🏥 Medical Insurance Cost Analysis (Python • Pandas • Seaborn)

This project analyzes how demographic and lifestyle variables influence U.S. medical insurance charges using the well-known **Insurance Dataset**.

The goal is to explore the impact of:

- **Smoking status**
- **BMI and BMI categories**
- **Sex**
- **Region** on insurance costs.

🔧 Tools Used

- **Python:** Pandas, NumPy
- **Visualization:** Matplotlib, Seaborn
- **Skills Demonstrated:**
  - Data cleaning
  - Feature engineering
  - Groupby summarization
  - Healthcare cost insights
  - Visualization & storytelling

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

sns.set(style="whitegrid")
%matplotlib inline
```

1. Load Data

```
df = pd.read_csv("insurance.csv")
df.head()
```

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

2. Data Overview

Check dataset size, structure, and basic statistics.

```
df.shape
```

```
(1338, 7)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1338 non-null   int64
 1   sex       1338 non-null   object
 2   bmi       1338 non-null   float64
 3   children  1338 non-null   int64
 4   smoker    1338 non-null   object
 5   region    1338 non-null   object
 6   charges   1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

```
df.describe()
```

	age	bmi	children	charges
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.663397	1.094918	13270.422265
std	14.049960	6.098187	1.205493	12110.011237
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.296250	0.000000	4740.287150
50%	39.000000	30.400000	1.000000	9382.033000
75%	51.000000	34.693750	2.000000	16639.912515
max	64.000000	53.130000	5.000000	63770.428010

```
df.isnull().sum()
```

```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

```
df.duplicated().sum()
```

```
1
```

3. Data Cleaning and Feature Engineering

- Remove duplicate rows
- Standardize column names
- Create BMI categories (underweight / normal / overweight / obese)

```
# 1) Remove duplicate row
df = df.drop_duplicates()
df.shape
```

```
(1337, 7)
```

```
# 2) Clean column names: strip spaces, make lowercase
df.columns = df.columns.str.strip().str.lower()
df.columns
```

```
Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges'], dtype='object')
```

```
# 3) Create BMI category bands
bins =[0, 18.5, 25, 30, 100]
labels = ["underweight", "normal", "overweight", "obese"]

df["bmi_band"] = pd.cut(df["bmi"], bins=bins, labels=labels, right=False)
df.head()
```

	age	sex	bmi	children	smoker	region	charges	bmi_band
0	19	female	27.900	0	yes	southwest	16884.92400	overweight
1	18	male	33.770	1	no	southeast	1725.55230	obese
2	28	male	33.000	3	no	southeast	4449.46200	obese
3	33	male	22.705	0	no	northwest	21984.47061	normal
4	32	male	28.880	0	no	northwest	3866.85520	overweight

4. Descriptive Analysis (Groupby)

We summarize average charges by key risk factors.

```
df.groupby("smoker")["charges"].mean().round(2)
```

```
smoker
no      8440.66
yes    32050.23
Name: charges, dtype: float64
```

```
df.groupby("region")["charges"].mean().round(2).sort_values(ascending=False)
```

```
region
southeast    14735.41
northeast    13406.38
northwest    12450.84
southwest    12346.94
Name: charges, dtype: float64
```

```
df.groupby("bmi_band")["charges"].mean().round(2).sort_values(ascending=False)
```

```
bmi_band
obese          15572.04
overweight     10987.51
normal         10409.34
underweight     8852.20
Name: charges, dtype: float64
```

```
df.groupby("sex")["charges"].mean().round(2)
```

```
sex
female    12569.58
male      13975.00
Name: charges, dtype: float64
```

```
# Charges by smoker and sex
charges_smoker_sex = (
    df.groupby(["smoker", "sex"])["charges"]
      .agg(["count", "mean", "median"])
      .round(2)
      .reset_index()
)
charges_smoker_sex
```

	smoker	sex	count	mean	median
0	no	female	547	8762.30	7639.42
1	no	male	516	8099.70	6986.10
2	yes	female	115	30679.00	28950.47
3	yes	male	159	33042.01	36085.22

```
# Charges by BMI band and smoker
charges_bmi_smoker = (
    df.groupby(["bmi_band", "smoker"])["charges"]
      .agg(["count", "mean", "median"])
      .round(2)
      .reset_index()
      .sort_values(["bmi_band", "smoker"])
)
charges_bmi_smoker
```

	bmi_band	smoker	count	mean	median
0	underweight	no	15	5532.99	3732.63
1	underweight	yes	5	18809.82	15006.58
2	normal	no	175	7685.66	6593.51
3	normal	yes	50	19942.22	19479.90
4	overweight	no	312	8257.96	7063.92
5	overweight	yes	74	22495.87	21215.43
6	obese	no	561	8855.53	8083.92
7	obese	yes	145	41557.99	40904.20

```
# Charges by region
charges_region = (
    df.groupby("region")["charges"]
      .agg(["count", "mean", "median"])
      .round(2)
```

```
        .reset_index()
        .sort_values("mean", ascending=False)
)
charges_region
```

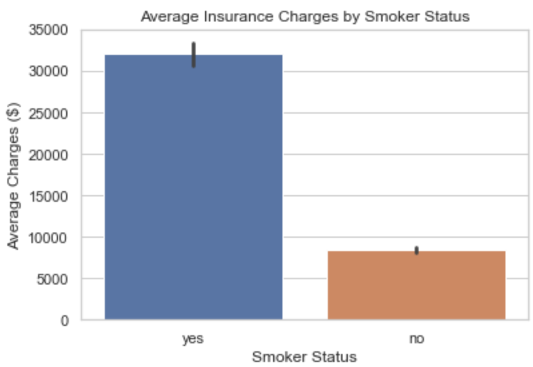
	region	count	mean	median
2	southeast	364	14735.41	9294.13
0	northeast	324	13406.38	10057.65
1	northwest	324	12450.84	8976.98
3	southwest	325	12346.94	8798.59

5. Visualizations

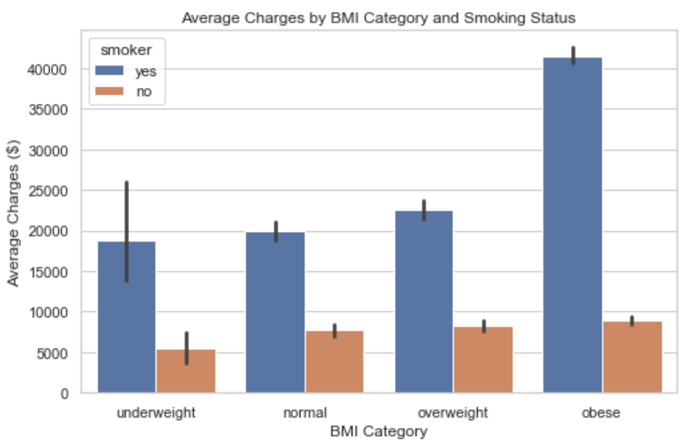
We visualize how smoking status and BMI categories relate to insurance charges.

```
import numpy as np  # in case not already imported elsewhere

plt.figure(figsize=(6,4))
sns.barplot(data=df, x="smoker", y="charges")
plt.title("Average Insurance Charges by Smoker Status")
plt.xlabel("Smoker Status")
plt.ylabel("Average Charges ($)")
plt.show()
```




```
plt.figure(figsize=(8,5))
sns.barplot(data=df, x="bmi_band", y="charges", hue="smoker")
plt.title("Average Charges by BMI Category and Smoking Status")
plt.xlabel("BMI Category")
plt.ylabel("Average Charges ($)")
plt.show()
```



📌 Final Summary & Key Insights

1. Smoking is the strongest cost driver.

Smokers pay **3–4× higher average charges** than non-smokers.
This is consistent across all BMI categories.

2. BMI strongly impacts medical costs.

Obese beneficiaries show the **highest average charges**, followed by overweight individuals.

3. Combining obesity + smoking creates the highest risk group.

Obese smokers incur the largest medical cost burden.

4. Regional differences exist.

The **Southeast** has the highest average charges, while the Southwest is lower.

5. Sex differences are modest.

Males have slightly higher average charges compared to females.

What This Project Demonstrates

- Ability to clean and structure raw data
- Use of pandas groupby and aggregations
- Creating features (BMI categories)
- Data storytelling with visualizations
- Extracting meaningful healthcare insights

```
import os
os.makedirs("outputs", exist_ok=True)

df.to_csv("outputs/insurance_clean.csv", index=False)
charges_smoker_sex.to_csv("outputs/charges_smoker_sex.csv", index=False)
charges_bmi_smoker.to_csv("outputs/charges_bmi_smoker.csv", index=False)
charges_region.to_csv("outputs/charges_region.csv", index=False)
```

```
Start coding or generate with AI.
```