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Basic Statistical Data Representation

Link to repo: emma's github repo

```
# To load the libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

```
# To load the dataset
datos = pd.read_csv('https://raw.githubusercontent.com/emmasofiaar/arte_analitica/refs/heads/main/survey.csv')
datos.head()
```

	Timestamp	Age	Gender	Country	state	self_employed	family_history	treatment	work_interfere	no_employees	...	leav
0	2014-08-27 11:29:31	37	Female	United States	IL	NaN	No	Yes	Often	6-25	...	Somewha eas
1	2014-08-27 11:29:37	44	M	United States	IN	NaN	No	No	Rarely	More than 1000	...	Don knov
2	2014-08-27 11:29:44	32	Male	Canada	NaN	NaN	No	No	Rarely	6-25	...	Somewha difficul
3	2014-08-27 11:29:46	31	Male	United Kingdom	NaN	NaN	Yes	Yes	Often	26-100	...	Somewha difficul
4	2014-08-27 11:30:22	31	Male	United States	TX	NaN	No	No	Never	100-500	...	Don knov

5 rows × 27 columns

```
# Shape of the data
print("Shape:", datos.shape)

# Column names and types
print("Info:")
datos.info()

# Check for missing values
print("Missing values:")
print(datos.isnull().sum())
```

```
Shape: (1259, 27)
Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1259 entries, 0 to 1258
Data columns (total 27 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Timestamp                  1259 non-null   object
 1   Age                        1259 non-null   int64
 2   Gender                     1259 non-null   object
 3   Country                    1259 non-null   object
 4   state                      744 non-null    object
 5   self_employed              1241 non-null   object
 6   family_history             1259 non-null   object
 7   treatment                  1259 non-null   object
 8   work_interfere             995 non-null    object
 9   no_employees               1259 non-null   object
 10  remote_work                1259 non-null   object
 11  tech_company               1259 non-null   object
 12  benefits                   1259 non-null   object
 13  care_options               1259 non-null   object
 14  wellness_program           1259 non-null   object
 15  seek_help                  1259 non-null   object
 16  anonymity                  1259 non-null   object
 17  leave                      1259 non-null   object
 18  mental_health_consequence  1259 non-null   object
 19  phys_health_consequence    1259 non-null   object
 20  coworkers                  1259 non-null   object
```

```
 21  supervisor                 1259 non-null   object
 22  mental_health_interview    1259 non-null   object
 23  phys_health_interview      1259 non-null   object
 24  mental_vs_physical         1259 non-null   object
 25  obs_consequence            1259 non-null   object
 26  comments                   164 non-null    object
dtypes: int64(1), object(26)
memory usage: 265.7+ KB
Missing values:
Timestamp                      0
Age                            0
Gender                         0
Country                        0
state                        515
self_employed                 18
family_history                 0
treatment                      0
work_interfere               264
no_employees                   0
remote_work                    0
tech_company                   0
benefits                       0
care_options                   0
wellness_program               0
seek_help                      0
anonymity                      0
leave                          0
mental_health_consequence      0
phys_health_consequence        0
coworkers                      0
```

```
# Categóricas
categorical_cols = datos.select_dtypes(include=['object']).columns
print("Variables categóricas:", list(categorical_cols))

# Numéricas
numerical_cols = datos.select_dtypes(include=['int64', 'float64']).columns
print("Variables numéricas:", list(numerical_cols))
```

```
Variables categóricas: ['Timestamp', 'Gender', 'Country', 'state', 'self_employed', 'family_history', 'treatment', 'work_int
Variables numéricas: ['Age']
```

```
# Ver nombres de columnas (todas las variables del dataset)
print("Columnas del dataset:")
print(datos.columns)
```

```
Columnas del dataset:
Index(['Timestamp', 'Age', 'Gender', 'Country', 'state', 'self_employed',
       'family_history', 'treatment', 'work_interfere', 'no_employees',
       'remote_work', 'tech_company', 'benefits', 'care_options',
       'wellness_program', 'seek_help', 'anonymity', 'leave',
       'mental_health_consequence', 'phys_health_consequence', 'coworkers',
       'supervisor', 'mental_health_interview', 'phys_health_interview',
       'mental_vs_physical', 'obs_consequence', 'comments'],
      dtype='object')
```

```
# Mostrar info general
print("\n== Tipos de datos ==")
print(datos.dtypes)

print("\n== Variables y análisis ==")
for col in datos.columns:
    print(f"\nVariable: {col}")
    print(f"Tipo de dato: {datos[col].dtype}")

    if pd.api.types.is_numeric_dtype(datos[col]):
        print("Valores nulos:", datos[col].isnull().sum())
        print("Mínimo:", datos[col].min())
        print("Máximo:", datos[col].max())
        print("Promedio:", datos[col].mean())
    elif pd.api.types.is_datetime64_any_dtype(datos[col]):
        print("Rango de fechas:", datos[col].min(), "→", datos[col].max())
    else:
        print("Valores únicos:", datos[col].nunique())
        print("Categorías:", datos[col].unique()[:10])  # Solo muestra los primeros 10
```

```
Variable: mental_health_consequence
Tipo de dato: object
Valores únicos: 3
Categorías: ['No' 'Maybe' 'Yes']

Variable: phys_health_consequence
Tipo de dato: object
Valores únicos: 3
Categorías: ['No' 'Yes' 'Maybe']

Variable: coworkers
Tipo de dato: object
Valores únicos: 3
Categorías: ['Some of them' 'No' 'Yes']

Variable: supervisor
Tipo de dato: object
Valores únicos: 3
Categorías: ['Yes' 'No' 'Some of them']

Variable: mental_health_interview
Tipo de dato: object
Valores únicos: 3
Categorías: ['No' 'Yes' 'Maybe']

Variable: phys_health_interview
Tipo de dato: object
Valores únicos: 3
Categorías: ['Maybe' 'No' 'Yes']

Variable: mental_vs_physical
Tipo de dato: object
Valores únicos: 3
Categorías: ['Yes' "Don't know" 'No']

Variable: obs_consequence
Tipo de dato: object
Valores únicos: 2
Categorías: ['No' 'Yes']

Variable: comments
Tipo de dato: object
Valores únicos: 160
Categorías: [nan
 "I'm not on my company's health insurance which could be part of the reason I answered Don't know to so many questions."
 'I have chronic low-level neurological issues that have mental health side effects. One of my supervisors has also experien
 "My company does provide healthcare but not to me as I'm on a fixed-term contract. The mental healthcare I use is provided
 'Relatively new job. Ask again later'
 'Sometimes I think  about using drugs for my mental health issues. If i use drugs I feel better'
 'I selected my current employer based on its policies about self care and the quality of their overall health and wellness
 "Our health plan has covered my psychotherapy and my antidepressant medication. My manager has been aware but discreet thro
 "I just started a new job last week hence a lot of don't know's"
 "In addition to my own mental health issues I've known several coworkers that may be suffering and I don't know how to tell
```

```
# mean, median, and std deviation
# Filtrar edades fuera de un rango razonable (por ejemplo, menores de 10 o mayores de 100)
datos_clean = datos[(datos['Age'] >= 10) & (datos['Age'] <= 100)]

# Estadísticas descriptivas después de la limpieza
numerical_cols = datos_clean.select_dtypes(include=['int64', 'float64']).columns
print("== Análisis estadístico de variables numéricas (limpiadas) ==")
print(datos_clean[numerical_cols].describe().T[['mean', '50%', 'std']].rename(columns={"50%": "median"}))
```

```
== Análisis estadístico de variables numéricas (limpiadas) ==
          mean  median       std
Age  32.059904    31.0  7.309669
```

- El promedio (32 años) y la mediana (30 años) están relativamente cercanos.
- Esto indica que la distribución de la edad es ligeramente sesgada a la derecha (hay algunas edades mayores que elevan el promedio).
- La desviación estándar (7.3) sugiere una variabilidad moderada.

Mental Health in Tech Survey

This dataset contains results from a survey focused on mental health in the tech workplace. It includes anonymous responses from people working in tech-related jobs, addressing their mental health history, workplace environment, company support, and attitudes toward mental illness.

Boxplots for Age Distribution by Mental Health Treatment

We are examining the distribution of ages for people who have received mental health treatment versus those who have not.

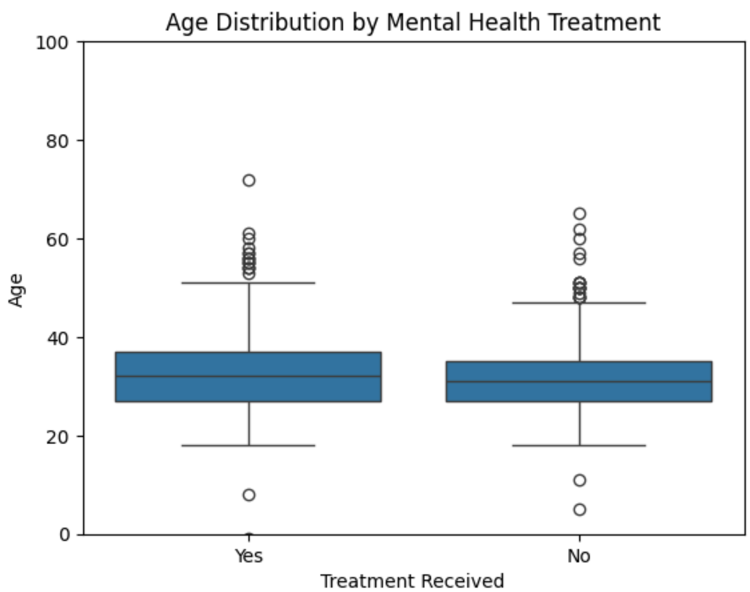
```
# Remove rows with NaN values in 'Age' or 'treatment'
cleaned_data = datos.dropna(subset=['Age', 'treatment'])

# To create the boxplot
plt.figure()
sns.boxplot(data=cleaned_data, x='treatment', y='Age')

# Set axis labels and title
plt.title('Age Distribution by Mental Health Treatment')
plt.xlabel('Treatment Received')
plt.ylabel('Age')

# Visualization
plt.ylim(0, 100)

plt.show()
```



The median age for those that have received treatment and those that haven't is quite similar, however, we can see that there's a greater spread of ages in the group of those that have received mental health treatment than i the one of those that haven't. Similarly, the whiskers of the box that represents those who have received mental health treatment are longer, meaning that there is a larger variation in age present in thsi group. Lastly, we can see that there are a lot of outliers present in both groups.

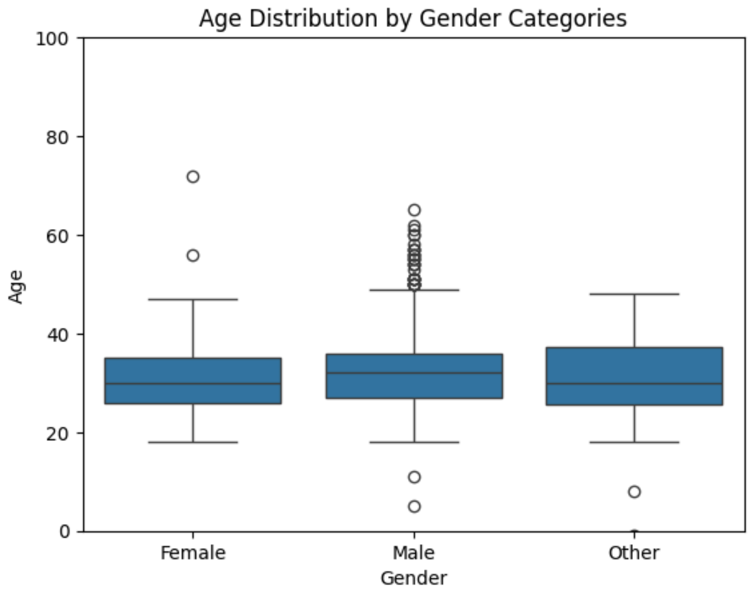
Boxplots for Age by Gender

We are comparing the age distribution between the different genders available in the dataset.

```
# Normalizing gender entries
def clean_gender(gender):
    gender = gender.strip().lower()
    if gender in ['Male', 'male', 'm', 'man', 'cis male', 'malr', 'mail', 'cis man']:
        return 'Male'
    elif gender in ['Female','female', 'f', 'woman', 'cis female', 'femake', 'cis-female/femme']:
        return 'Female'
    elif 'trans' in gender or 'non-binary' in gender or 'nb' in gender:
        return 'Other'
    else:
        return 'Other'
```

```
cleaned_data['gender_cleaned'] = cleaned_data['Gender'].apply(clean_gender)

# Boxplot
plt.figure()
sns.boxplot(data=cleaned_data, x='gender_cleaned', y='Age')
plt.title('Age Distribution by Gender Categories')
plt.xlabel('Gender')
plt.ylabel('Age')
plt.ylim(0, 100)
plt.show()
```



From this boxplot we can see that the majority of people polled belong to the same age group, regardless of gender. We had to clean the gender entries in the dataset since there were a lot of different answers that made our boxplot quite cluttered. The spread of the ages is wider in the "Other" category, although this is possibly due to fewer data points and the outliers are way more visible in the "Male" and "Female" columns.

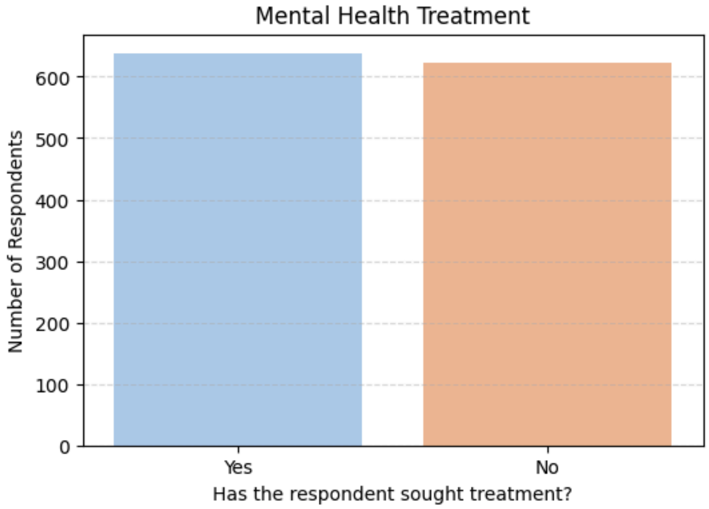
Histogram for Age Distribution

```
plt.figure(figsize=(6, 4))
sns.countplot(data=cleaned_data, x='treatment', hue='treatment', palette='pastel', legend=False)

plt.title('Mental Health Treatment')
plt.xlabel('Has the respondent sought treatment?')
plt.ylabel('Number of Respondents')



plt.grid(True, axis='y', linestyle='--', alpha=0.5)
plt.show()
```



As we can see from the histogram the respondents are equally split between those who have sought mental health treatment and those who haven't. This suggests that there is no strong skew in the tech industry in terms of seeking or not seeking mental health treatment.

Correlation

```
# Filtrar edades razonables y crear copia segura
datos_clean = datos[(datos['Age'] >= 10) & (datos['Age'] <= 100)].copy()

# Convertir columnas ordinales a numéricas (puedes agregar más si lo deseas)
if 'leave' in datos_clean.columns:
    datos_clean['leave_num'] = datos_clean['leave'].map({
        'Very easy': 1,
        'Somewhat easy': 2,
        'Neither easy nor difficult': 3,
        'Somewhat difficult': 4,
        'Very difficult': 5
    })

if 'care_options' in datos_clean.columns:
    datos_clean['care_options_num'] = datos_clean['care_options'].map({
        'Yes': 1, 'Not sure': 2, 'No': 3
    })

if 'benefits' in datos_clean.columns:
    datos_clean['benefits_num'] = datos_clean['benefits'].map({
        'Yes': 1, 'Don’t know': 2, 'No': 3
    })

# Seleccionar solo columnas numéricas
numerical_cols = datos_clean.select_dtypes(include=['int64', 'float64'])

# Calcular y mostrar matriz de correlación
correlation_matrix = numerical_cols.corr()

print("Matriz de correlación entre variables numéricas:")
print(correlation_matrix)
```

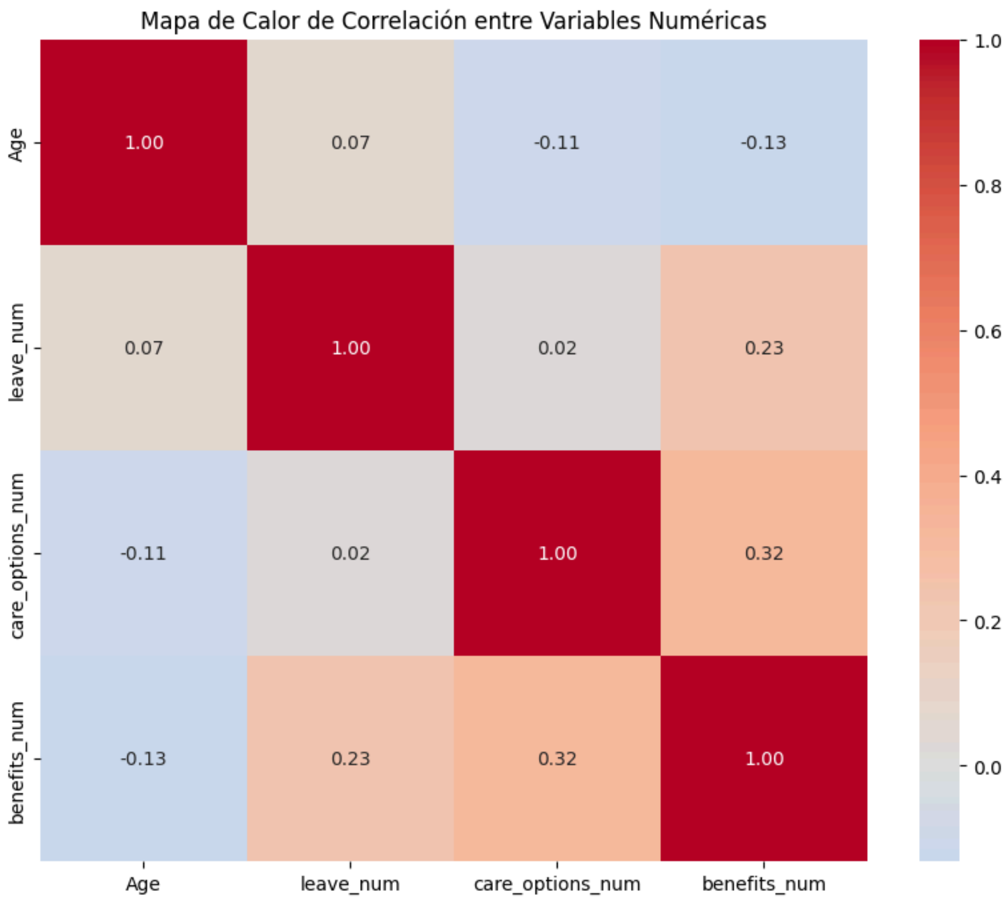
```
Matriz de correlación entre variables numéricas:
                       Age  leave_num  care_options_num  benefits_num
Age               1.000000   0.068077         -0.105241     -0.131962
leave_num         0.068077   1.000000          0.022879      0.229170
care_options_num -0.105241   0.022879          1.000000      0.316053
benefits_num     -0.131962   0.229170          0.316053      1.000000
```

```
plt.figure(figsize=(10, 8))

# Crear el heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0, fmt=".2f")

# Título del gráfico
plt.title("Mapa de Calor de Correlación entre Variables Numéricas")
```

```
# Mostrar el gráfico
plt.show()
```



The correlation showed in the heatmap show that there's not a high correlation between the variables.

Conclusion

Something interesting that I found in this dataset is the negative correlation between the age of the respondents and their perception of if they have access to mental health resources in the workspace. While we could expect that the personnel with more experience would have more access or would be better informed about these resources, the data shows the opposite, younger employees report more access to mental health resources than their seniors.
