J1 – Statistics

Entrée [1]:

```
import numpy as np
import scipy.stats as st

import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
```

EDA

Paiments Olist

Ouvrez `olist_order_payments.csv` et réalisez les différentes requêtes d'opération statistiques ci-dessous.

Entrée [3]:

```
olist = pd.read_csv('olist_order_payments_dataset.csv')
olist
```

	order_id	payment_sequential	payment_type	payment_installments	pay
0	b81ef226f3fe1789b1e8b2acac839d17	1	credit_card	8	
1	a9810da82917af2d9aefd1278f1dcfa0	1	credit_card	1	
2	25e8ea4e93396b6fa0d3dd708e76c1bd	1	credit_card	1	
3	ba78997921bbcdc1373bb41e913ab953	1	credit_card	8	
4	42fdf880ba16b47b59251dd489d4441a	1	credit_card	2	
...	...	...	...	...	
103881	0406037ad97740d563a178ecc7a2075c	1	boleto	1	
103882	7b905861d7c825891d6347454ea7863f	1	credit_card	2	
103883	32609bbb3dd69b3c066a6860554a77bf	1	credit_card	1	
103884	b8b61059626efa996a60be9bb9320e10	1	credit_card	5	

Entrée [4]:

```
olist.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 103886 entries, 0 to 103885
Data columns (total 5 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   order_id              103886 non-null  object 
 1   payment_sequential    103886 non-null  int64  
 2   payment_type          103886 non-null  object 
 3   payment_installments  103886 non-null  int64  
 4   payment_value         103886 non-null  float64
dtypes: float64(1), int64(2), object(2)
memory usage: 4.0+ MB
```

Entrée [7]:

```
olist.payment_value.describe().to_frame()
```

Out[7]:

	payment_value
count	103886.000000
mean	154.100380
std	217.494064
min	0.000000
25%	56.790000
50%	100.000000
75%	171.837500
max	13664.080000

Entrée [8]:

```
olist['payment_value'].value_counts()
```

Out[8]:

```
50.00      324
20.00      274
100.00     255
77.57      250
35.00      165
          ... 
264.64       1
1071.83      1
563.95       1
38.07        1
363.31       1
Name: payment_value, Length: 29077, dtype: int64
```

Entrée [9]:

```
olist['payment_value'].isna().value_counts()
```

Out[9]:

```
False    103886
Name: payment_value, dtype: int64
```

Statistiques descriptives

Entrée [10]:

```
np.mean(olist.payment_value)
```

Out[10]:

```
154.10038041698365
```

Entrée [11]:

```
np.median(olist.payment_value)
```

Out[11]:

```
100.0
```

Entrée [12]:

```
np.var(olist.payment_value)
```

Out[12]:

```
47303.21247430867
```

Entrée [13]:

```
st.mode(olist.payment_value)
```

Out[13]:

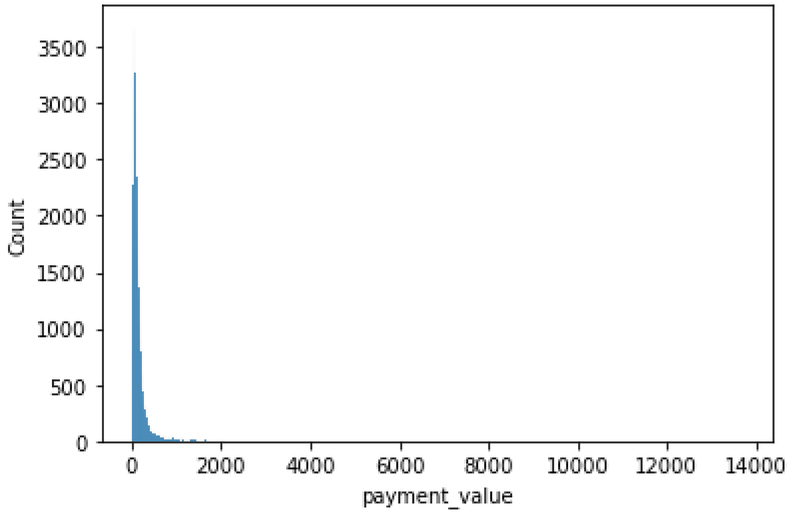
```
ModeResult(mode=array([50.]), count=array([324]))
```

Entrée [14]:

```
sns.histplot(olist['payment_value'])
```

Out[14]:

```
<AxesSubplot:xlabel='payment_value', ylabel='Count'>
```

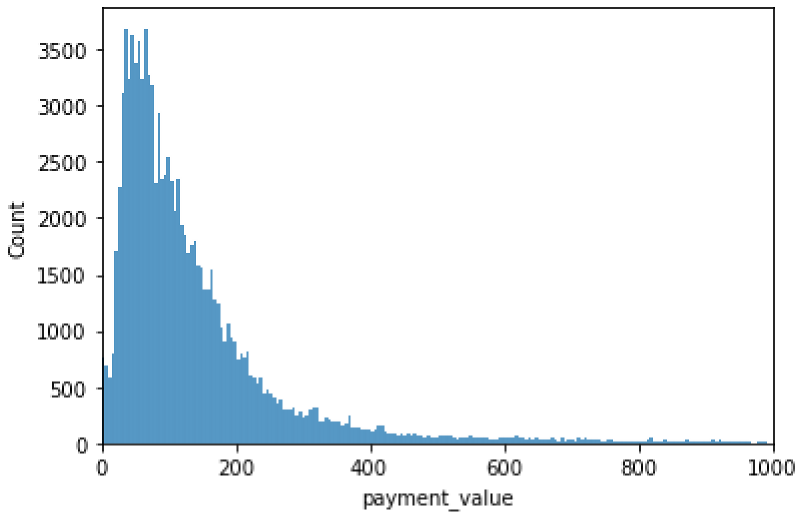


Entrée [15]:

```
sns.histplot(olist['payment_value'])
plt.xlim([0,1000])
```

Out[15]:

```
(0.0, 1000.0)
```



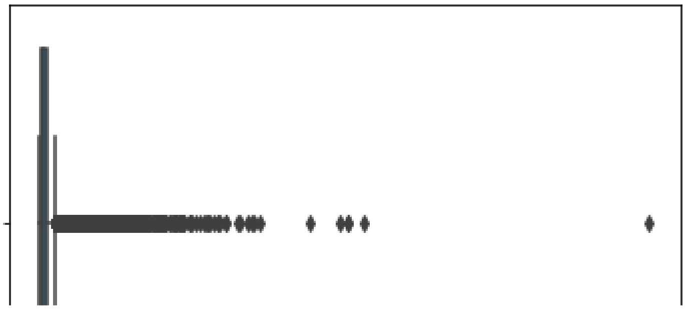
Entrée [16]:

```
sns.boxplot(olist['payment_value'])
```

```
C:\Users\azade\anaconda3\lib\site-packages\seaborn\_decorators.py:36: F
utureWarning: Pass the following variable as a keyword arg: x. From ver
sion 0.12, the only valid positional argument will be `data`, and passi
ng other arguments without an explicit keyword will result in an error
or misinterpretation.
  warnings.warn(
```

Out[16]:

<AxesSubplot:xlabel='payment_value'>



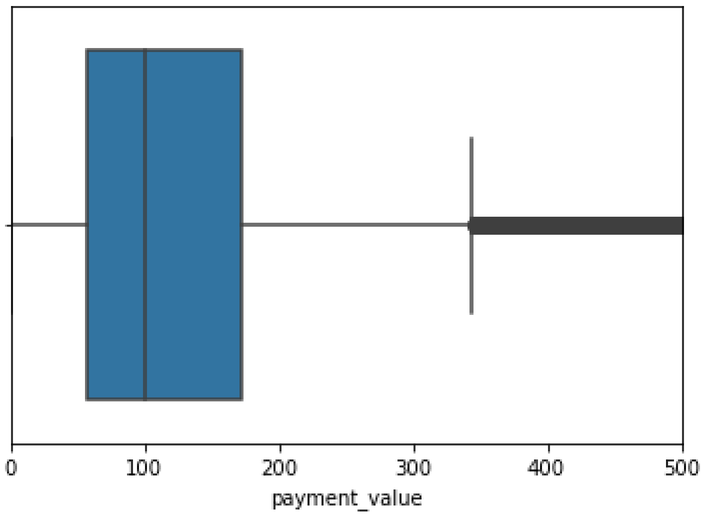
Entrée [17]:

```
sns.boxplot(olist['payment_value'])
plt.xlim([0,500])
```

```
C:\Users\azade\anaconda3\lib\site-packages\seaborn\_decorators.py:36: Futu
reWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterp
retation.
  warnings.warn(
```

Out[17]:

(0.0, 500.0)



Entrée [18]:

```
np.corrcoef(olist.payment_value, olist.payment_installments)
```

Out[18]:

```
array([[1.        , 0.33081084],
       [0.33081084, 1.        ]])
```

Entrée [19]:

```
olist['payment_value'].corr(olist['payment_installments'])
```

Out[19]:

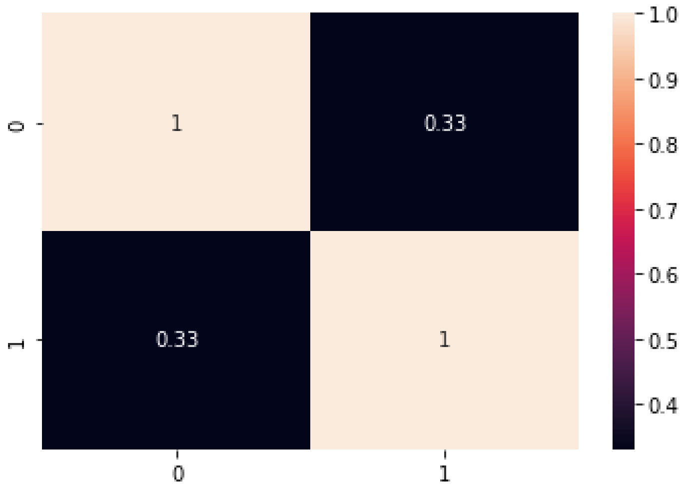
```
0.3308108445189853
```

Entrée [20]:

```
sns.heatmap(np.corrcoef(olist.payment_value, olist.payment_installments),annot=True)
```

Out[20]:

```
<AxesSubplot:>
```



Probabilités avec Numpy – Simuler des lois statistiques

- Nombres aléatoires

Entrée [21]:

```
# nombre aléatoire dans le sous-package random
np.random.random()
```

Out[21]:

```
0.07126593960121741
```

Entrée [22]:

```
# L'attribut size permet de choisir la taille de l'array
np.random.random(size=(2, 5))
```

Out[22]:

```
array([[0.66232657, 0.40335644, 0.07296428, 0.02458101, 0.69979427],
       [0.20419468, 0.75891551, 0.36083995, 0.57150036, 0.09909991]])
```

Entrée [23]:

```
#choisi un entier aléatoire
np.random.randint(1000)
```

Out[23]:

```
484
```

Entrée [24]:

```
#choisi cinq entiers aléatoires entre entre 100 et 1000
np.random.randint(100, 1000, size=5)
```

Out[24]:

```
array([849, 943, 225, 198, 560])
```

- Variables aléatoires (tirer des échantillons depuis une distribution spécifique)

Entrée [25]:

```
# choisi 4 valeurs entre 0 et 10 selon une loi uniforme
np.random.uniform(0, 10, size=4)
```

Out[25]:

```
array([1.75966464, 7.54115299, 8.44563621, 8.27153944])
```

Entrée [26]:

```
# choisi 2 valeurs deux fois de suite avec loc = moyenne et sclae = ecart type selon une
np.random.normal(loc=10, scale=1e-5, size=(2,2))
```

Out[26]:

```
array([[ 9.99998679, 10.00002328],
       [ 9.99998528,  9.9999814 ]])
```

Il existe pleins d'autres lois statistiques: [https://numpy.org/doc/1.16/reference/routines.random.html (https://numpy.org/doc/1.16/reference/routines.random.html)](https://numpy.org/doc/1.16/reference/routines.random.html).

Bootstrapping, inference, intervalles de confiance

Oeufs de pâques

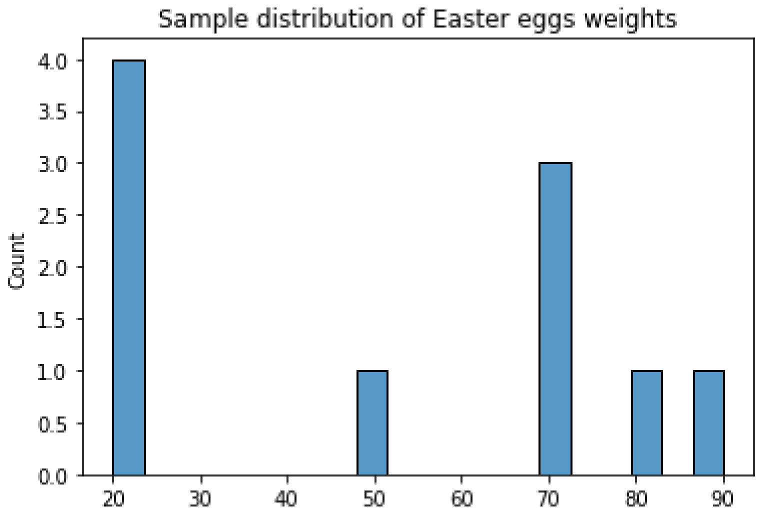
On a reçu une très grande cargaisons d'oeufs de Pâques et on veut déterminer le poids moyen de ces oeufs pour vérifier la qualité de la marchandise. Pour cela on ne va pas peser l'ensemble de la cargaison mais simplement 10 oeufs.

Entrée [39]:

```
eggs = [20, 20, 20, 20, 70, 70, 70, 50, 90, 80]
```

Entrée [40]:

```
# Sample distribution
sns.histplot(x=eggs, bins=20)
plt.title('Sample distribution of Easter eggs weights')
plt.show()
```



- Intervalle de confiance

Entrée [41]:

```
mu = np.mean(eggs)
sigma = np.std(eggs)
z = sigma / np.sqrt(len(eggs))
print('Mean:', mu, '\nStdev:', sigma, '\nStandard error:', z)
```

```
Mean: 51.0
Stdev: 27.0
Standard error: 8.538149682454623
```

Entrée [42]:

```
#calculons l'intervalle de confiance à 95%
confidence_interval = (mu - 1.96*z, mu + 1.96*z)
confidence_interval
```

Out[42]:

```
(34.26522662238894, 67.73477337761106)
```

- Intervalle de confiance bootstrappée

Entrée [43]:

```
sample_mean = np.mean(eggs)
sample_mean
```

Out[43]:

```
51.0
```

Entrée [44]:

```
bootstrap_means = []
#faisons l'opération 5000 fois
for i in range(5000):
    #créer un nouvel échantillon entre les 10 valeurs de départ dans eggs
    temp_sample = np.random.choice(eggs, replace=True, size=len(eggs))
    #prenons la moyenne de cet échantillon
    temp_mean = np.mean(temp_sample)
    #mettons cette moyenne dans une liste
    bootstrap_means.append(temp_mean)
```

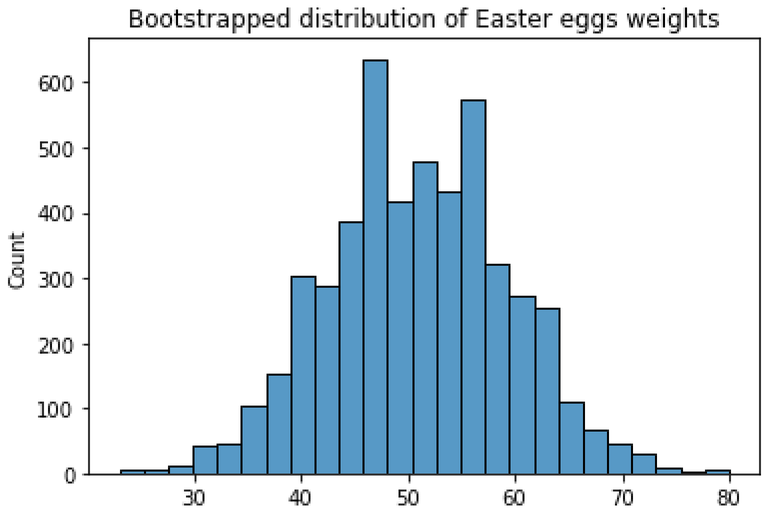
Entrée [45]:

```
print(temp_sample)
print(bootstrap_means)
```

```
[20 90 70 80 20 80 80 70 70 70]
[51.0, 41.0, 64.0, 57.0, 45.0, 57.0, 43.0, 53.0, 42.0, 51.0, 70.0, 37.
0, 58.0, 68.0, 51.0, 44.0, 39.0, 51.0, 53.0, 39.0, 45.0, 55.0, 53.0, 5
1.0, 45.0, 47.0, 47.0, 57.0, 45.0, 50.0, 56.0, 52.0, 43.0, 58.0, 47.0,
46.0, 46.0, 47.0, 57.0, 44.0, 25.0, 59.0, 48.0, 38.0, 67.0, 54.0, 46.0,
58.0, 47.0, 35.0, 51.0, 43.0, 50.0, 53.0, 56.0, 58.0, 35.0, 59.0, 57.0,
51.0, 47.0, 42.0, 53.0, 54.0, 67.0, 41.0, 58.0, 59.0, 45.0, 37.0, 51.0,
49.0, 46.0, 50.0, 52.0, 46.0, 51.0, 40.0, 45.0, 59.0, 64.0, 35.0, 58.0,
48.0, 40.0, 46.0, 51.0, 61.0, 61.0, 41.0, 47.0, 56.0, 42.0, 67.0, 41.0,
55.0, 49.0, 40.0, 52.0, 49.0, 51.0, 54.0, 39.0, 46.0, 48.0, 62.0, 49.0,
65.0, 44.0, 57.0, 53.0, 35.0, 49.0, 63.0, 51.0, 40.0, 48.0, 41.0, 62.0,
45.0, 53.0, 45.0, 47.0, 56.0, 46.0, 39.0, 46.0, 60.0, 46.0, 58.0, 54.0,
60.0, 52.0, 61.0, 55.0, 59.0, 53.0, 52.0, 53.0, 68.0, 56.0, 48.0, 51.0,
75.0, 50.0, 41.0, 51.0, 35.0, 57.0, 51.0, 43.0, 54.0, 51.0, 58.0, 43.0,
54.0, 48.0, 53.0, 44.0, 43.0, 39.0, 36.0, 66.0, 44.0, 62.0, 61.0, 53.0,
47.0, 49.0, 63.0, 58.0, 63.0, 32.0, 45.0, 37.0, 51.0, 56.0, 60.0, 64.0,
31.0, 47.0, 40.0, 50.0, 46.0, 49.0, 46.0, 47.0, 72.0, 55.0, 46.0, 37.0,
46.0, 37.0, 60.0, 55.0, 49.0, 45.0, 58.0, 45.0, 60.0, 61.0, 50.0, 53.0,
47.0, 47.0, 45.0, 43.0, 45.0, 55.0, 53.0, 69.0, 49.0, 56.0, 44.0, 58.0,
```

Entrée [46]:

```
# Bootstrapped distribution
sns.histplot(x=bootstrap_means, bins=25)
plt.title('Bootstrapped distribution of Easter eggs weights')
plt.show()
```



Entrée [47]:

```
# Confidence interval based on bootstrapped distribution of means
centiles = np.percentile(bootstrap_means, [2.5, 97.5])
print(centiles)
bootstrapped_ci = (round(centiles[0], 2), round(centiles[1], 2))
bootstrapped_ci
```

```
[35. 67.]
```

Out[47]:

```
(35.0, 67.0)
```

Usine de chaussures

Imaginons que l'on possède une usine qui produit des chaussures. On veut être capable de caractériser la taille moyenne des chaussures et être sûr qu'elles répondre à certaines spécificités. Notre usine produit des centaines de chaussures tous les jours, et il est impossible de mesurer la taille de toutes les chaussures. On a accès à un échantillon de 100 chaussures. On va bootstrapper ces 100 tailles de chaussures pour obtenir un intervalle de confiance de 95% de la taille moyenne de nos chaussures.

Commencons par examiner la liste `shoe_lengths` qui référence les 100 tailles de chaussures observées.

Entrée [48]:

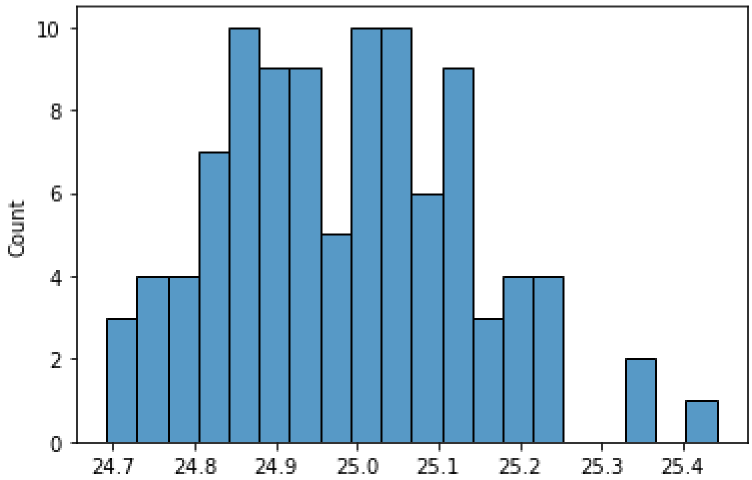
```
#ici on créé une liste qui initialise 100 tailles de chaussures
#un peu au hasard pour notre exemple
shoe_lengths = np.random.normal(25, 0.15, 100)
shoe_lengths
```

Out[48]:

```
array([24.84710574, 24.81337349, 25.16510234, 24.78816146, 24.89269172,
       25.14646148, 24.69817331, 25.0688573 , 24.87036012, 24.8206271 ,
       25.12225557, 24.88041133, 24.83233129, 25.02862316, 25.03991346,
       24.74640764, 24.91035103, 24.99696955, 25.13087622, 24.85832823,
       24.84184332, 24.95568332, 24.91720475, 25.2490908 , 25.12309325,
       24.98535221, 25.25205295, 24.83714877, 24.96163615, 25.15073402,
       25.01967335, 25.03276916, 24.90478953, 25.02919862, 24.69211873,
       25.01603889, 24.86908972, 24.9029353 , 25.08801187, 25.0356099 ,
       25.03698985, 24.98906587, 24.86250818, 24.946283  , 24.99187859,
       25.03180945, 24.80529368, 24.72992907, 25.24235237, 25.20554661,
       24.93336373, 25.18490071, 24.94560833, 25.01928667, 25.07069833,
       25.33308162, 24.90424012, 24.86710779, 25.02733187, 25.1980969 ,
       24.8640097 , 24.78944577, 25.13954789, 25.0244407 , 25.07721381,
       25.11920115, 25.05847149, 25.22708983, 25.10425119, 25.35889569,
       24.80903479, 24.72165025, 24.88283821, 25.441276  , 25.03094181,
       25.04998516, 24.8642059 , 24.94355911, 24.76474193, 24.9227773 ,
       24.89369866, 25.19809848, 24.9547957 , 24.93736336, 24.86833965,
       24.78994401, 25.11946894, 24.76183844, 25.1413125 , 25.0754761 ,
       24.95130925, 24.90470812, 25.06146286, 25.09346987, 24.92597898,
       24.78020902, 24.84849783, 25.04738226, 25.00031402, 25.13533665])
```

Entrée [49]:

```
sns.histplot(shoe_lengths, bins=20);
```



- Intervalle de confiance théorique

Entrée [50]:

```
mu = np.mean(shoe_lengths)
sigma = np.std(shoe_lengths)
z = sigma / np.sqrt(len(shoe_lengths))
print('Mean:', mu, '\nStdev:', sigma, '\nStandard error:', z)

confidence_interval = (mu - 1.96*z, mu + 1.96*z)
confidence_interval
```

```
Mean: 24.985294112603125
Stdev: 0.1525333281121378
Standard error: 0.01525333281121378
```

Out[50]:

```
(24.955397580293145, 25.015190644913105)
```

- Intervalle de confiance bootstrappée

Encore une fois, le bootstrapping consiste à tirer pleins d'échantillons de taille `len(shoe_lengths)` (100 içi) de manière aléatoire avec remplacement (par exemple >1000), et en suite calculer la taille moyenne de chaque échantillon.

Entrée [51]:

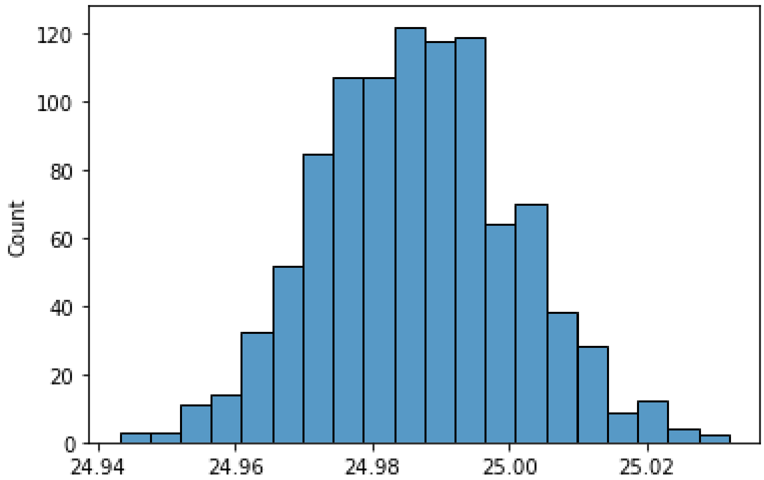
```
bootstrap_means = []
for i in range(1000):
    temp_sample = np.random.choice(shoe_lengths, replace=True, size=len(shoe_lengths))
    temp_mean = np.mean(temp_sample)
    bootstrap_means.append(temp_mean)

bootstrap_means
```

Out[51]:

```
[24.979398080530753,
 24.992349416689052,
 24.979779269393166,
 25.006784966674385,
 24.975675422504988,
 24.984938288410152,
 24.996428188147185,
 24.99585847104416,
 24.974893365001744,
 24.993066042769144,
 25.014183504274506,
 24.998337692400376,
 24.95362142128748,
 24.988951991038967,
 24.990926394672236,
 24.9933403460701,
 25.012041640999687,
 25.00308220185215,
```

Entrée [52]:

```
sns.histplot(bootstrap_means, bins=20);
```



Enfin, on calcul un intervalle de confiance de 95% bootstrappé (`boot_95_ci`) en utilisant `np.percentile()` .

Entrée [53]:

```
# Ici on en déduit que si on prend n'importe quel échantillon il y a 95%
# de chance que notre taille moyenne se trouve dans l'intervalle de confiance
# par extension, la population totale est un échantillon, donc la vraie taille
#moyenne a 95% de chance de se trouver dans cette intervalle
boot_95_ci = np.percentile(bootstrap_means, [2.5, 97.5])
print("95% Bootstrapped CI = {}".format(boot_95_ci))
```

```
95% Bootstrapped CI = [24.95966672 25.01457473]
```