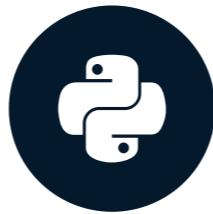


# Simple random and systematic sampling

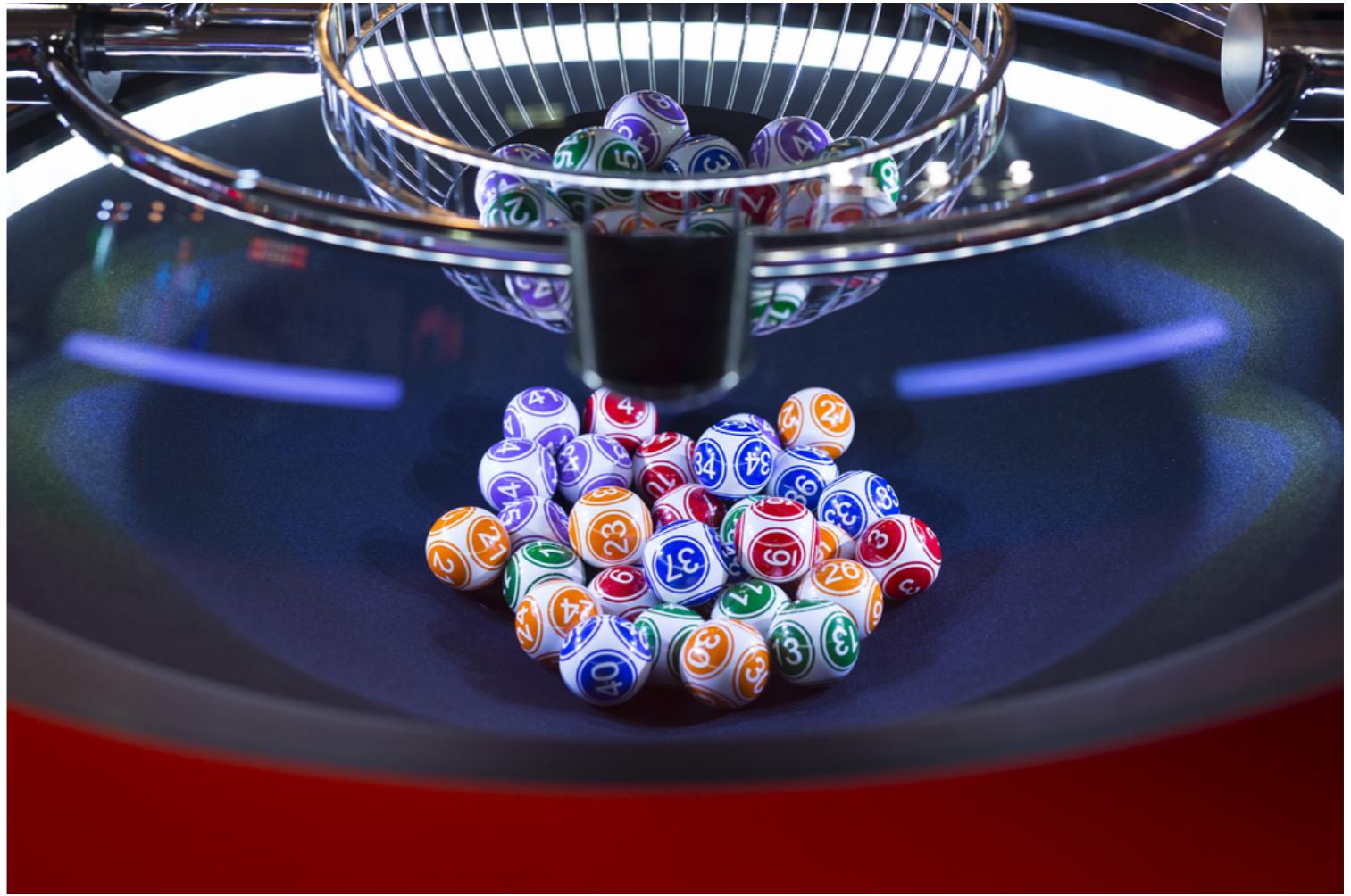
SAMPLING IN PYTHON



**James Chapman**

Curriculum Manager, DataCamp

# Simple random sampling



# Simple random sampling of coffees



# Simple random sampling with pandas

```
coffee_ratings.sample(n=5, random_state=19000113)
```

|     | total_cup_points | variety        | country_of_origin | aroma | flavor | \ |
|-----|------------------|----------------|-------------------|-------|--------|---|
| 437 | 83.25            | None           | Colombia          | 7.92  | 7.75   |   |
| 285 | 83.83            | Yellow Bourbon | Brazil            | 7.92  | 7.50   |   |
| 784 | 82.08            | None           | Colombia          | 7.50  | 7.42   |   |
| 648 | 82.58            | Caturra        | Colombia          | 7.58  | 7.50   |   |
| 155 | 84.58            | Caturra        | Colombia          | 7.42  | 7.67   |   |

|     | aftertaste | body | balance |  |  |  |
|-----|------------|------|---------|--|--|--|
| 437 | 7.25       | 7.83 | 7.58    |  |  |  |
| 285 | 7.33       | 8.17 | 7.50    |  |  |  |
| 784 | 7.42       | 7.67 | 7.42    |  |  |  |
| 648 | 7.42       | 7.67 | 7.42    |  |  |  |
| 155 | 7.75       | 8.08 | 7.83    |  |  |  |

# Systematic sampling



# Systematic sampling - defining the interval

```
sample_size = 5  
pop_size = len(coffee_ratings)  
print(pop_size)
```

1338

```
interval = pop_size // sample_size  
print(interval)
```

267

# Systematic sampling - selecting the rows

```
coffee_ratings.iloc[::interval]
```

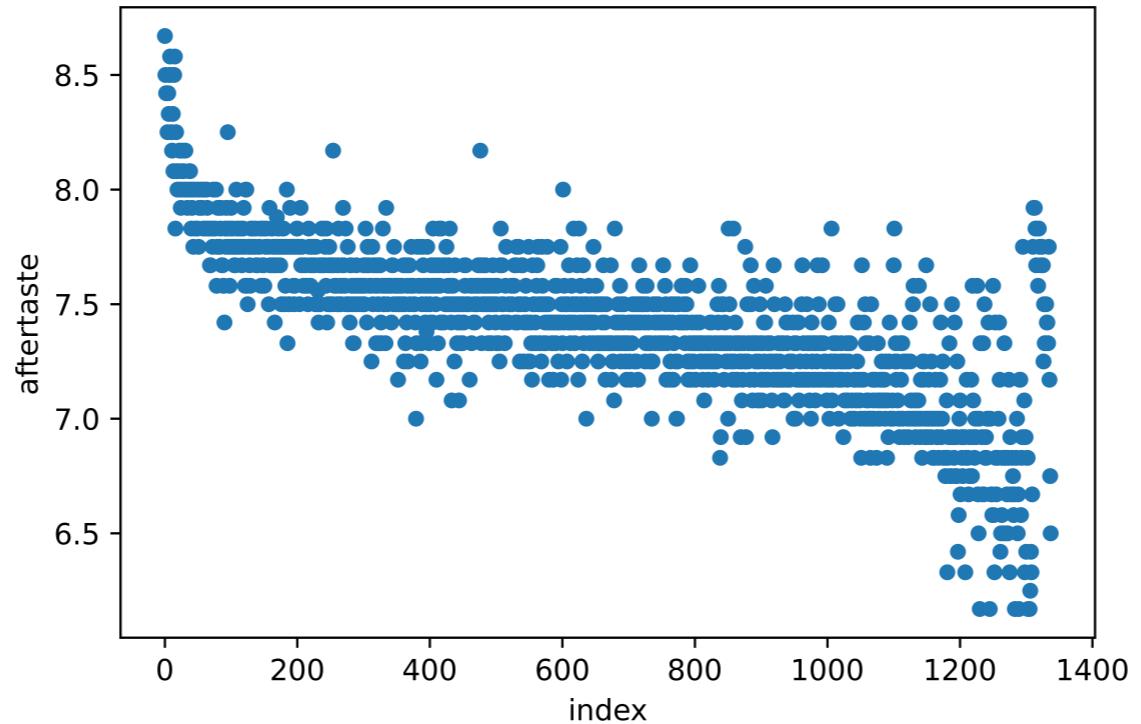
|      | total_cup_points | variety | country_of_origin | aroma | flavor | aftertaste | \ |
|------|------------------|---------|-------------------|-------|--------|------------|---|
| 0    | 90.58            | None    | Ethiopia          | 8.67  | 8.83   | 8.67       |   |
| 267  | 83.92            | None    | Colombia          | 7.83  | 7.75   | 7.58       |   |
| 534  | 82.92            | Bourbon | El Salvador       | 7.50  | 7.50   | 7.75       |   |
| 801  | 82.00            | Typica  | Taiwan            | 7.33  | 7.50   | 7.17       |   |
| 1068 | 80.50            | Other   | Taiwan            | 7.17  | 7.17   | 7.17       |   |

|      | body | balance |
|------|------|---------|
| 0    | 8.50 | 8.42    |
| 267  | 7.75 | 7.75    |
| 534  | 7.92 | 7.83    |
| 801  | 7.50 | 7.33    |
| 1068 | 7.17 | 7.25    |

# The trouble with systematic sampling

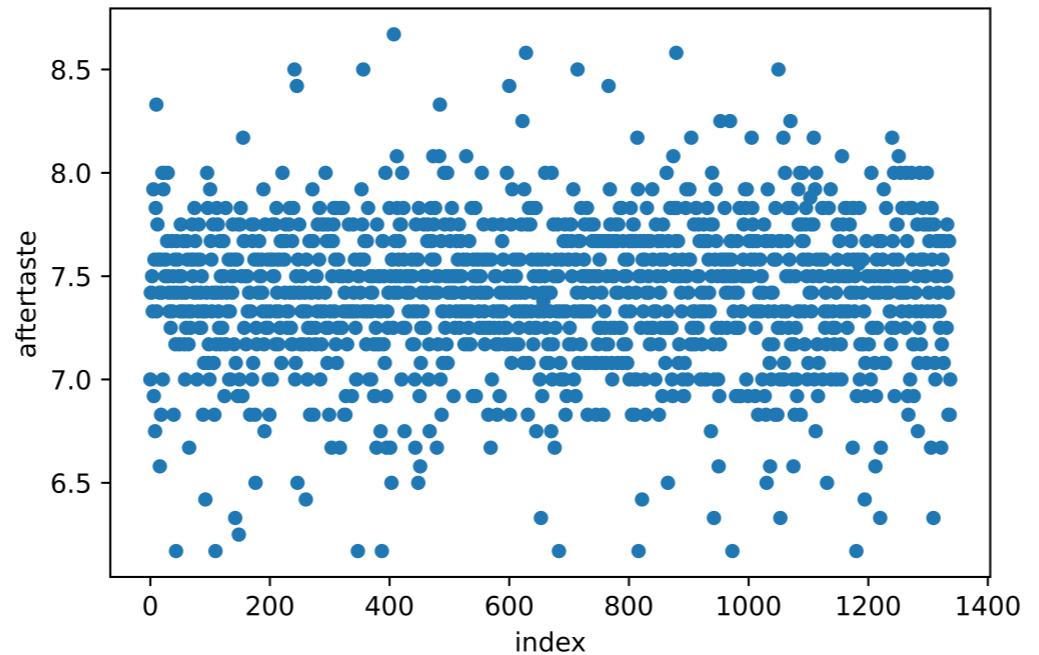
```
coffee_ratings_with_id = coffee_ratings.reset_index()  
coffee_ratings_with_id.plot(x="index", y="aftertaste", kind="scatter")  
plt.show()
```



Systematic sampling is only safe if we don't see a pattern in this scatter plot

# Making systematic sampling safe

```
shuffled = coffee_ratings.sample(frac=1)  
shuffled = shuffled.reset_index(drop=True).reset_index()  
shuffled.plot(x="index", y="aftertaste", kind="scatter")  
plt.show()
```



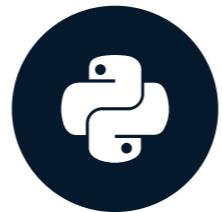
Shuffling rows + systematic sampling is the same as simple random sampling

# **Let's practice!**

**SAMPLING IN PYTHON**

# Stratified and weighted random sampling

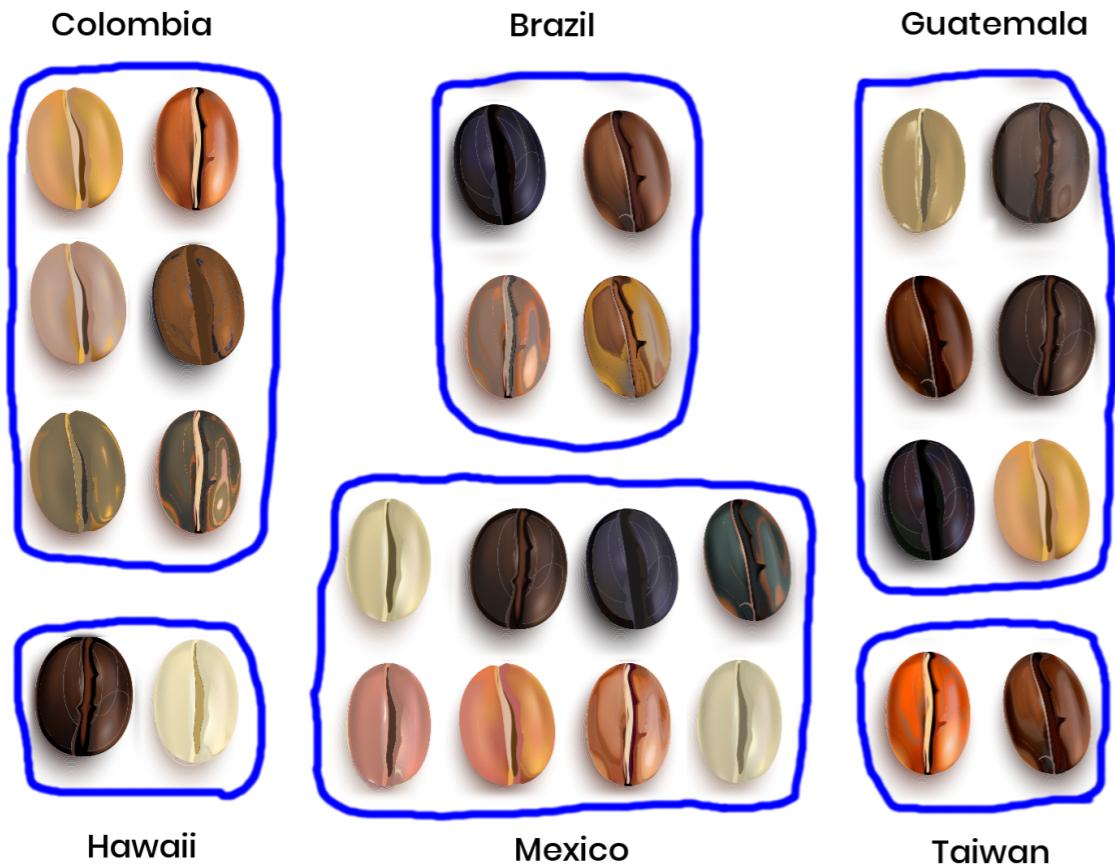
SAMPLING IN PYTHON



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# Coffees by country



```
top_counts = coffee_ratings['country_of_origin'].value_counts()  
top_counts.head(6)
```

| country_of_origin      |              |
|------------------------|--------------|
| Mexico                 | 236          |
| Colombia               | 183          |
| Guatemala              | 181          |
| Brazil                 | 132          |
| Taiwan                 | 75           |
| United States (Hawaii) | 73           |
|                        | dtype: int64 |

<sup>1</sup> The dataset lists Hawaii and Taiwan as countries for convenience, as they are notable coffee-growing regions.

# Filtering for 6 countries

```
top_counted_countries = ["Mexico", "Colombia", "Guatemala",
    "Brazil", "Taiwan", "United States (Hawaii)"]

top_counted_subset = coffee_ratings['country_of_origin'].isin(top_counted_countries)

coffee_ratings_top = coffee_ratings[top_counted_subset]
```

# Counts of a simple random sample

```
coffee_ratings_samp = coffee_ratings_top.sample(frac=0.1, random_state=2021)
```

```
coffee_ratings_samp['country_of_origin'].value_counts(normalize=True)
```

```
country_of_origin
Mexico          0.250000
Guatemala      0.204545
Colombia        0.181818
Brazil          0.181818
United States (Hawaii) 0.102273
Taiwan          0.079545
dtype: float64
```

# Comparing proportions

Population:

```
Mexico          0.268182  
Colombia       0.207955  
Guatemala      0.205682  
Brazil          0.150000  
Taiwan          0.085227  
United States (Hawaii) 0.082955  
Name: country_of_origin, dtype: float64
```

10% simple random sample:

```
Mexico          0.250000  
Guatemala      0.204545  
Colombia        0.181818  
Brazil          0.181818  
United States (Hawaii) 0.102273  
Taiwan          0.079545  
Name: country_of_origin, dtype: float64
```

# Proportional stratified sampling

```
coffee_ratings_strat = coffee_ratings_top.groupby("country_of_origin")\\  
.sample(frac=0.1, random_state=2021)
```

```
coffee_ratings_strat['country_of_origin'].value_counts(normalize=True)
```

```
Mexico          0.272727  
Guatemala      0.204545  
Colombia        0.204545  
Brazil          0.147727  
Taiwan          0.090909  
United States (Hawaii) 0.079545  
Name: country_of_origin, dtype: float64
```

# Equal counts stratified sampling

```
coffee_ratings_eq = coffee_ratings_top.groupby("country_of_origin")\\  
    .sample(n=15, random_state=2021)
```

```
coffee_ratings_eq['country_of_origin'].value_counts(normalize=True)
```

```
Taiwan          0.166667  
Brazil         0.166667  
United States (Hawaii) 0.166667  
Guatemala     0.166667  
Mexico         0.166667  
Colombia       0.166667  
Name: country_of_origin, dtype: float64
```

# Weighted random sampling

- Specify weights to adjust the relative probability of a row being sampled

```
import numpy as np  
coffee_ratings_weight = coffee_ratings_top  
condition = coffee_ratings_weight['country_of_origin'] == "Taiwan"
```

```
coffee_ratings_weight['weight'] = np.where(condition, 2, 1)
```

```
coffee_ratings_weight = coffee_ratings_weight.sample(frac=0.1, weights="weight")
```

# Weighted random sampling results

10% weighted sample:

```
coffee_ratings_weight['country_of_origin'].value_counts(normalize=True)
```

```
Brazil          0.261364
Mexico          0.204545
Guatemala      0.204545
Taiwan          0.170455
Colombia        0.090909
United States (Hawaii) 0.068182
Name: country_of_origin, dtype: float64
```

# **Let's practice!**

**SAMPLING IN PYTHON**

# Cluster sampling

SAMPLING IN PYTHON



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# Stratified sampling vs. cluster sampling

## Stratified sampling

- Split the population into subgroups
- Use simple random sampling on every subgroup

## Cluster sampling

- Use simple random sampling to pick some subgroups
- Use simple random sampling on only those subgroups

# Varieties of coffee



```
varieties_pop = list(coffee_ratings['variety'].unique())
```

```
[None, 'Other', 'Bourbon', 'Catimor',  
'Ethiopian Yirgacheffe', 'Caturra',  
'SL14', 'Sumatra', 'SL34', 'Hawaiian Kona',  
'Yellow Bourbon', 'SL28', 'Gesha', 'Catuai',  
'Pacamara', 'Typica', 'Sumatra Lintong',  
'Mundo Novo', 'Java', 'Peaberry', 'Pacas',  
'Mandheling', 'Ruiru 11', 'Arusha',  
'Ethiopian Heirlooms', 'Moka Peaberry',  
'Sulawesi', 'Blue Mountain', 'Marigojipe',  
'Pache Comun']
```

# Stage 1: sampling for subgroups



```
import random  
varieties_samp = random.sample(varieties_pop, k=3)
```

```
['Hawaiian Kona', 'Bourbon', 'SL28']
```

# Stage 2: sampling each group

```
variety_condition = coffee_ratings['variety'].isin(varieties_samp)  
coffee_ratings_cluster = coffee_ratings[variety_condition]
```

```
coffee_ratings_cluster['variety'] = coffee_ratings_cluster['variety'].cat.remove_unused_categories()
```

```
coffee_ratings_cluster.groupby("variety")\\  
.sample(n=5, random_state=2021)
```

# Stage 2 output

|               | total_cup_points | variety | country_of_origin | ...                    |
|---------------|------------------|---------|-------------------|------------------------|
| variety       |                  |         |                   |                        |
| Bourbon       | 575              | 82.83   | Bourbon           | Guatemala              |
|               | 560              | 82.83   | Bourbon           | Guatemala              |
|               | 524              | 83.00   | Bourbon           | Guatemala              |
|               | 1140             | 79.83   | Bourbon           | Guatemala              |
|               | 318              | 83.67   | Bourbon           | Brazil                 |
| Hawaiian Kona | 1291             | 73.67   | Hawaiian Kona     | United States (Hawaii) |
|               | 1266             | 76.25   | Hawaiian Kona     | United States (Hawaii) |
|               | 488              | 83.08   | Hawaiian Kona     | United States (Hawaii) |
|               | 461              | 83.17   | Hawaiian Kona     | United States (Hawaii) |
|               | 117              | 84.83   | Hawaiian Kona     | United States (Hawaii) |
| SL28          | 137              | 84.67   | SL28              | Kenya                  |
|               | 452              | 83.17   | SL28              | Kenya                  |
|               | 224              | 84.17   | SL28              | Kenya                  |
|               | 66               | 85.50   | SL28              | Kenya                  |
|               | 559              | 82.83   | SL28              | Kenya                  |

# Multistage sampling

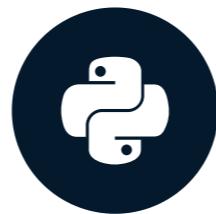
- Cluster sampling is a type of multistage sampling
- Can have > 2 stages
- E.g., countrywide surveys may sample states, counties, cities, and neighborhoods

# **Let's practice!**

**SAMPLING IN PYTHON**

# Comparing sampling methods

SAMPLING IN PYTHON



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Curriculum Manager, DataCamp

# Review of sampling techniques - setup

```
top_counted_countries = ["Mexico", "Colombia", "Guatemala",
    "Brazil", "Taiwan", "United States (Hawaii)"]

subset_condition = coffee_ratings['country_of_origin'].isin(top_counted_countries)
coffee_ratings_top = coffee_ratings[subset_condition]

coffee_ratings_top.shape
```

```
(880, 8)
```

# Review of simple random sampling

```
coffee_ratings_srs = coffee_ratings_top.sample(frac=1/3, random_state=2021)
```

```
coffee_ratings_srs.shape
```

```
(293, 8)
```

# Review of stratified sampling

```
coffee_ratings_strat = coffee_ratings_top.groupby("country_of_origin")\\  
    .sample(frac=1/3, random_state=2021)
```

```
coffee_ratings_strat.shape
```

```
(293, 8)
```

# Review of cluster sampling

```
import random

top_countries_samp = random.sample(top_counted_countries, k=2)
top_condition = coffee_ratings_top['country_of_origin'].isin(top_countries_samp)
coffee_ratings_cluster = coffee_ratings_top[top_condition]
coffee_ratings_cluster['country_of_origin'] = coffee_ratings_cluster['country_of_origin']\
    .cat.remove_unused_categories()

coffee_ratings_clust = coffee_ratings_cluster.groupby("country_of_origin")\
    .sample(n=len(coffee_ratings_top) // 6)
```

```
coffee_ratings_clust.shape
```

```
(292, 8)
```

# Calculating mean cup points

## Population

```
coffee_ratings_top['total_cup_points'].mean()
```

```
81.94700000000002
```

## Simple random sample

```
coffee_ratings_srs['total_cup_points'].mean()
```

```
81.95982935153583
```

## Stratified sample

```
coffee_ratings_strat['total_cup_points'].mean()
```

```
81.92566552901025
```

## Cluster sample

```
coffee_ratings_clust['total_cup_points'].mean()
```

```
82.03246575342466
```

# Mean cup points by country: simple random

Population:

```
coffee_ratings_top.groupby("country_of_origin")\
    ['total_cup_points'].mean()
```

```
country_of_origin
Brazil           82.405909
Colombia         83.106557
Guatemala       81.846575
Mexico           80.890085
Taiwan           82.001333
United States (Hawaii) 81.820411
Name: total_cup_points, dtype: float64
```

Simple random sample:

```
coffee_ratings_srs.groupby("country_of_origin")\
    ['total_cup_points'].mean()
```

```
country_of_origin
Brazil           82.414878
Colombia         82.925536
Guatemala       82.045385
Mexico           81.100714
Taiwan           81.744333
United States (Hawaii) 82.008000
Name: total_cup_points, dtype: float64
```

# Mean cup points by country: stratified

Population:

```
coffee_ratings_top.groupby("country_of_origin")\
    ['total_cup_points'].mean()
```

```
country_of_origin
Brazil           82.405909
Colombia         83.106557
Guatemala       81.846575
Mexico           80.890085
Taiwan           82.001333
United States (Hawaii) 81.820411
Name: total_cup_points, dtype: float64
```

Stratified sample:

```
coffee_ratings_strat.groupby("country_of_origin")\
    ['total_cup_points'].mean()
```

```
country_of_origin
Brazil           82.499773
Colombia         83.288197
Guatemala       81.727667
Mexico           80.994684
Taiwan           81.846800
United States (Hawaii) 81.051667
Name: total_cup_points, dtype: float64
```

# Mean cup points by country: cluster

Population:

```
coffee_ratings_top.groupby("country_of_origin")\
    ['total_cup_points'].mean()
```

```
country_of_origin
Brazil           82.405909
Colombia         83.106557
Guatemala       81.846575
Mexico           80.890085
Taiwan           82.001333
United States (Hawaii) 81.820411
Name: total_cup_points, dtype: float64
```

Cluster sample:

```
coffee_ratings_clust.groupby("country_of_origin")\
    ['total_cup_points'].mean()
```

```
country_of_origin
Colombia        83.128904
Mexico          80.936027
Name: total_cup_points, dtype: float64
```

# **Let's practice!**

**SAMPLING IN PYTHON**