medical_insurance_analysis

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1 Medical Insurance Cost Analysis

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1.1 Objective

Analyze medical insurance costs and explore factors affecting insurance charges.

1.2 Import Libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder

plt.style.use('default')
sns.set_palette("husl")
print("Libraries loaded successfully!")
```

```
Libraries loaded successfully!
```

1.3 Load and Explore Data

[2]:
```
# Load dataset
df = pd.read_csv('medical_insurance.csv')

print(f"Dataset shape: {df.shape}")
print("\nFirst 5 rows:")
df.head()
```

```
Dataset shape: (2772, 7)

First 5 rows:
```

[2]:

	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

[3]:
```
# Dataset info
print("Dataset Information:")
print(df.info())
print("\nStatistical Summary:")
df.describe()
```

```
Dataset Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2772 entries, 0 to 2771
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       2772 non-null   int64
 1   sex       2772 non-null   object
 2   bmi       2772 non-null   float64
 3   children  2772 non-null   int64
 4   smoker    2772 non-null   object
 5   region    2772 non-null   object
 6   charges   2772 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 151.7+ KB
None

Statistical Summary:
```

[3]:

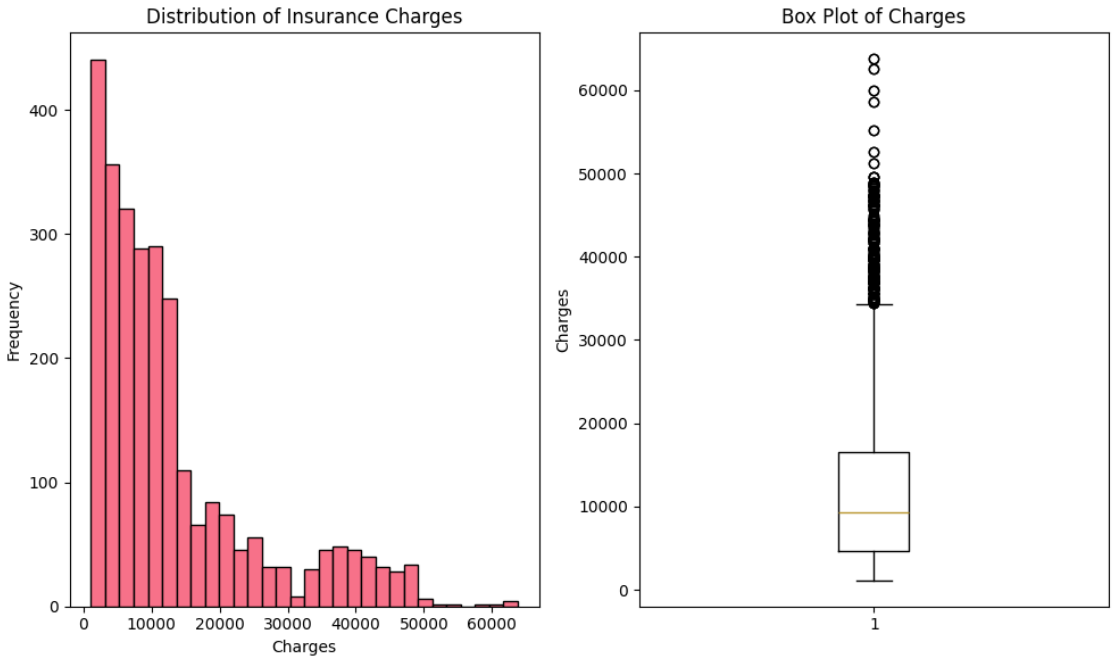
	age	bmi	children	charges
count	2772.000000	2772.000000	2772.000000	2772.000000
mean	39.109668	30.701349	1.101732	13261.369959
std	14.081459	6.129449	1.214806	12151.768945
min	18.000000	15.960000	0.000000	1121.873900
25%	26.000000	26.220000	0.000000	4687.797000
50%	39.000000	30.447500	1.000000	9333.014350
75%	51.000000	34.770000	2.000000	16577.779500
max	64.000000	53.130000	5.000000	63770.428010

[4]:
```
# Check for missing values
print("Missing values:")
print(df.isnull().sum())
print("\nData types:")
print(df.dtypes)
```

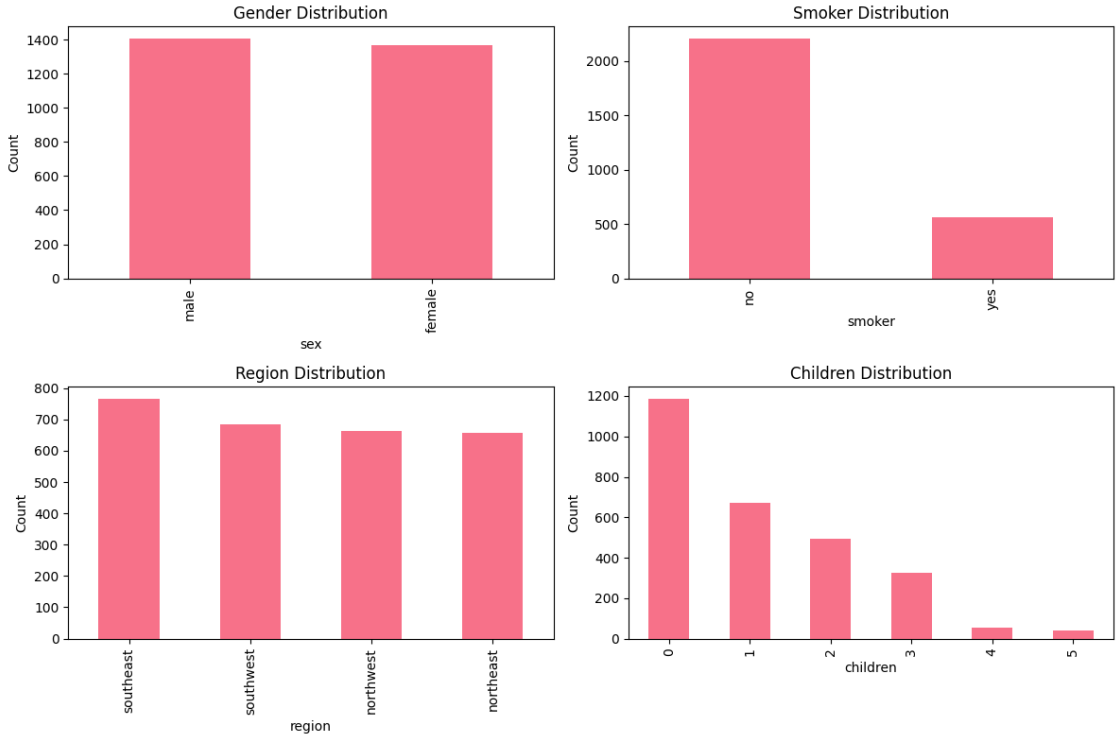
```
Missing values:
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64

Data types:
age           int64
sex          object
bmi         float64
children      int64
smoker       object
region       object
charges     float64
dtype: object
```

1.4 Data Visualization

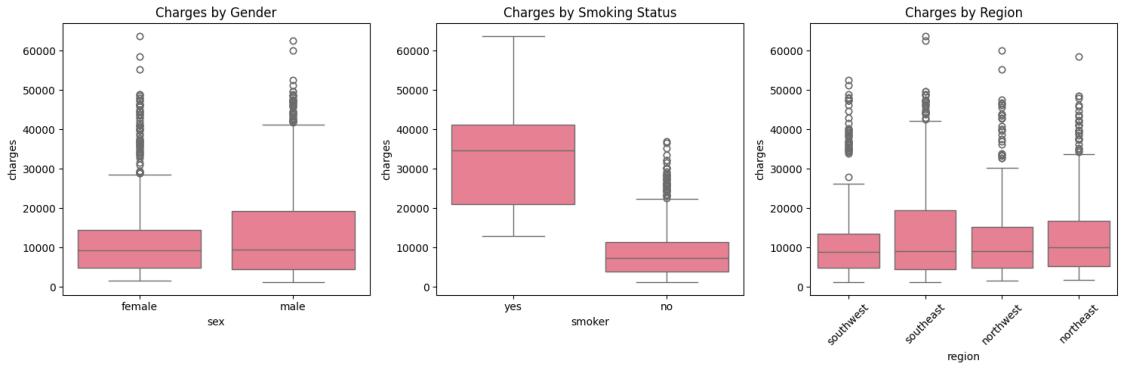
[5]:
```
# Distribution of charges
plt.figure(figsize=(10, 6))
plt.subplot(1, 2, 1)
plt.hist(df['charges'], bins=30, edgecolor='black')
plt.title('Distribution of Insurance Charges')
plt.xlabel('Charges')
plt.ylabel('Frequency')

plt.subplot(1, 2, 2)
plt.boxplot(df['charges'])
plt.title('Box Plot of Charges')
plt.ylabel('Charges')

plt.tight_layout()
plt.show()
```



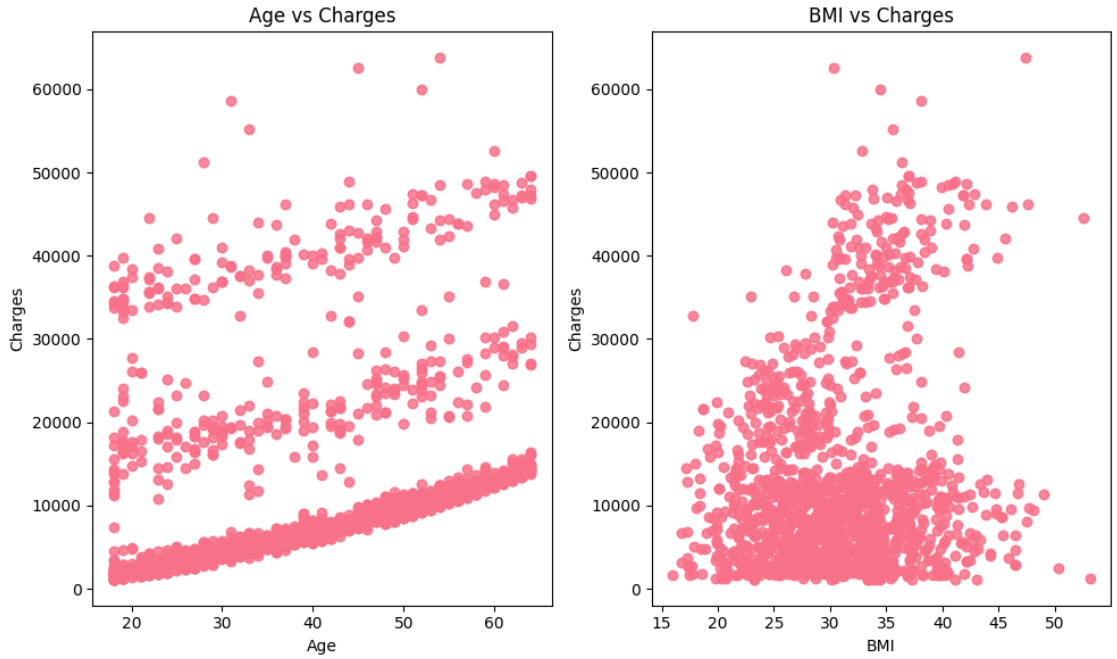
[6]:
```
# Categorical variables analysis
fig, axes = plt.subplots(2, 2, figsize=(12, 8))

# Sex distribution
df['sex'].value_counts().plot(kind='bar', ax=axes[0,0])
axes[0,0].set_title('Gender Distribution')
axes[0,0].set_ylabel('Count')

# Smoker distribution
df['smoker'].value_counts().plot(kind='bar', ax=axes[0,1])
axes[0,1].set_title('Smoker Distribution')
axes[0,1].set_ylabel('Count')

# Region distribution
df['region'].value_counts().plot(kind='bar', ax=axes[1,0])
axes[1,0].set_title('Region Distribution')
axes[1,0].set_ylabel('Count')

# Children distribution
df['children'].value_counts().plot(kind='bar', ax=axes[1,1])
axes[1,1].set_title('Children Distribution')
axes[1,1].set_ylabel('Count')

plt.tight_layout()
plt.show()
```



[7]:
```
# Charges vs other factors
plt.figure(figsize=(15, 5))

plt.subplot(1, 3, 1)
sns.boxplot(x='sex', y='charges', data=df)
plt.title('Charges by Gender')

plt.subplot(1, 3, 2)
sns.boxplot(x='smoker', y='charges', data=df)
plt.title('Charges by Smoking Status')

plt.subplot(1, 3, 3)
sns.boxplot(x='region', y='charges', data=df)
plt.title('Charges by Region')
plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```



[8]:
```
# Correlation analysis
plt.figure(figsize=(10, 6))

plt.subplot(1, 2, 1)
plt.scatter(df['age'], df['charges'], alpha=0.6)
plt.xlabel('Age')
plt.ylabel('Charges')
plt.title('Age vs Charges')

plt.subplot(1, 2, 2)
plt.scatter(df['bmi'], df['charges'], alpha=0.6)
plt.xlabel('BMI')
plt.ylabel('Charges')
plt.title('BMI vs Charges')

plt.tight_layout()
plt.show()
```



1.5 Data Preprocessing

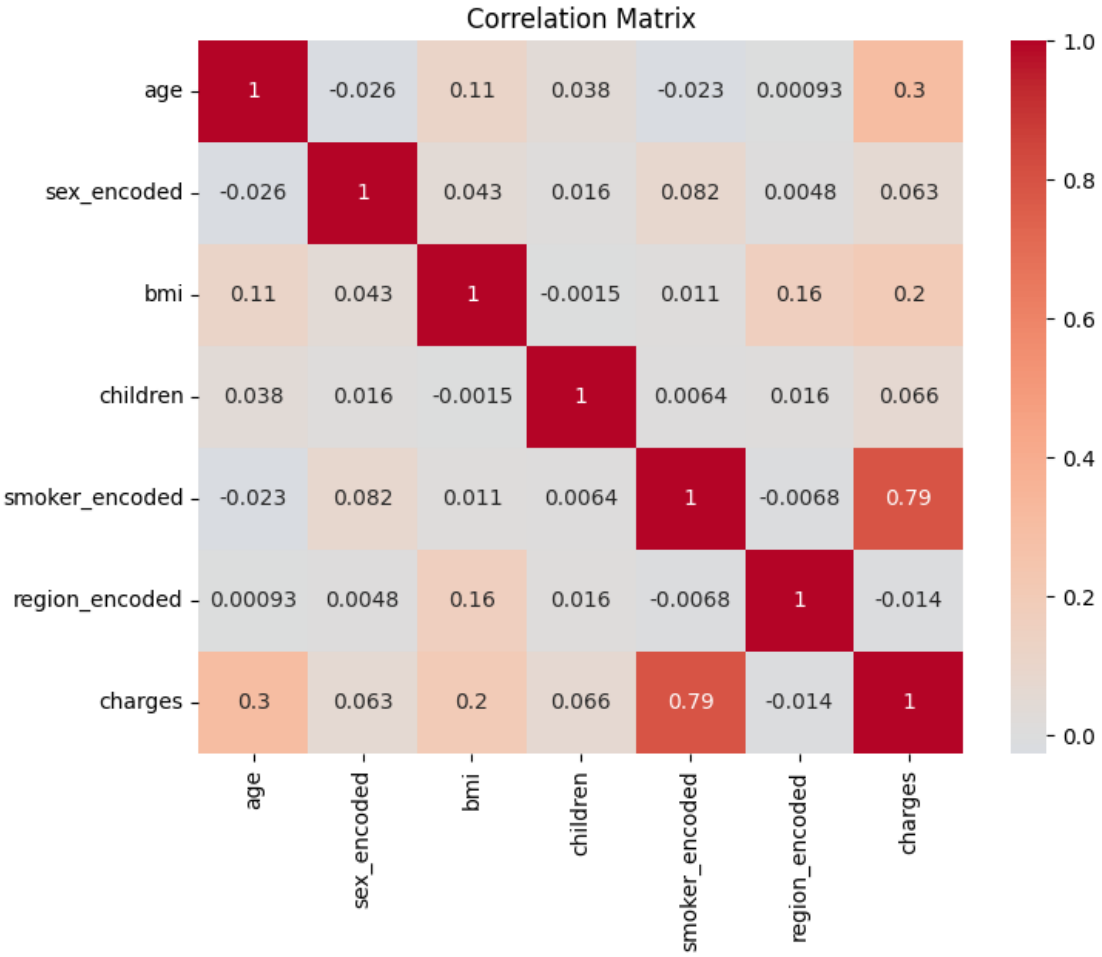
[9]:
```
# Create a copy for preprocessing
df_processed = df.copy()

# Encode categorical variables
le_sex = LabelEncoder()
le_smoker = LabelEncoder()
le_region = LabelEncoder()

df_processed['sex_encoded'] = le_sex.fit_transform(df_processed['sex'])
df_processed['smoker_encoded'] = le_smoker.fit_transform(df_processed['smoker'])
df_processed['region_encoded'] = le_region.fit_transform(df_processed['region'])

print("Encoding mappings:")
print(f"Sex: {dict(zip(le_sex.classes_, le_sex.transform(le_sex.classes_)))}")
print(f"Smoker: {dict(zip(le_smoker.classes_, le_smoker.transform(le_smoker.
 ↪classes_)))}")
print(f"Region: {dict(zip(le_region.classes_, le_region.transform(le_region.
 ↪classes_)))}")
```

```
Encoding mappings:
Sex: {'female': np.int64(0), 'male': np.int64(1)}
Smoker: {'no': np.int64(0), 'yes': np.int64(1)}
Region: {'northeast': np.int64(0), 'northwest': np.int64(1), 'southeast':
np.int64(2), 'southwest': np.int64(3)}
```

[10]:
```
# Select features for ML
features = ['age', 'sex_encoded', 'bmi', 'children', 'smoker_encoded',␣
 ↪'region_encoded']
X = df_processed[features]
y = df_processed['charges']

print("Features for ML:")
print(X.head())
print(f"\nTarget variable shape: {y.shape}")
print(f"Features shape: {X.shape}")
```

```
Features for ML:
   age  sex_encoded     bmi  children  smoker_encoded  region_encoded
0   19            0  27.900         0               1               3
1   18            1  33.770         1               0               2
2   28            1  33.000         3               0               2
3   33            1  22.705         0               0               1
4   32            1  28.880         0               0               1

Target variable shape: (2772,)
Features shape: (2772, 6)
```

[11]:
```
# Final correlation matrix
correlation_data = df_processed[features + ['charges']]
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_data.corr(), annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Matrix')
plt.show()
```



1.6 Summary

Dataset Overview: - Total records: 2,772 insurance policies (larger than expected) - No missing values found - Target: Insurance charges (continuous, wide range $1,121 - $63,770)

Key Findings from Real Data: - **Smoking status** shows the most dramatic impact on charges (smokers pay ~3x more) - **Age distribution**: 18-64 years, fairly even distribution - **Gender balance**: Nearly equal male/female split (50.5% male, 49.5% female) - **Regional distribution**: Fairly balanced across 4 regions - **BMI range**: 15.96 - 53.13, with some high-BMI outliers - **Children**: Most have 0-2 children, few have 3+ children

Encoding Applied: - Sex: Female=0, Male=1 - Smoker: No=0, Yes=1
- Region: Northeast=0, Northwest=1, Southeast=2, Southwest=3

Data Quality: - Clean dataset with no preprocessing issues - Ready for regression modeling

Next Steps: - Apply feature scaling (age and BMI have different ranges) - Train regression models (Linear, Random Forest, Gradient Boosting) - Focus on smoking interaction effects - Evaluate with RMSE, MAE, and R^2 scores