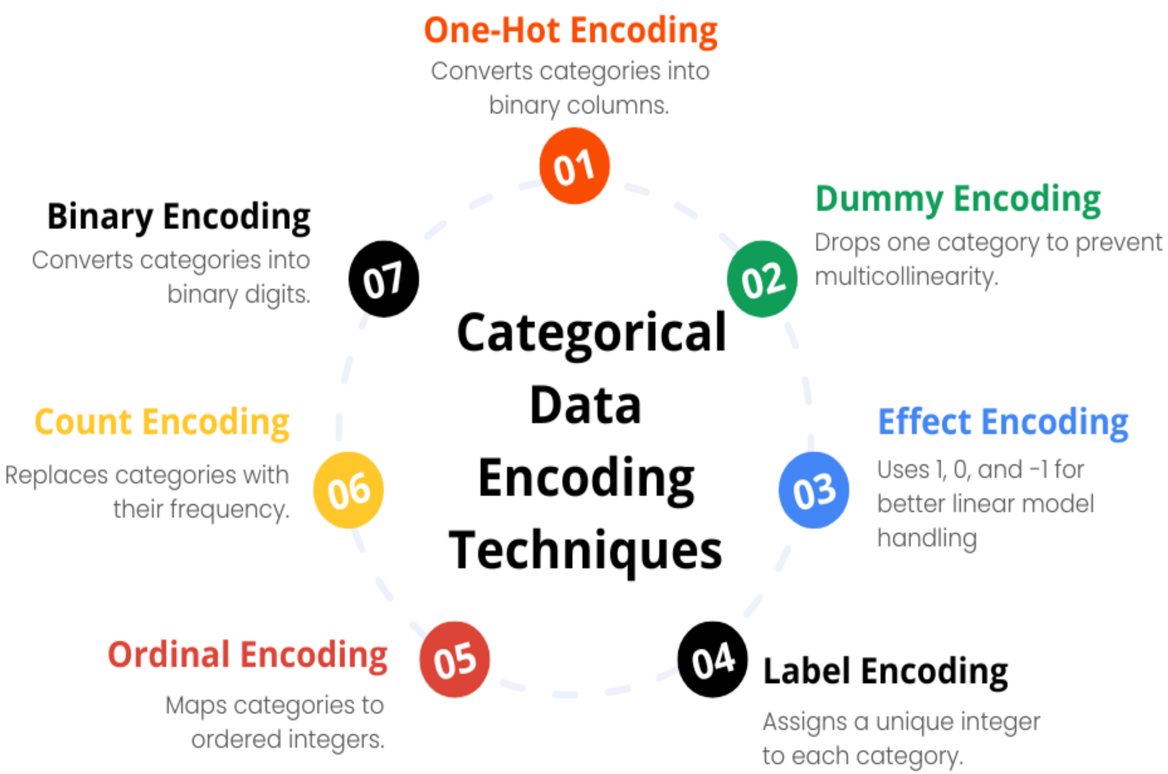
La classification naïve bayésienne

- **Encoding : Encode categorical data as numbers**



https://blog.dailydoseofds.com/p/7-categorical-data-encoding-techniques

La classification naïve bayésienne

- **Encoding : One-Hot Encoding**

Human-Readable

Pet
Cat
Dog
Turtle
Fish

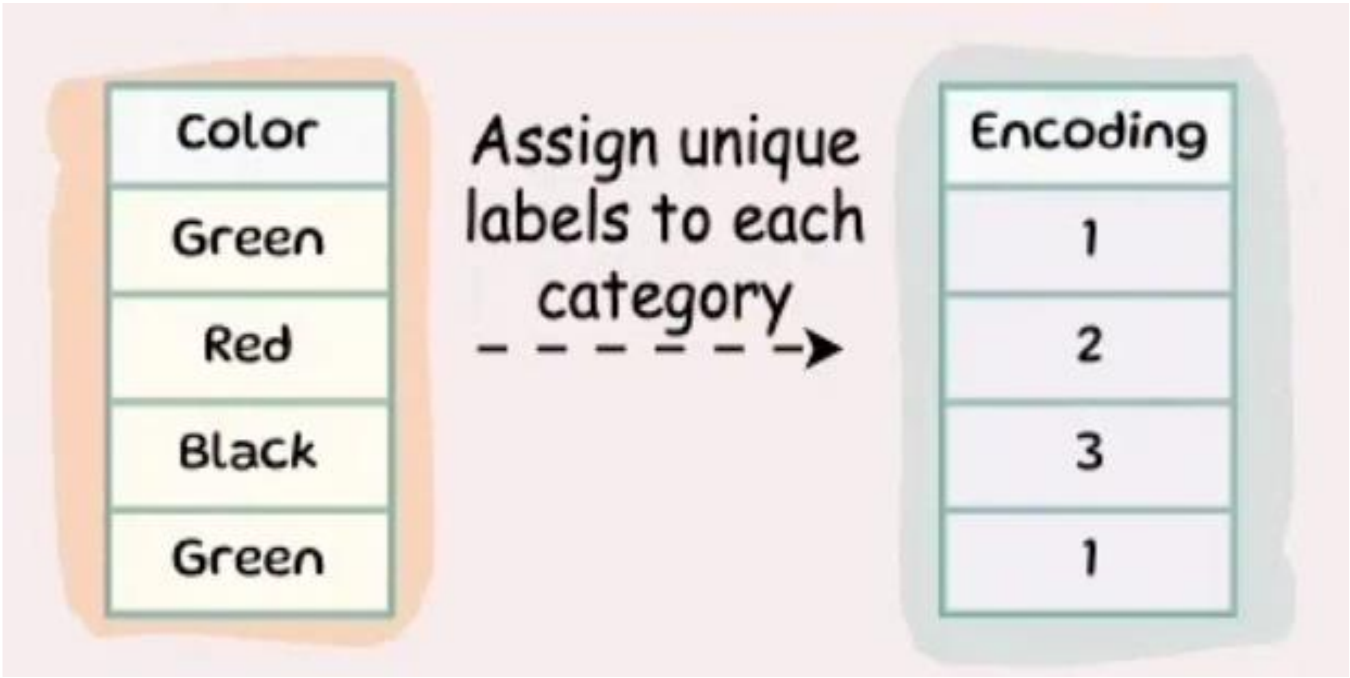
Machine-Readable

Cat	Dog	Turtle	Fish
1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

La classification naïve bayésienne

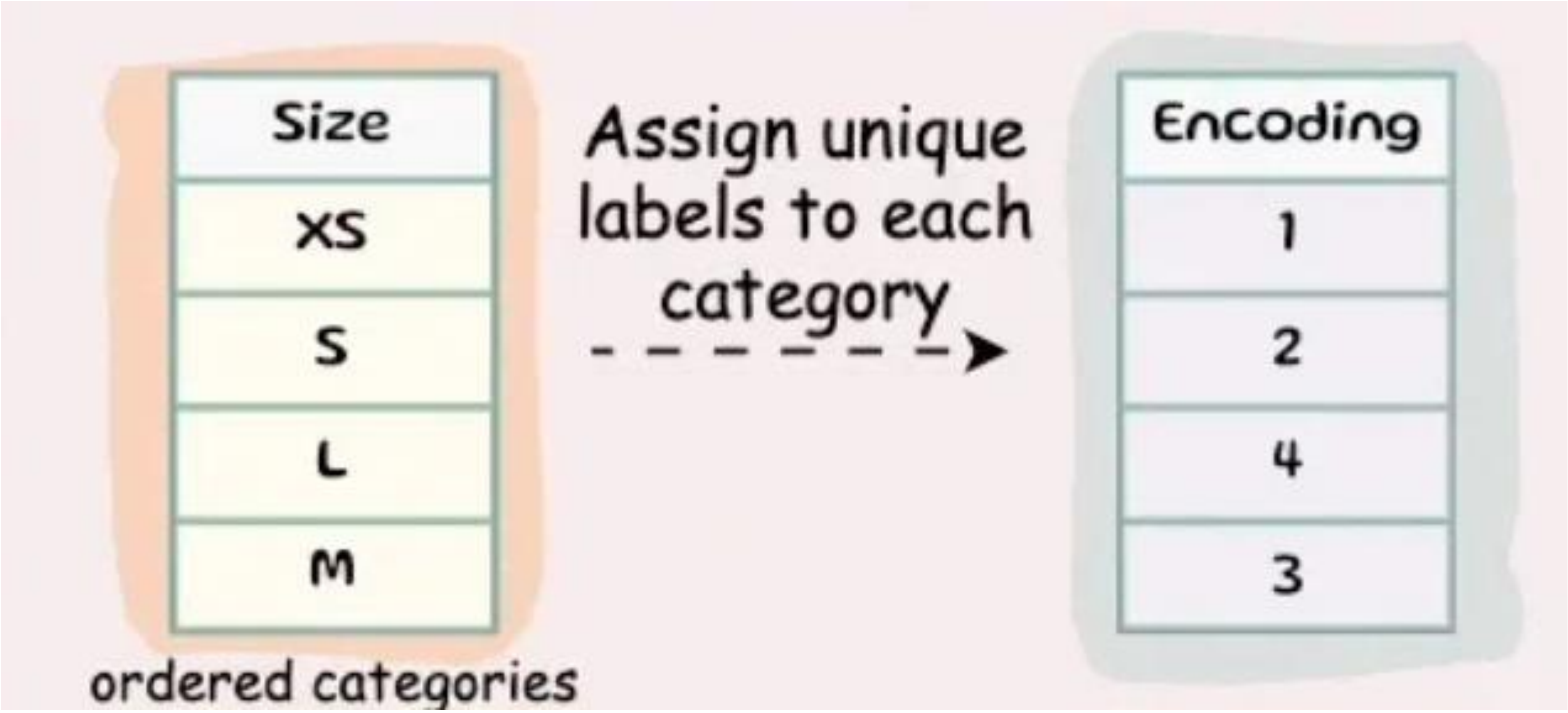
- **Encoding : Label Encoding**

Human-Readable Machine-Readable



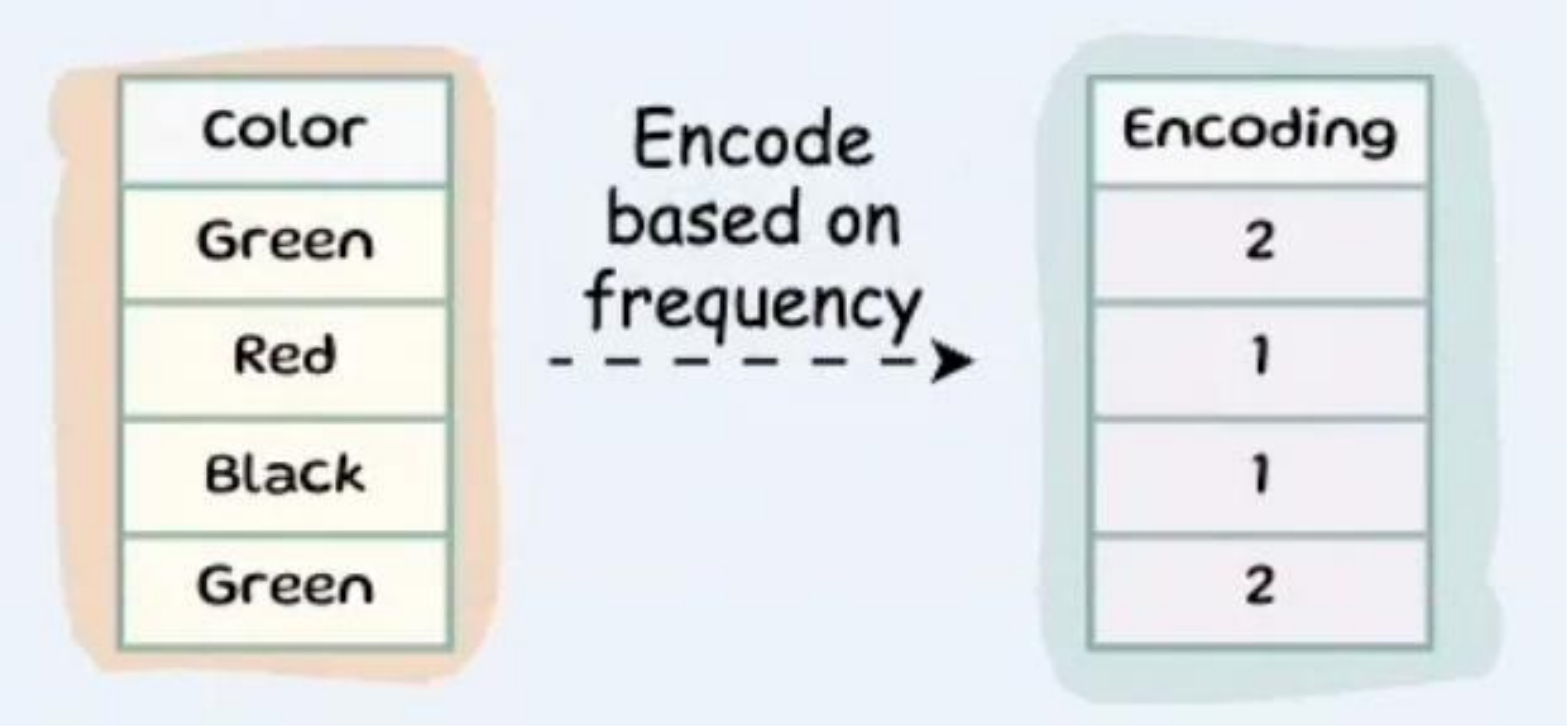
La classification naïve bayésienne

- **Encoding : Ordinal Encoding**



La classification naïve bayésienne

- **Encoding : Count Encoding**



La classification naïve bayésienne

- **Encoding : Binary Encoding**

Temperature
Hot
Cold
Very Hot
Warm
Hot
Warm
Warm
Hot
Hot
Cold

Order
1
2
3
4
1
4
4
1
1
2

Binary
001
010
011
100
001
100
100
001
001
010

Temperature_0	Temperature_1	Temperature_2
0	0	1
0	1	0
0	1	1
1	0	0
0	0	1
1	0	0
1	0	0
0	0	1
0	0	1
0	1	0

La classification naïve bayésienne

- **Encoding : Label Encoding**

```
le = LabelEncoder()

le.fit(X_train)

X_train_le = le.transform(X_train)
```

La classification naïve bayésienne

- **Encoding : Label Encoding**

```
le = LabelEncoder()

le.fit(X_train)

X_train_le = le.transform(X_train)


X_test_le = le.transform(X_test)
```

La classification naïve bayésienne

- **Encoding : Label Encoding**

```
encoders = {}      # to store a LabelEncoder for each column

for col in X_train.columns:
    le = LabelEncoder()
    le.fit(X_train[col])
    X_train_le[col] = le.transform(X_train[col])
    encoders[col] = le              # Save encoder for later use
```

La classification naïve bayésienne

- **Encoding : Label Encoding**

```
print(encoders["age"].classes_)
```

Output : array([‘Adulte’, ‘Jeune', ‘Senior'], dtype=object)

Adulte → 0
Jeune → 1
Senior → 2

La classification naïve bayésienne

- **Encoding : Label Encoding**

```
enc_values = [0, 1, 2]

decoded =  encoders["age"].inverse_transform(enc_values)

print(decoded)
```

Output : [‘Adulte’, ‘Jeune', ‘Senior']

Adulte → 0
Jeune → 1
Senior → 2

La classification naïve bayésienne

- **Encoding : Label Encoding**

```
for col in X_test.columns:
    X_test_le[col] = encoders[col].transform(X_test[col])
```

La classification naïve bayésienne

- **Train the model CategoricalNB**

CategoricalNB

```
class sklearn.naive_bayes.CategoricalNB(*, alpha=1.0, force_alpha=True,
fit_prior=True, class_prior=None, min_categories=None)
```
[source]

clf = CategoricalNB(alpha=1.0)

clf.fit(X_train_le,   y_train)

La classification naïve bayésienne

- **Train the model CategoricalNB**

Attributes:

category_count_ : ***list of arrays of shape (n_features,)***

Holds arrays of shape (n_classes, n_categories of respective feature) for each feature. Each array provides the number of samples encountered for each class and category of the specific feature.

class_count_ : ***ndarray of shape (n_classes,)***

Number of samples encountered for each class during fitting. This value is weighted by the sample weight when provided.

classes_ : ***ndarray of shape (n_classes,)***

Class labels known to the classifier

La classification naïve bayésienne

```
X_train
```

	age	S1	S2
0	jeune	f	v
7	adulte	v	v
2	adulte	f	f
9	senior	v	v
4	senior	f	v
3	senior	v	f
6	adulte	v	f

```
y_train
```

```
0    faible
7     moyen
2    faible
9     eleve
4     moyen
3     eleve
6     moyen
```

```
clf.feature_names_in_
```

```
array(['age', 'S1', 'S2'], dtype=object)
```

```
clf.classes_
```

```
array(['eleve', 'faible', 'moyen'], dtype=
```

```
clf.class_count_
```

```
array([2., 2., 3.])
```

P(cls)

La classification naïve bayésienne

- Array per feature
- Array (row, col) = (cls, feature_values)
- P(xi|cls)

```
X_train
```

	age	S1	S2
0	jeune	f	v
7	adulte	v	v
2	adulte	f	f
9	senior	v	v
4	senior	f	v
3	senior	v	f
6	adulte	v	f

```
y_train
```

```
0    faible
7     moyen
2    faible
9     eleve
4     moyen
3     eleve
6     moyen
```

```
clf.category_count_
```

```
[array([[0., 0., 2.],
        [1., 1., 0.],
        [2., 0., 1.]]),
 array([[0., 2.],
        [2., 0.],
        [1., 2.]]),
 array([[1., 1.],
        [1., 1.],
        [1., 2.]])]
```

La classification naïve bayésienne

- **Predict and Evaluate : Accuracy**

```
for col in X_test.columns:
    X_test_le[col] = encoders[col].transform(X_test[col])

y_preds = clf.predict(X_test_le)

accuracy_score(y_test, y_preds)

classification_report(y_test, y_preds)
```

La classification naïve bayésienne

- **Predict class of a new example :** **Senior, V, F, ?**

y_pred = clf.predict([2, 1, 0]) # Based on ***encoded_values***

Adulte → 0
Jeune → 1
Senior → 2

F → 0
V → 1

F → 0
V → 1

```
> array(['eleve'], dtype='<U6')
```

La classification naïve bayésienne

- **Predict class of a new example :** **Senior, V, F, ?**

y_pred = clf.predict_proba([2, 1, 0])

Adulte → 0
Jeune → 1
Senior → 2

F → 0
V → 1

F → 0
V → 1

```
> array([[0.40540541, 0.27027027, 0.32432432]])
```

La classification naïve bayésienne

- **Predict class of a new example : Senior, V, F, ?**

```
# New example
new_sample = pd.DataFrame([["Senior", "V", "F"]],
                          columns=["age", "S1", "S2"])


# Encode it
for col in new_sample.columns:
   new_sample_le[col] = encoders[col].transform(new_sample[col])


# Predict
y_pred = clf.predict(new_sample_le)
```

La classification naïve bayésienne

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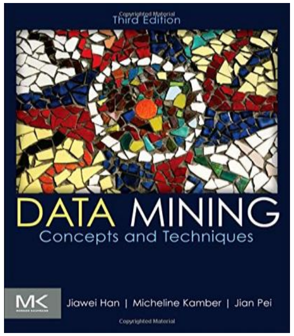
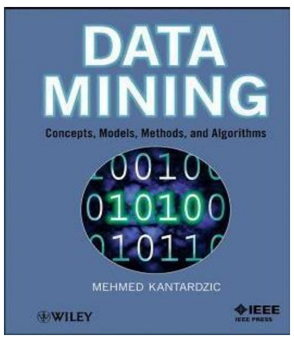
Ressources



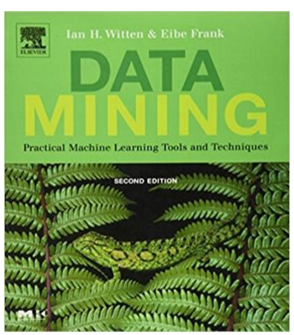
Data Mining : concepts and techniques, 3rd Edition

- ✓ Auteur : Jiawei Han, Micheline Kamber, Jian Pei
- ✓ Éditeur : Morgan Kaufmann Publishers
- ✓ Edition : Juin 2011 - 744 pages - ISBN 9780123814807



Data Mining : concepts, models, methods, and algorithms

- ✓ Auteur : Mehmed Kantardzi
- ✓ Éditeur : John Wiley & Sons
- ✓ Edition : Aout 2011 – 552 pages - ISBN : 9781118029121



Data Mining: Practical Machine Learning Tools and Techniques

- ✓ Auteur : Ian H. Witten & Eibe Frank
- ✓ Éditeur : Morgan Kaufmann Publishers
- ✓ Edition : Juin 2005 - 664 pages - ISBN : 0-12-088407-0