

# Addressing missing data

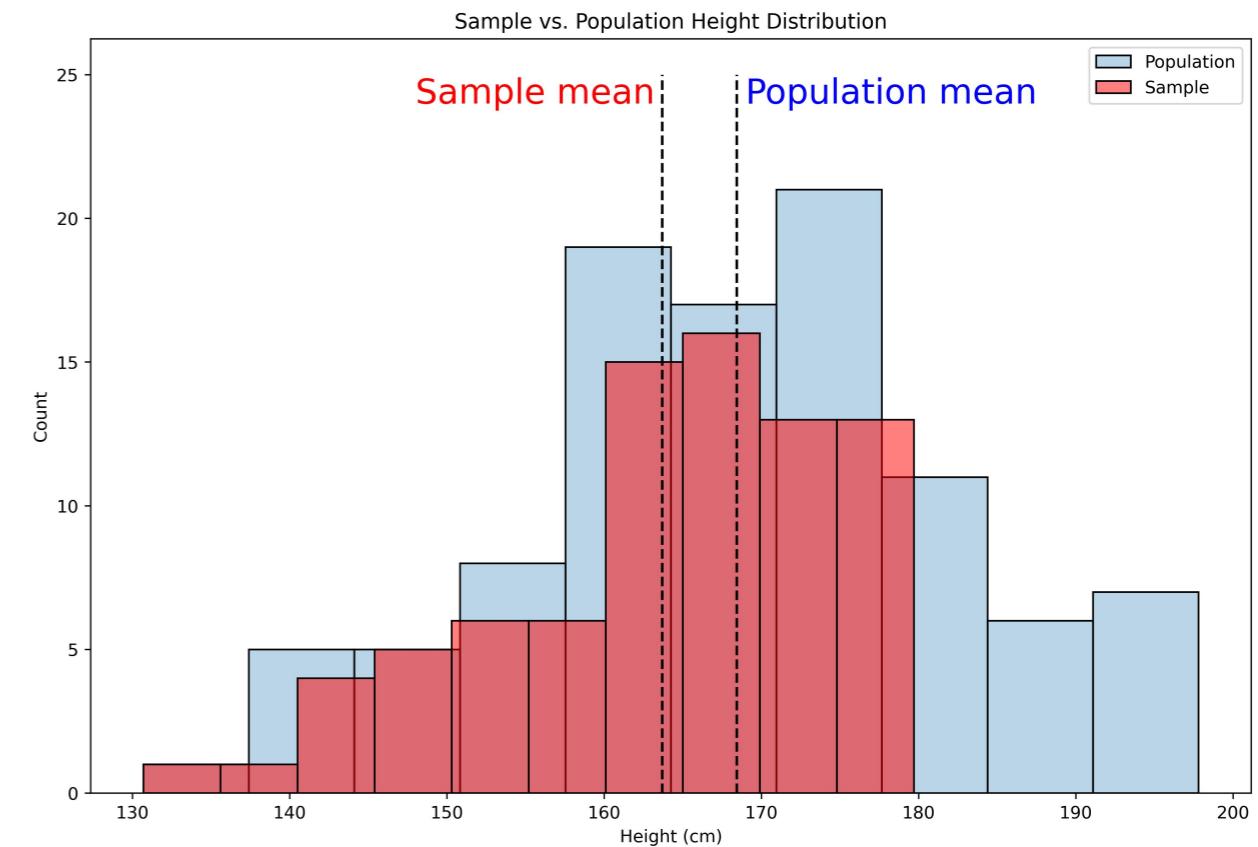
EXPLORATORY DATA ANALYSIS IN PYTHON



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# Why is missing data a problem?

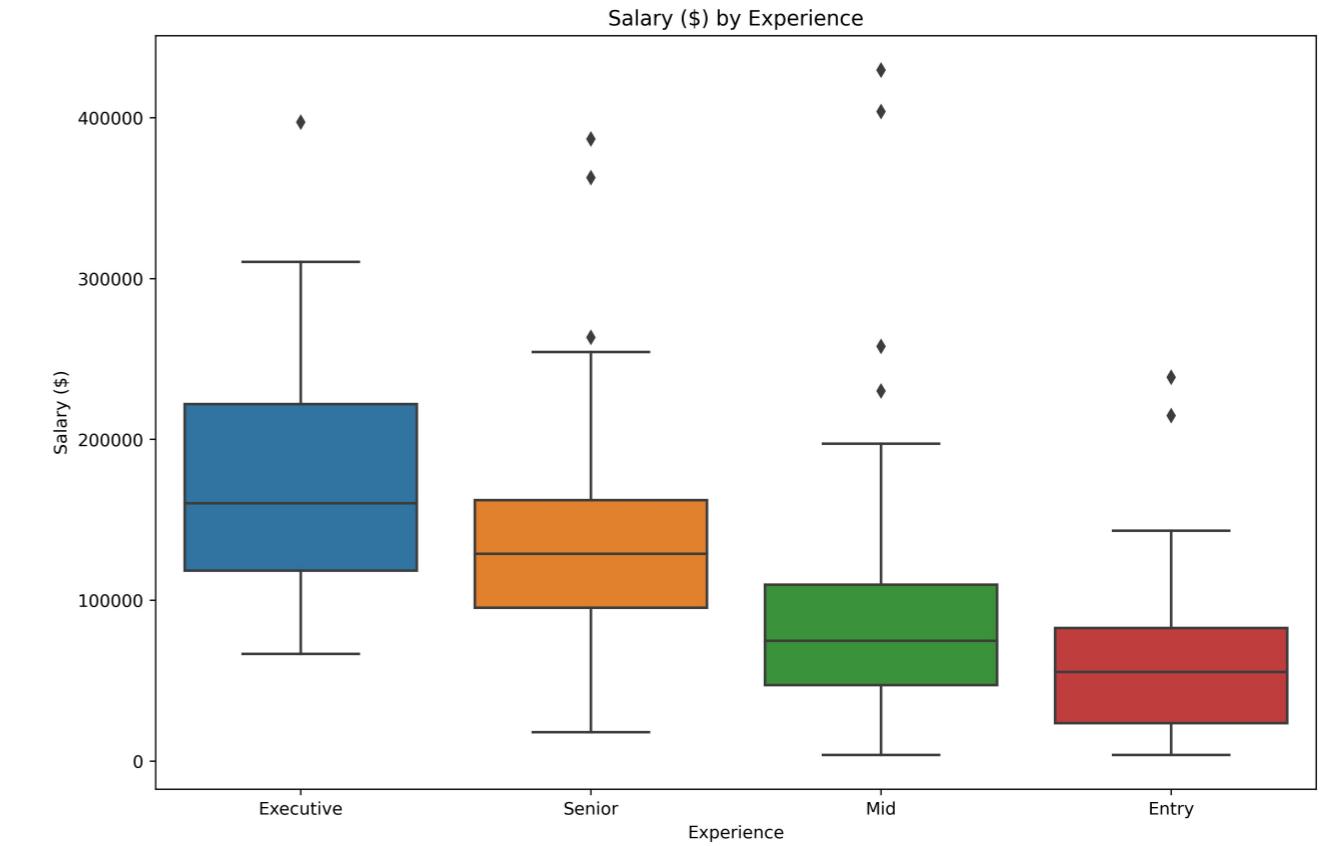
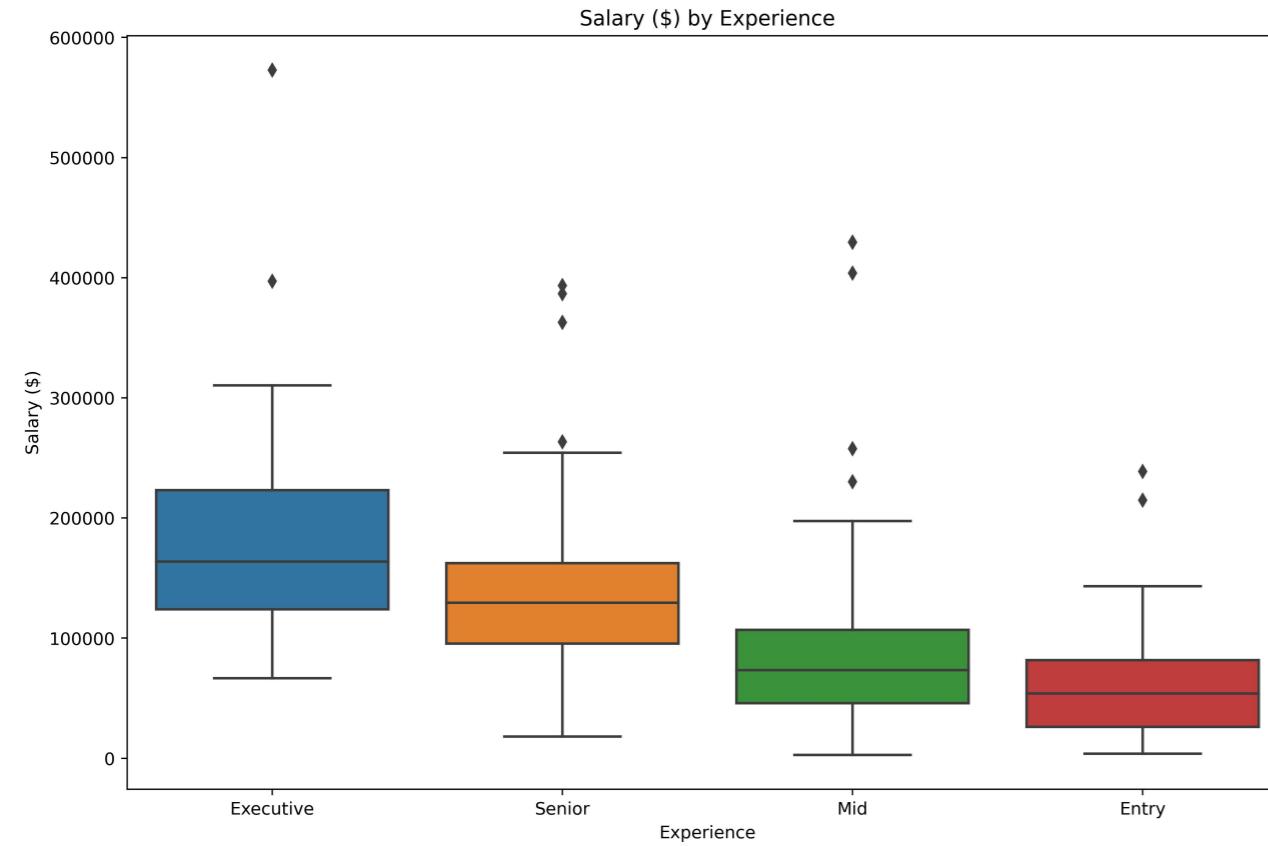
- Affects distributions
  - Missing heights of taller students
- Less representative of the population
  - Certain groups disproportionately represented, e.g., lacking data on oldest students
- Can result in drawing incorrect conclusions



# Data professionals' job data

Column	Description	Data type
Working_Year	Year the data was obtained	Float
Designation	Job title	String
Experience	Experience level e.g., "Mid" , "Senior"	String
Employment_Status	Type of employment contract e.g., "FT" , "PT"	String
Employee_Location	Country of employment	String
Company_Size	Labels for company size e.g., "S" , "M" , "L"	String
Remote_Working_Ratio	Percentage of time working remotely	Integer
Salary_USD	Salary in US dollars	Float

# Salary by experience level



# Checking for missing values

```
print(salaries.isna().sum())
```

```
Working_Year           12
Designation            27
Experience             33
Employment_Status      31
Employee_Location      28
Company_Size            40
Remote_Working_Ratio    24
Salary_USD              60
dtype: int64
```

# Strategies for addressing missing data

- Drop missing values
  - 5% or less of total values
- Impute mean, median, mode
  - Depends on distribution and context
- Impute by sub-group
  - Different experience levels have different median salary

# Dropping missing values

```
threshold = len(salaries) * 0.05  
print(threshold)
```

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# Dropping missing values

```
cols_to_drop = salaries.columns[salaries.isna().sum() <= threshold]
print(cols_to_drop)
```

```
Index(['Working_Year', 'Designation', 'Employee_Location',
       'Remote_Working_Ratio'],
      dtype='object')
```

```
salaries.dropna(subset=cols_to_drop, inplace=True)
```

# Imputing a summary statistic

```
cols_with_missing_values = salaries.columns[salaries.isna().sum() > 0]
print(cols_with_missing_values)
```

```
Index(['Experience', 'Employment_Status', 'Company_Size', 'Salary_USD'],
      dtype='object')
```

```
for col in cols_with_missing_values[:-1]:
    salaries[col].fillna(salaries[col].mode()[0])
```

# Checking the remaining missing values

```
print(salaries.isna().sum())
```

Working_Year	0
Designation	0
Experience	0
Employment_Status	0
Employee_Location	0
Company_Size	0
Remote_Working_Ratio	0
Salary_USD	41

# Imputing by sub-group

```
salaries_dict = salaries.groupby("Experience")["Salary_USD"].median().to_dict()  
print(salaries_dict)
```

```
{'Entry': 55380.0, 'Executive': 135439.0, 'Mid': 74173.5, 'Senior': 128903.0}
```

# Imputing by sub-group

```
salaries["Salary_USD"] = salaries["Salary_USD"].fillna(salaries["Experience"].map(salaries_dict))
```

# No more missing values!

```
print(salaries.isna().sum())
```

```
Working_Year          0  
Designation          0  
Experience           0  
Employment_Status    0  
Employee_Location    0  
Company_Size          0  
Remote_Working_Ratio  0  
Salary_USD            0  
dtype: int64
```

# **Let's practice!**

**EXPLORATORY DATA ANALYSIS IN PYTHON**

# Converting and analyzing categorical data

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# Previewing the data

```
print(salaries.select_dtypes("object").head())
```

	Designation	Experience	Employment_Status	Employee_Location	Company_Size
0	Data Scientist	Mid	FT	DE	L
1	Machine Learning Scientist	Senior	FT	JP	S
2	Big Data Engineer	Senior	FT	GB	M
3	Product Data Analyst	Mid	FT	HN	S
4	Machine Learning Engineer	Senior	FT	US	L

# Job titles

```
print(salaries["Designation"].value_counts())
```

Data Scientist	143
Data Engineer	132
Data Analyst	97
Machine Learning Engineer	41
Research Scientist	16
Data Science Manager	12
Data Architect	11
Big Data Engineer	8
Machine Learning Scientist	8
...	

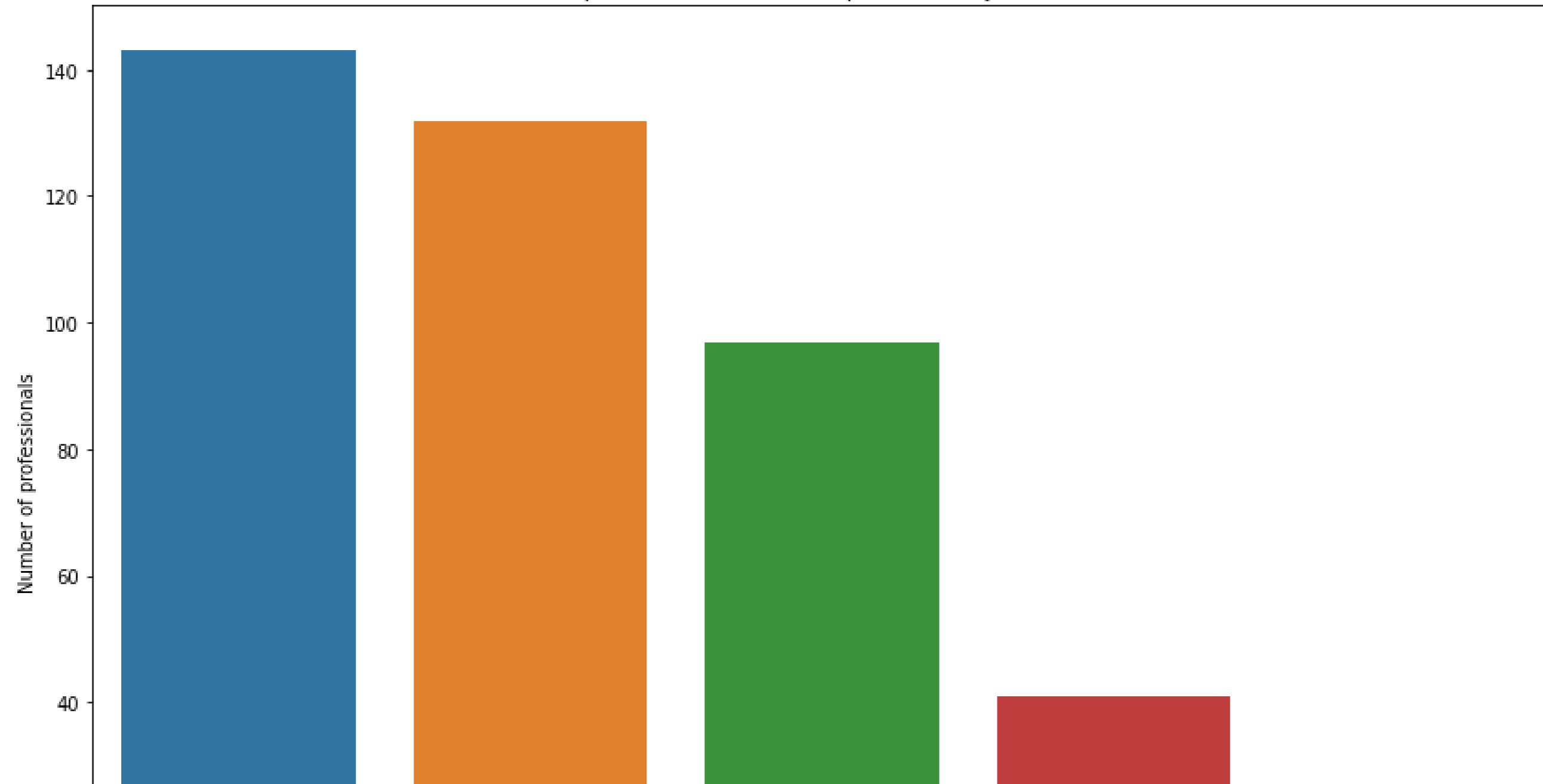
# Job titles

```
print(salaries["Designation"].nunique())
```

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# Job titles

Top 5 most common data professional job titles



# Extracting value from categories

- Current format limits our ability generate insights
- `pandas.Series.str.contains()`
  - Search a column for a specific string or multiple strings

```
salaries["Designation"].str.contains("Scientist")
```

```
0      True
1      True
2     False
3     False
...
604    False
605    False
606    True
Name: Designation, Length: 607, dtype: bool
```

# Finding multiple phrases in strings

- Words of interest: Machine Learning or AI

```
salaries["Designation"].str.contains("Machine Learning|AI")
```

```
0      False
1      True
2     False
3     False
...
604    False
605    False
606    True
Name: Designation, Length: 607, dtype: bool
```

# Finding multiple phrases in strings

- Words of interest: Any that start with Data

```
salaries["Designation"].str.contains("^Data")
```

```
0      True
1     False
2     False
3     False
...
604    True
605    True
606   False
Name: Designation, Length: 607, dtype: bool
```

# Finding multiple phrases in strings

```
job_categories = ["Data Science", "Data Analytics",  
                  "Data Engineering", "Machine Learning",  
                  "Managerial", "Consultant"]
```

# Finding multiple phrases in strings

```
data_science = "Data Scientist|NLP"  
data_analyst = "Analyst|Analytics"  
data_engineer = "Data Engineer|ETL|Architect|Infrastructure"  
ml_engineer = "Machine Learning|ML|Big Data|AI"  
manager = "Manager|Head|Director|Lead|Principal|Staff"  
consultant = "Consultant|Freelance"
```

# Finding multiple phrases in strings

```
conditions = [  
    (salaries["Designation"].str.contains(data_science)),  
    (salaries["Designation"].str.contains(data_analyst)),  
    (salaries["Designation"].str.contains(data_engineer)),  
    (salaries["Designation"].str.contains(ml_engineer)),  
    (salaries["Designation"].str.contains(manager)),  
    (salaries["Designation"].str.contains(consultant))  
]
```

# Creating the categorical column

```
salaries["Job_Category"] =
```

# Creating the categorical column

```
salaries["Job_Category"] = np.select(conditions,
```

# Creating the categorical column

```
salaries["Job_Category"] = np.select(conditions,  
                                      job_categories,
```

# Creating the categorical column

```
salaries["Job_Category"] = np.select(conditions,  
                                      job_categories,  
                                      default="Other")
```

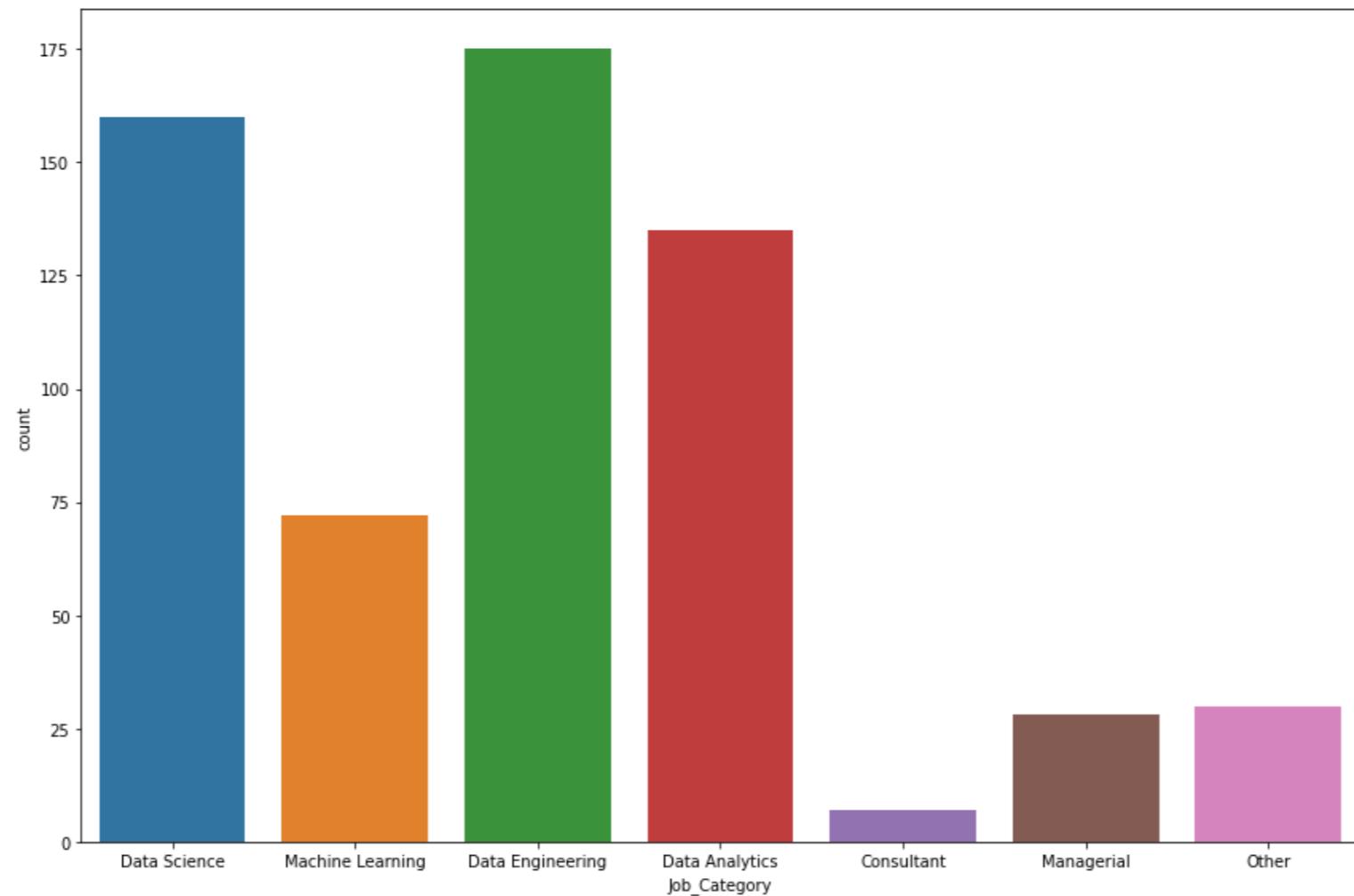
# Previewing job categories

```
print(salaries[["Designation", "Job_Category"]].head())
```

	Designation	Job_Category
0	Data Scientist	Data Science
1	Machine Learning Scientist	Machine Learning
2	Big Data Engineer	Data Engineering
3	Product Data Analyst	Data Analytics
4	Machine Learning Engineer	Machine Learning

# Visualizing job category frequency

```
sns.countplot(data=salaries, x="Job_Category")  
plt.show()
```

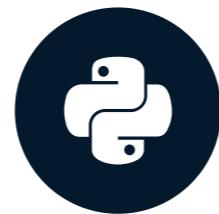


# **Let's practice!**

**EXPLORATORY DATA ANALYSIS IN PYTHON**

# Working with numeric data

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# The original salaries dataset

```
print(salaries.info())
```

# The original salaries dataset

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 594 entries, 0 to 593  
Data columns (total 9 columns):  
 #   Column           Non-Null Count  Dtype     
 --   --     
 0   Working_Year     594 non-null    int64    
 1   Designation      567 non-null    object    
 2   Experience       561 non-null    object    
 3   Employment_Status 563 non-null    object    
 4   Salary_In_Rupees 566 non-null    object    
 5   Employee_Location 554 non-null    object    
 6   Company_Location  570 non-null    object    
 7   Company_Size      535 non-null    object    
 8   Remote_Working_Ratio 571 non-null    float64  
dtypes: float64(1), int64(1), object(7)  
memory usage: 41.9+ KB  
None
```

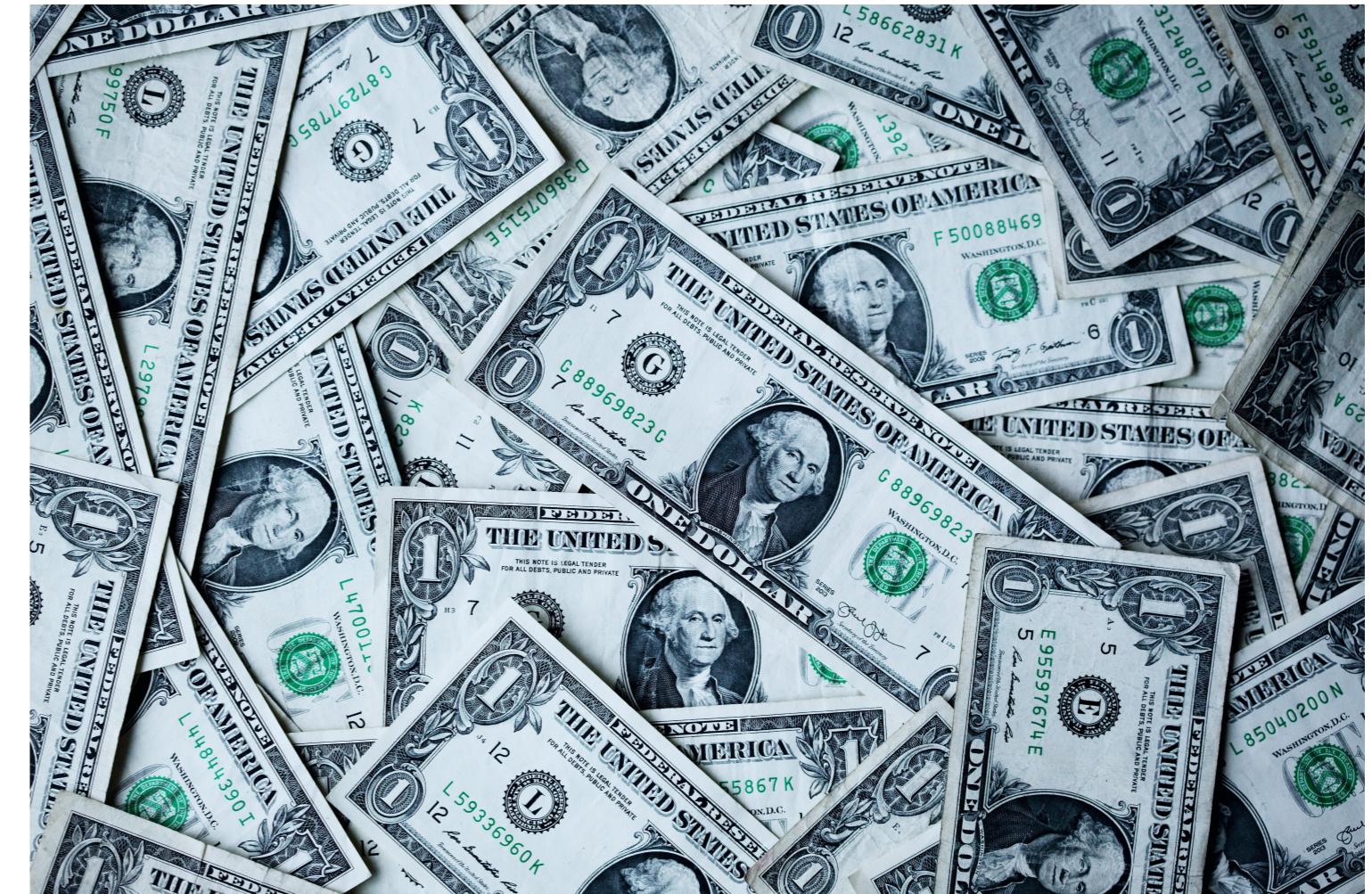
# Salary in rupees

```
print(salaries["Salary_In_Rupees"].head())
```

```
0    20,688,070.00  
1    8,674,985.00  
2    1,591,390.00  
3    11,935,425.00  
4    5,729,004.00  
  
Name: Salary_In_Rupees, dtype: object
```

# Converting strings to numbers

- Remove comma values in `Salary_In_Rupees`
- Convert the column to `float` data type
- Create a new column by converting the currency



# Converting strings to numbers

```
pd.Series.str.replace("characters to remove", "characters to replace them with")
```

```
salaries["Salary_In_Rupees"] = salaries["Salary_In_Rupees"].str.replace(",","")  
print(salary["Salary_In_Rupees"].head())
```

```
1    20688070.00  
2    8674985.00  
3    1591390.00  
4    11935425.00  
5    5729004.00  
  
Name: Salary_In_Rupees, dtype: object
```

# Converting strings to numbers

```
salaries["Salary_In_Rupees"] = salaries["Salary_In_Rupees"].astype(float)
```

- 1 Indian Rupee = 0.012 US Dollars

```
salaries["Salary_USD"] = salaries["Salary_In_Rupees"] * 0.012
```

# Previewing the new column

```
print(salaries[["Salary_In_Rupees", "Salary_USD"]].head())
```

	Salary_In_Rupees	Salary_USD
0	20688070.0	248256.840
1	8674985.0	104099.820
2	1591390.0	19096.680
3	11935425.0	143225.100
4	5729004.0	68748.048

# Adding summary statistics into a DataFrame

```
salaries.groupby("Company_Size")["Salary_USD"].mean()
```

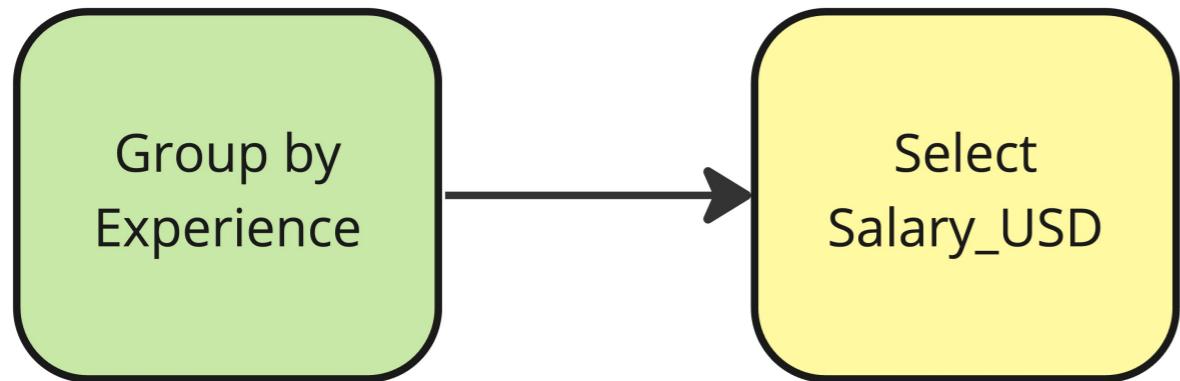
```
Company_Size
L    111934.432174
M    110706.628527
S     69880.980179
Name: Salary_USD, dtype: float64
```

# Adding summary statistics into a DataFrame

Group by  
Experience

```
salaries["std_dev"] = salaries.groupby("Experience")
```

# Adding summary statistics into a DataFrame



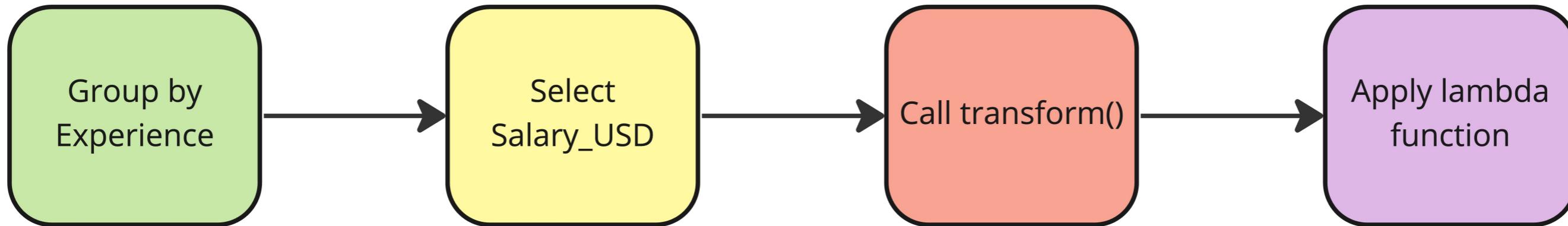
```
salaries["std_dev"] = salaries.groupby("Experience")["Salary_USD"]
```

# Adding summary statistics into a DataFrame



```
salaries["std_dev"] = salaries.groupby("Experience")["Salary_USD"].transform(
```

# Adding summary statistics into a DataFrame



```
salaries["std_dev"] = salaries.groupby("Experience")["Salary_USD"].transform(lambda x: x.std())
```

# Adding summary statistics into a DataFrame

```
print(salaries[["Experience", "std_dev"]].value_counts())
```

Experience	std_dev	
SE	52995.385395	257
MI	63217.397343	197
EN	43367.256303	83
EX	86426.611619	24

# Adding summary statistics into a DataFrame

```
salaries["median_by_comp_size"] = salaries.groupby("Company_Size") \  
    ["Salary_USD"].transform(lambda x: x.median())
```

```
print(salaries[["Company_Size", "median_by_comp_size"]].head())
```

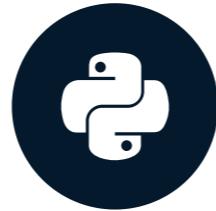
	Company_Size	median_by_comp_size
0	S	60833.424
1	M	105914.964
2	S	60833.424
3	L	95483.400
4	L	95483.400

# **Let's practice!**

**EXPLORATORY DATA ANALYSIS IN PYTHON**

# Handling outliers

EXPLORATORY DATA ANALYSIS IN PYTHON



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# What is an outlier?

- An observation far away from other data points
  - Median house price: \$400,000
  - Outlier house price: \$5,000,000
- Should consider why the value is different:
  - Location, number of bedrooms, overall size etc



<sup>1</sup> Image credit: <https://unsplash.com/@ralphkayden>

# Using descriptive statistics

```
print(salaries["Salary_USD"].describe())
```

```
count      518.000
mean     104905.826
std      62660.107
min      3819.000
25%     61191.000
50%     95483.000
75%    137496.000
max    429675.000
Name: Salary_USD, dtype: float64
```

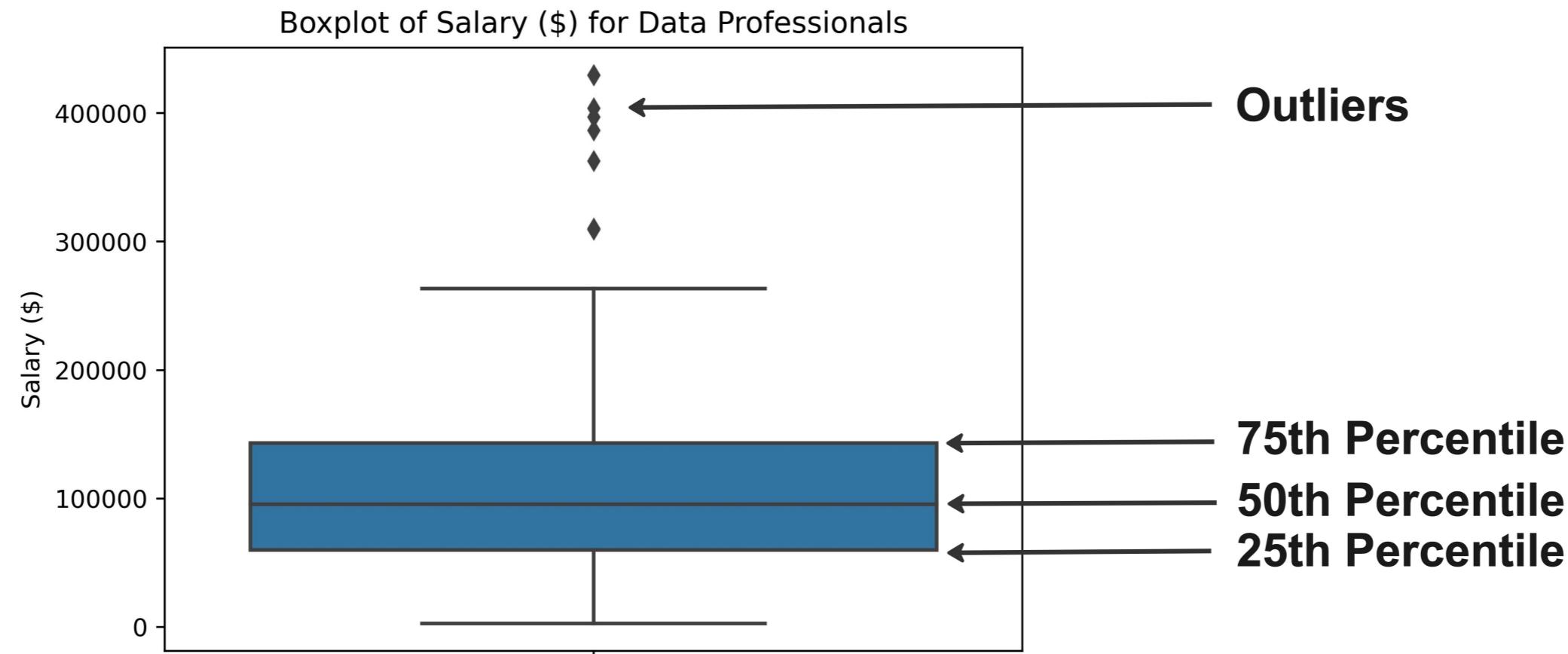
# Using the interquartile range

## Interquartile range (IQR)

- IQR = 75th - 25th percentile

# IQR in box plots

```
sns.boxplot(data=salaries,  
             y="Salary_USD")  
plt.show()
```



# Using the interquartile range

## Interquartile range (IQR)

- IQR = 75th - 25th percentile
- Upper Outliers > 75th percentile + (1.5 \* IQR)
- Lower Outliers < 25th percentile - (1.5 \* IQR)

# Identifying thresholds

```
# 75th percentile  
seventy_fifth = salaries["Salary_USD"].quantile(0.75)  
  
# 25th percentile  
twenty_fifth = salaries["Salary_USD"].quantile(0.25)  
  
# Interquartile range  
salaries_iqr = seventy_fifth - twenty_fifth  
  
print(salaries_iqr)
```

```
76305.0
```

# Identifying outliers

```
# Upper threshold  
upper = seventy_fifth + (1.5 * salaries_iqr)  
  
# Lower threshold  
lower = twenty_fifth - (1.5 * salaries_iqr)  
  
print(upper, lower)
```

```
251953.5 -53266.5
```

# Subsetting our data

```
salaries[(salaries["Salary_USD"] < lower) | (salaries["Salary_USD"] > upper)] \\\n    [["Experience", "Employee_Location", "Salary_USD"]]
```

	Experience	Employee_Location	Salary_USD
29	Mid	US	429675.0
67	Mid	US	257805.0
80	Senior	US	263534.0
83	Mid	US	429675.0
133	Mid	US	403895.0
410	Executive	US	309366.0
441	Senior	US	362837.0
445	Senior	US	386708.0
454	Senior	US	254368.0

# Why look for outliers?

- Outliers are extreme values
  - may not accurately represent our data
- Can change the mean and standard deviation
- Statistical tests and machine learning models need normally distributed data

# What to do about outliers?

## Questions to ask:

- Why do these outliers exist?
  - More senior roles / different countries pay more
  - Consider leaving them in the dataset
- Is the data accurate?
  - Could there have been an error in data collection?
    - If so, remove them

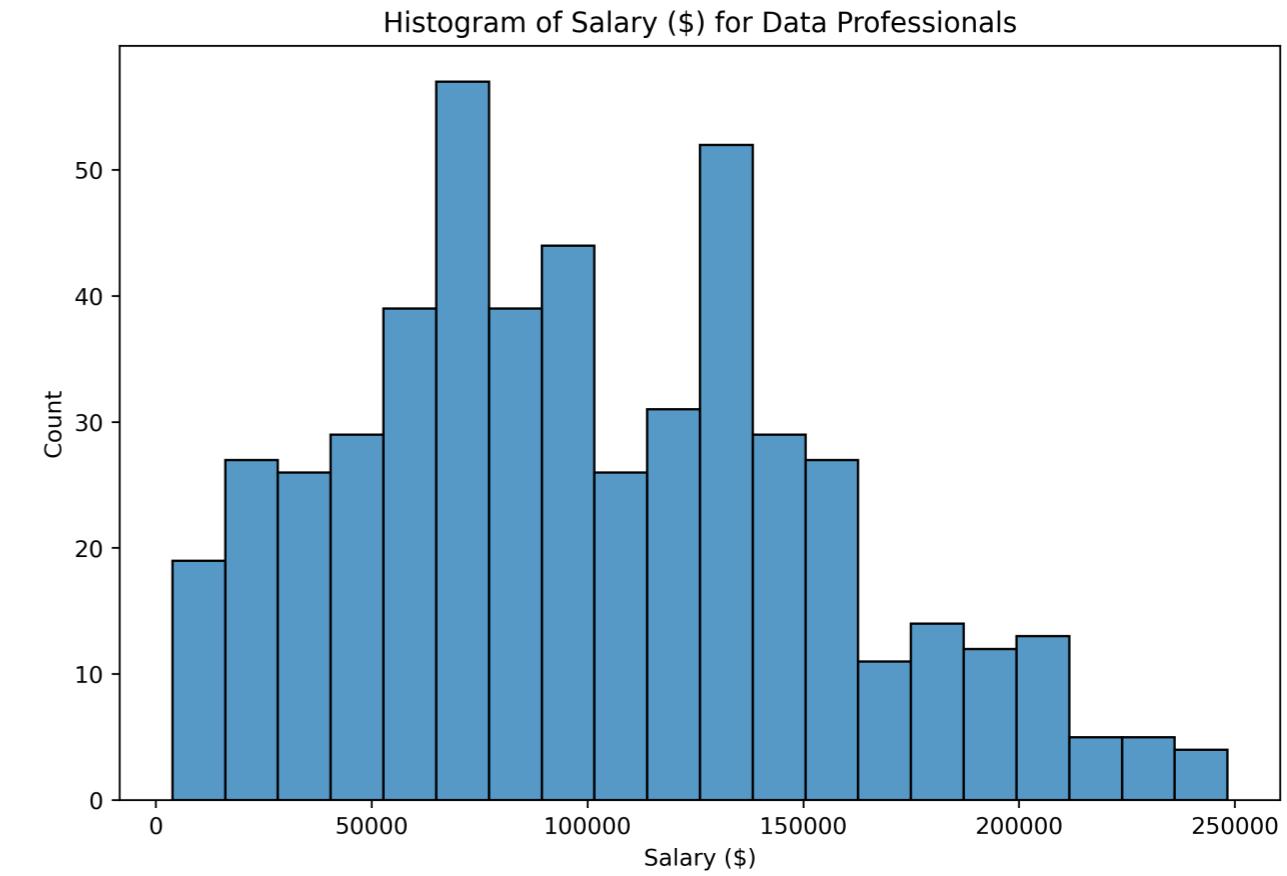
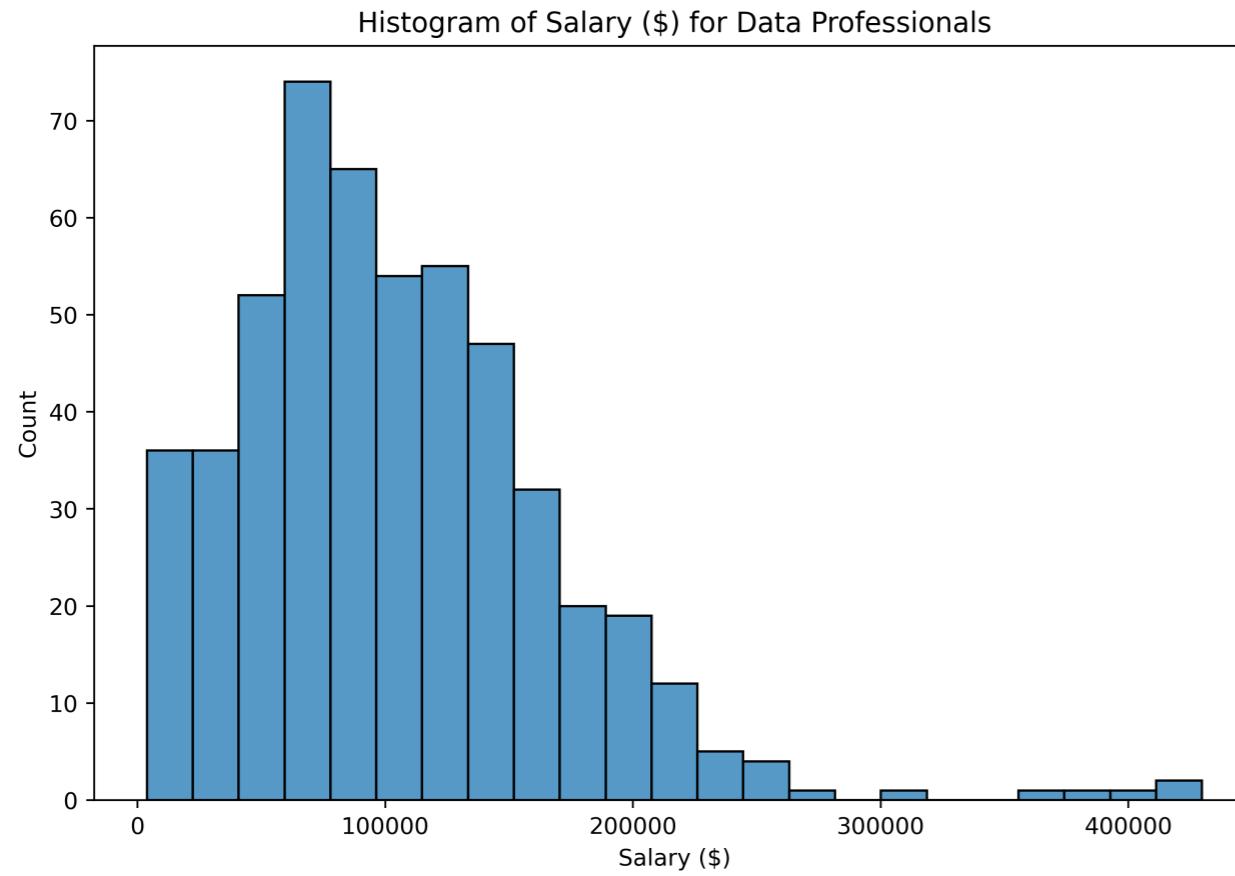
# Dropping outliers

```
no_outliers = salaries[salaries["Salary_USD"] > lower] & (salaries["Salary_USD"] < upper)
```

```
print(no_outliers["Salary_USD"].describe())
```

```
count      509.000000
mean     100674.567780
std      53643.050057
min      3819.000000
25%     60928.000000
50%     95483.000000
75%    134059.000000
max    248257.000000
Name: Salary_USD, dtype: float64
```

# Distribution of salaries



# **Let's practice!**

**EXPLORATORY DATA ANALYSIS IN PYTHON**