Adidas Web Store

January 26, 2025

1 Adidas Web Store Data Analysis

In this project, Data Analysis has been performed on three datasets related to Adidas Shoes. The primary goal is to combine the datasets and investigate the pricing differences across various countries, focusing on the average price variation by shoe category and country.

The analysis aims to uncover insights into the pricing trends for Adidas shoes, with a specific emphasis on how prices differ based on shoe categories and the countries represented in the datasets. By merging the data, I walked through some steps to get to the desired dataset.

[1]:
```
import pandas as pd #import the Pandas Library
```

[2]:
```
# Reading the first dataset which has infromation about the country code and␣
↪the currency
country = pd.read_csv('country_dim.csv')
country.head()
```

[2]:
```
  country_code currency shoe_metric
0           DE     euro          eu
1           US      usd         usa
2           BE     euro          eu
3           UK   pounds          uk
```

[3]:
```
country.drop(columns=['shoe_metric'], inplace=True) # dropping the shoe_metric␣
↪column
```

[4]:
```
country.head()
```

[4]:
```
  country_code currency
0           DE     euro
1           US      usd
2           BE     euro
3           UK   pounds
```

[5]:
```
# Reading the second dataset which has infromation about the shoes fact
shoe_fact = pd.read_csv('shoes_fact.csv')
shoe_fact
```

[5]:
```
        Unnamed: 0      id  price  category    size  availability        date  \
0            63575  HP9426   60.0  sneakers      36             0  07/01/2025
1            63576  HP9426   60.0  sneakers  36 2/3             0  07/01/2025
2            63577  HP9426   60.0  sneakers  37 1/3             0  07/01/2025
3            63578  HP9426   60.0  sneakers      38             0  07/01/2025
4            63579  HP9426   60.0  sneakers  38 2/3             1  07/01/2025
…              …       …     …        …       …          …
299151      847278  JI4476  160.0  sneakers  47 1/3             3  2025-01-16
299152      847279  JI4476  160.0  sneakers      48             0  2025-01-16
299153      847280  JI4476  160.0  sneakers  48 2/3             0  2025-01-16
299154      847281  JI4476  160.0  sneakers  49 1/3             2  2025-01-16
299155      847282  JI4476  160.0  sneakers  50 2/3             0  2025-01-16

       country_code
0                DE
1                DE
2                DE
3                DE
4                DE
…             …
299151           BE
299152           BE
299153           BE
299154           BE
299155           BE

[299156 rows x 8 columns]
```

[6]:
```python
# dropping the unnecessary columns specifically 'shoe_metric', "Unnamed: 0",
↪"availability", "date", and "size
shoe_fact.drop(columns=['Unnamed: 0','size','availability','date'],inplace=True)
shoe_fact
```

[6]:
```
            id  price  category country_code
0       HP9426   60.0  sneakers           DE
1       HP9426   60.0  sneakers           DE
2       HP9426   60.0  sneakers           DE
3       HP9426   60.0  sneakers           DE
4       HP9426   60.0  sneakers           DE
…          …     …        …            …
299151  JI4476  160.0  sneakers           BE
299152  JI4476  160.0  sneakers           BE
299153  JI4476  160.0  sneakers           BE
299154  JI4476  160.0  sneakers           BE
299155  JI4476  160.0  sneakers           BE

[299156 rows x 4 columns]
```

[7]:
```
shoe_fact.id.duplicated().sum()
```

[7]: 297146

[8]:
```
shoe_fact = shoe_fact.drop_duplicates(subset=['id','country_code'],keep="first")
shoe_fact
```

[8]:
```
             id  price           category country_code
0        HP9426   60.0           sneakers           DE
20       HQ4199  180.0           sneakers           DE
36       JQ2552  160.0           sneakers           DE
58       JI1896   80.0           sneakers           DE
80       IE8976  180.0           sneakers           DE
…           …      …                  …          …
289291   IF4212  144.0  athletic_sneakers           US
289337   IE6438   50.0  athletic_sneakers           US
289456   H02334  110.0  athletic_sneakers           US
291675   IF1360   70.0        occer-shoes           US
291711   IH3814   54.0        occer-shoes           US

[3403 rows x 4 columns]
```

[9]:
```
shoe_fact.country_code.unique()
```

[9]: array(['DE', 'UK', 'BE', 'US'], dtype=object)

[10]:
```
shoe_fact.duplicated().any()
```

[10]: False

2 Merging of the Shoe Fact and Country Data Set

[11]:
```
# Merging the two datasets i.e. Country and Shoes Fact
country_shoes_fact = pd.merge(shoe_fact,country, on='country_code', how='left')
country_shoes_fact
```

[11]:
```
           id  price           category country_code currency
0      HP9426   60.0           sneakers           DE     euro
1      HQ4199  180.0           sneakers           DE     euro
2      JQ2552  160.0           sneakers           DE     euro
3      JI1896   80.0           sneakers           DE     euro
4      IE8976  180.0           sneakers           DE     euro
…        …      …                  …          …       …
3398   IF4212  144.0  athletic_sneakers           US      usd
3399   IE6438   50.0  athletic_sneakers           US      usd
3400   H02334  110.0  athletic_sneakers           US      usd
3401   IF1360   70.0        occer-shoes           US      usd
```

```
3402  IH3814   54.0        occer-shoes           US      usd

[3403 rows x 5 columns]
```

[12]:
```
#Converting currency for standardization to Euros:

country_shoes_fact['currency'].unique()
```

[12]:
```
array(['euro', 'pounds', 'usd'], dtype=object)
```

[13]:
```
#In order to standardize the data for the analysis,
#I decide to convert all 'price' data to Euro (therefore converting other␣
↪currencies such as $ and £ to EUR).

def convert_euros(df):
    if df.currency =='euro':
        return df.price
    if df.currency=='pounds':
        return df.price*0.85
    if df.currency=='usd':
        return df.price*1.03
    else:
        raise ValueError(f"Currency not recognized:{df.currency}")

country_shoes_fact['Prices in Euros']= country_shoes_fact.apply(convert_euros,␣
↪axis=1)
```

[14]:
```
country_shoes_fact
```

[14]:
```
          id  price           category country_code currency  Prices in Euros
0     HP9426   60.0           sneakers           DE     euro            60.00
1     HQ4199  180.0           sneakers           DE     euro           180.00
2     JQ2552  160.0           sneakers           DE     euro           160.00
3     JI1896   80.0           sneakers           DE     euro            80.00
4     IE8976  180.0           sneakers           DE     euro           180.00
…       …     …                  …          …       …              …
3398  IF4212  144.0  athletic_sneakers           US      usd           148.32
3399  IE6438   50.0  athletic_sneakers           US      usd            51.50
3400  H02334  110.0  athletic_sneakers           US      usd           113.30
3401  IF1360   70.0        occer-shoes           US      usd            72.10
3402  IH3814   54.0        occer-shoes           US      usd            55.62

[3403 rows x 6 columns]
```

[15]:
```
country_shoes_fact.drop(columns=['price','currency'], inplace=True)
```

[16]:
```
country_shoes_fact
```

[16]:
```
        id           category country_code  Prices in Euros
0     HP9426           sneakers           DE            60.00
1     HQ4199           sneakers           DE           180.00
2     JQ2552           sneakers           DE           160.00
3     JI1896           sneakers           DE            80.00
4     IE8976           sneakers           DE           180.00
…       …                 …          …              …
3398  IF4212  athletic_sneakers           US           148.32
3399  IE6438  athletic_sneakers           US            51.50
3400  H02334  athletic_sneakers           US           113.30
3401  IF1360        occer-shoes           US            72.10
3402  IH3814        occer-shoes           US            55.62

[3403 rows x 4 columns]
```

[17]:
```
country_shoes_fact.rename(columns={"country_code": 'country'}, inplace= True)
```

[18]:
```
country_shoes_fact
```

[18]:
```
        id           category country  Prices in Euros
0     HP9426           sneakers      DE            60.00
1     HQ4199           sneakers      DE           180.00
2     JQ2552           sneakers      DE           160.00
3     JI1896           sneakers      DE            80.00
4     IE8976           sneakers      DE           180.00
…       …                 …     …              …
3398  IF4212  athletic_sneakers      US           148.32
3399  IE6438  athletic_sneakers      US            51.50
3400  H02334  athletic_sneakers      US           113.30
3401  IF1360        occer-shoes      US            72.10
3402  IH3814        occer-shoes      US            55.62

[3403 rows x 4 columns]
```

[19]:
```
# Reading the shoes dimenions third dataset

shoes_dim = pd.read_csv('shoes_dim.csv')
```

[20]:
```
shoes_dim
```

[20]:
```
        id                          name best_for_wear  \
0     HP9426             Breaknet 2.0 Schuh          City
1     HQ4199      Ultraboost 1.0 Laufschuh          City
2     JQ2552    Adizero Boston 12 Laufschuh        Racing
3     JI1896                    NY 90 Schuh       Neutral
4     IE8976      Ultraboost 1.0 Laufschuh       Neutral
…       …                             …            …
```

```
3297  IF4212      Chris Nikic Adizero Boston 12 Wide Shoes         Race
3298  IE6438                           Run 60s Shoes Kids       Walking
3299  H02334                         NMD_R1 Refined Shoes       Comfort
3300  IF1360                F50 Pro Firm Ground Cleats Kids       Outside
3301  IH3814  F50 Women's League Mid-Cut Turf Soccer Shoes       Outside

     gender                                          image_url  \
0         U  https://assets.adidas.com/images/w_600,f_auto,…
1         U  https://assets.adidas.com/images/w_600,f_auto,…
2         U  https://assets.adidas.com/images/w_600,f_auto,…
3         U  https://assets.adidas.com/images/w_600,f_auto,…
4         U  https://assets.adidas.com/images/w_600,f_auto,…
…       …                                                …
3297      U  https://assets.adidas.com/images/w_600,f_auto,…
3298      K  https://assets.adidas.com/images/w_600,f_auto,…
3299      K  https://assets.adidas.com/images/w_600,f_auto,…
3300      K  https://assets.adidas.com/images/w_600,f_auto,…
3301      W  https://assets.adidas.com/images/w_600,f_auto,…

        dominant_color         sub_color1         sub_color2
0          Cloud White         Core Black        Cloud White
1           Core Black         Core Black         Beam Green
2          Cloud White         Core Black          Lucid Red
3          Cloud White        Cloud White      Crystal White
4             Grey One         Grey Three           Grey One
…                    …                  …                  …
3297   Screaming Orange        Cloud White        Bright Blue
3298       Cloud White   Collegiate Green    Collegiate Gold
3299       Cloud White        Cloud White           Grey One
3300             Turbo       Aurora Black  Platinum Metallic
3301             Turbo       Aurora Black  Platinum Metallic

[3302 rows x 8 columns]
```

[21]:
```
shoes_dim.drop(columns=['best_for_wear','image_url','sub_color1','sub_color2'],␣
↪inplace=True)
shoes_dim
```

[21]:
```
          id                                          name gender  \
0     HP9426                             Breaknet 2.0 Schuh      U
1     HQ4199                       Ultraboost 1.0 Laufschuh      U
2     JQ2552                    Adizero Boston 12 Laufschuh      U
3     JI1896                                    NY 90 Schuh      U
4     IE8976                       Ultraboost 1.0 Laufschuh      U
…        …                                             …      …
3297  IF4212       Chris Nikic Adizero Boston 12 Wide Shoes      U
3298  IE6438                             Run 60s Shoes Kids      K
```

```
3299  H02334                           NMD_R1 Refined Shoes      K
3300  IF1360                 F50 Pro Firm Ground Cleats Kids      K
3301  IH3814  F50 Women's League Mid-Cut Turf Soccer Shoes      W

        dominant_color
0          Cloud White
1           Core Black
2          Cloud White
3          Cloud White
4             Grey One
…                    …
3297  Screaming Orange
3298       Cloud White
3299       Cloud White
3300             Turbo
3301             Turbo

[3302 rows x 4 columns]
```

[22]:
```
shoes_dim.id.duplicated().any()
```

[22]:
```
True
```

[23]:
```
shoes_dim = shoes_dim.drop_duplicates(subset=['id'], keep="first")
shoes_dim
```

[23]:
```
          id                                          name gender  \
0     HP9426                          Breaknet 2.0 Schuh      U
1     HQ4199                      Ultraboost 1.0 Laufschuh      U
2     JQ2552                    Adizero Boston 12 Laufschuh      U
3     JI1896                                  NY 90 Schuh      U
4     IE8976                      Ultraboost 1.0 Laufschuh      U
…        …                                             …    …
3297  IF4212      Chris Nikic Adizero Boston 12 Wide Shoes      U
3298  IE6438                           Run 60s Shoes Kids      K
3299  H02334                           NMD_R1 Refined Shoes      K
3300  IF1360                 F50 Pro Firm Ground Cleats Kids      K
3301  IH3814  F50 Women's League Mid-Cut Turf Soccer Shoes      W

        dominant_color
0          Cloud White
1           Core Black
2          Cloud White
3          Cloud White
4             Grey One
…                    …
3297  Screaming Orange
```

```
3298       Cloud White
3299       Cloud White
3300             Turbo
3301             Turbo

[2010 rows x 4 columns]
```

[24]:
```python
shoes_dim.duplicated().any()
```

[24]:
```
False
```

[25]:
```python
shoes_info = shoes_dim.groupby(['id', 'gender']).agg(
    {
        'name': 'last',
        'dominant_color': 'first'
    }
).reset_index()
```

[26]:
```python
shoes_info
```

[26]:
```
          id gender                                            name  \
0     011040      U                          World Cup Fußballschuh
1     015110      U                       Copa Mundial Fußballschuh
2     019228      U                       Mundial Team Fußballschuh
3     019310      U                               Mundial Goal Schuh
4     033200      U                         Kaiser 5 Cup Fußballschuh
…        …      …                                               …
2005  JS3050      M    Adizero Impact Turf Silver Speed Baseball Shoes
2006  JS3083      K         Texas Tech x Mahomes Ultrarun 5 Shoes Kids
2007  JS3222      M                     Equipment Edge Runner 1 Shoes
2008  Q47235      M                    Tracefinder Trailrunning-Schuh
2009  S29146      U  Five Ten Trailcross GORE-TEX Mountainbiking-Schuh

        dominant_color
0                Black
1                Black
2                Black
3           Core Black
4                Black
…                    …
2005   Silver Metallic
2006   Team Power Red 2
2007     Crystal White
2008        Core Black
2009        Core Black

[2010 rows x 4 columns]
```

[27]:
```
shoes_info['name']= shoes_info['name'].str.replace('Fußballschuh','FootBall␣
↪Shoes')
shoes_info['name']= shoes_info['name'].str.replace('-Schuh',' Shoes')
shoes_info['name']= shoes_info['name'].str.replace('Laufschuh', 'Shoes')
shoes_info['name']= shoes_info['name'].str.replace('Schuh','Shoes')
```

[28]:
```
shoes_info
```

[28]:
```
          id gender                                          name  \
0     011040      U                      World Cup FootBall Shoes
1     015110      U                   Copa Mundial FootBall Shoes
2     019228      U                   Mundial Team FootBall Shoes
3     019310      U                            Mundial Goal Shoes
4     033200      U                   Kaiser 5 Cup FootBall Shoes
…        …     …                                             …
2005  JS3050      M    Adizero Impact Turf Silver Speed Baseball Shoes
2006  JS3083      K          Texas Tech x Mahomes Ultrarun 5 Shoes Kids
2007  JS3222      M                      Equipment Edge Runner 1 Shoes
2008  Q47235      M                     Tracefinder Trailrunning Shoes
2009  S29146      U  Five Ten Trailcross GORE-TEX Mountainbiking Shoes

        dominant_color
0                Black
1                Black
2                Black
3           Core Black
4                Black
…                    …
2005   Silver Metallic
2006  Team Power Red 2
2007     Crystal White
2008        Core Black
2009        Core Black

[2010 rows x 4 columns]
```

2.1 Final Merging - First Merge + Shoes_info

[29]:
```
adidas_shoes_df = pd.merge(country_shoes_fact, shoes_info, on= 'id',␣
↪how='inner')
```

[30]:
```
adidas_shoes_df
```

[30]:
```
          id         category country  Prices in Euros gender  \
0     HP9426         sneakers      DE            60.00      U
1     HP9426         sneakers      UK            42.50      U
2     HP9426         sneakers      BE            60.00      U
```

```
3     HQ4199           sneakers      DE          180.00      U
4     HQ4199           sneakers      UK          136.00      U
…      …                 …       …            …      …
3398  IF4212  athletic_sneakers      US          148.32      U
3399  IE6438  athletic_sneakers      US           51.50      K
3400  H02334  athletic_sneakers      US          113.30      K
3401  IF1360        occer-shoes      US           72.10      K
3402  IH3814        occer-shoes      US           55.62      W

                                            name    dominant_color
0                               Breaknet 2.0 Shoes       Cloud White
1                               Breaknet 2.0 Shoes       Cloud White
2                               Breaknet 2.0 Shoes       Cloud White
3                             Ultraboost 1.0 Shoes        Core Black
4                             Ultraboost 1.0 Shoes        Core Black
…                                                …              …
3398      Chris Nikic Adizero Boston 12 Wide Shoes  Screaming Orange
3399                            Run 60s Shoes Kids       Cloud White
3400                            NMD_R1 Refined Shoes       Cloud White
3401                 F50 Pro Firm Ground Cleats Kids             Turbo
3402  F50 Women's League Mid-Cut Turf Soccer Shoes             Turbo

[3403 rows x 7 columns]
```

[31]:
```python
adidas_shoes_df.duplicated().any()
```

[31]:
```
False
```

[32]:
```python
adidas_shoes_df.category.value_counts()
```

[32]:
```
sneakers                1023
running-shoes            711
us/athletic_sneakers     591
outdoor-shoes            556
tennis-shoes             144
us/soccer-shoes          102
gym_training-shoes        88
us/workout-shoes          54
football-shoes            48
us/walking-shoes          27
us/running-shoes          24
us/tennis-shoes           17
athletic_sneakers          8
us/hiking-shoes            5
walking-shoes              3
occer-shoes                2
Name: category, dtype: int64
```

[33]:
```
#The variable names are stored in a disorganized manner.
#I will update the 'category' column to accurately reflect the shoe types.

adidas_shoes_df['category'] = adidas_shoes_df['category'].replace({
    'occer-shoes' : 'football-shoes',
    'us/tennis-shoes' : 'tennis-shoes',
    'us/running-shoes' : 'running-shoes',
    'us/hiking-shoes' : 'hiking-shoes',
    'us/walking-shoes' : 'walking-shoes',
    'us/workout-shoes' : 'gym_training-shoes',
    'us/soccer-shoes' : 'football-shoes',
    'us/athletic_sneakers' : 'athletic_sneakers'
})

adidas_shoes_df.category.value_counts()
```

[33]:
```
sneakers              1023
running-shoes          735
athletic_sneakers      599
outdoor-shoes          556
tennis-shoes           161
football-shoes         152
gym_training-shoes     142
walking-shoes           30
hiking-shoes             5
Name: category, dtype: int64
```

[34]:
```
adidas_shoes_df.columns
```

[34]:
```
Index(['id', 'category', 'country', 'Prices in Euros', 'gender', 'name',
       'dominant_color'],
      dtype='object')
```

2.2 Distribution of Targated Variable Price

[35]:
```
import matplotlib.pyplot as plt
```

[36]:
```
plt.figure(figsize = (8,5))
plt.hist(adidas_shoes_df['Prices in Euros'], bins = 50, edgecolor='black',␣
 ↪color = 'red')
plt.xlabel('Prices in Euros')
plt.ylabel('Frequency')
plt.title('Distribution of Shoe Prices')
plt.show()
```

2.3 Statistics Using Python

[37]:
```
from scipy.stats.mstats import normaltest
statistics, pvalue = normaltest(adidas_shoes_df['Prices in Euros'])

print(f"Test Statistic:{statistics}")
print(f"Test pvalue:{pvalue}")
```

```
Test Statistic:742.9104524197614
Test pvalue:4.775787372744617e-162
```

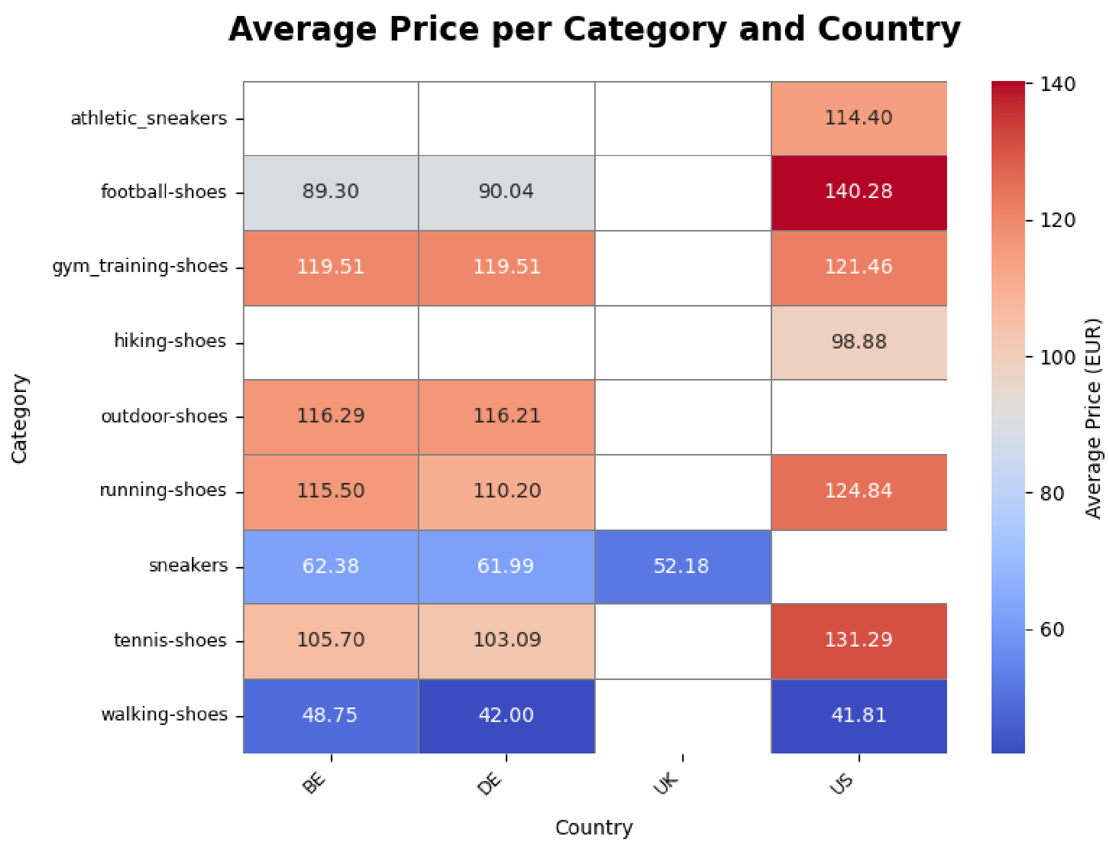
[38]:
```
if pvalue < 0.05:
    print("The data does not follow a normal distribution (reject H0).")
else:
    print("The data follows a normal distribution (cannot reject H0).")
```

```
The data does not follow a normal distribution (reject H0).
```

The variable 'price', as already observed in the graph and later confirmed by the normality test, does not follow a normal distribution and is skewed to the right. Moving forward within the scope of Analysis, we aim to visualize how price varies based on different features: specifically, by country and shoe category. It is worth noting that the 'category' variable in the UK only includes the 'sneakers' instance.

[39]:
```
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
category_country_prices = adidas_shoes_df.groupby(['category',␣
↪'country'])['Prices in Euros'].mean().unstack()

plt.figure(figsize=(8, 6))
sns.heatmap(
    category_country_prices,
    annot=True,
    fmt=".2f",
    cmap="coolwarm",
    cbar=True,
    linewidths=0.5,
    linecolor='gray',
    cbar_kws={'label': 'Average Price (EUR)'}
)
plt.title('Average Price per Category and Country', fontsize=16, weight='bold',␣
↪pad=20)
plt.xlabel('Country', fontsize=10, labelpad=10)
plt.ylabel('Category', fontsize=10, labelpad=10)
plt.xticks(rotation=45, ha='right', fontsize=9)
plt.yticks(fontsize=9)
plt.tight_layout()
plt.show()
```

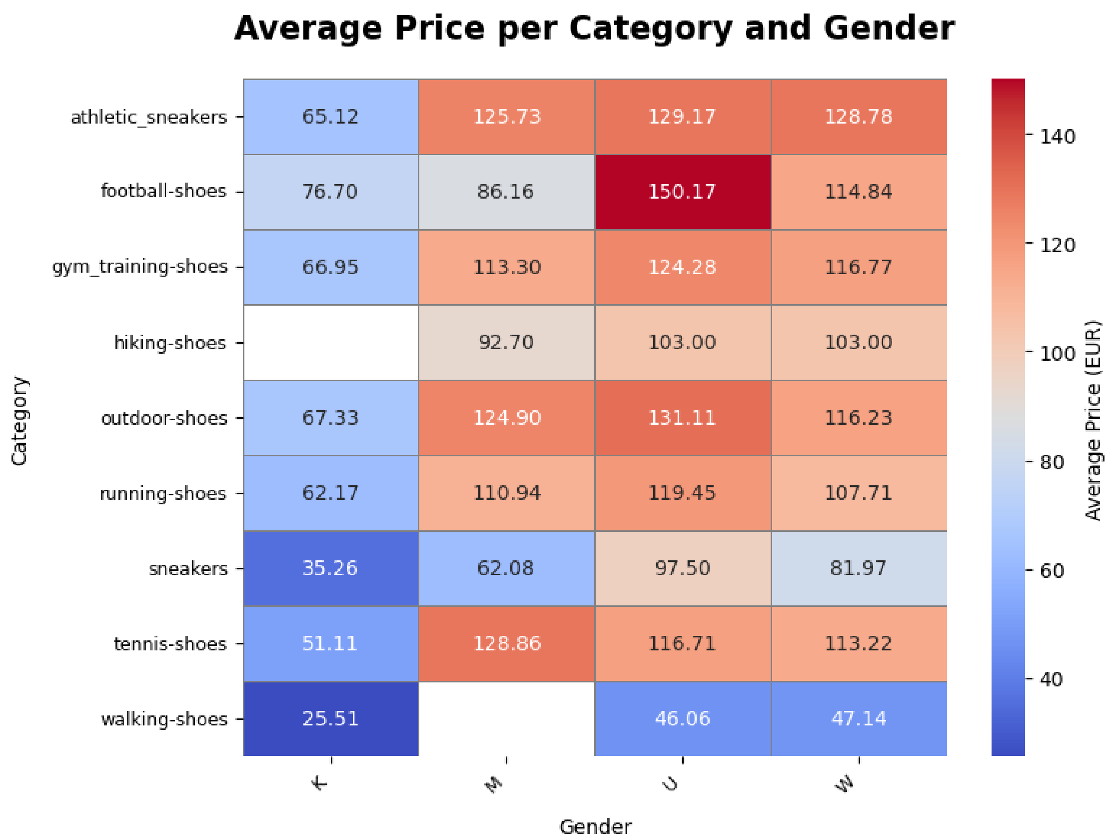


It is interesting to note that prices tend to be higher in the United States compared to European countries, particularly for football shoes (possibly due to the lower popularity of this sport overseas), and tennis shoes.

[40]:
```
category_gender_prices = adidas_shoes_df.groupby(['category',␣
↪'gender'])['Prices in Euros'].mean().unstack()

plt.figure(figsize=(8, 6))
sns.heatmap(
    category_gender_prices,
    annot=True,
    fmt=".2f",
    cmap="coolwarm",
    cbar=True,
    linewidths=0.5,
    linecolor='gray',
    cbar_kws={'label': 'Average Price (EUR)'}
)
plt.title('Average Price per Category and Gender', fontsize=16, weight='bold',␣
↪pad=20)
```

```
plt.xlabel('Gender', fontsize=10, labelpad=10)
plt.ylabel('Category', fontsize=10, labelpad=10)
plt.xticks(rotation=45, ha='right', fontsize=9)
plt.yticks(fontsize=9)
plt.tight_layout()
plt.show()
```

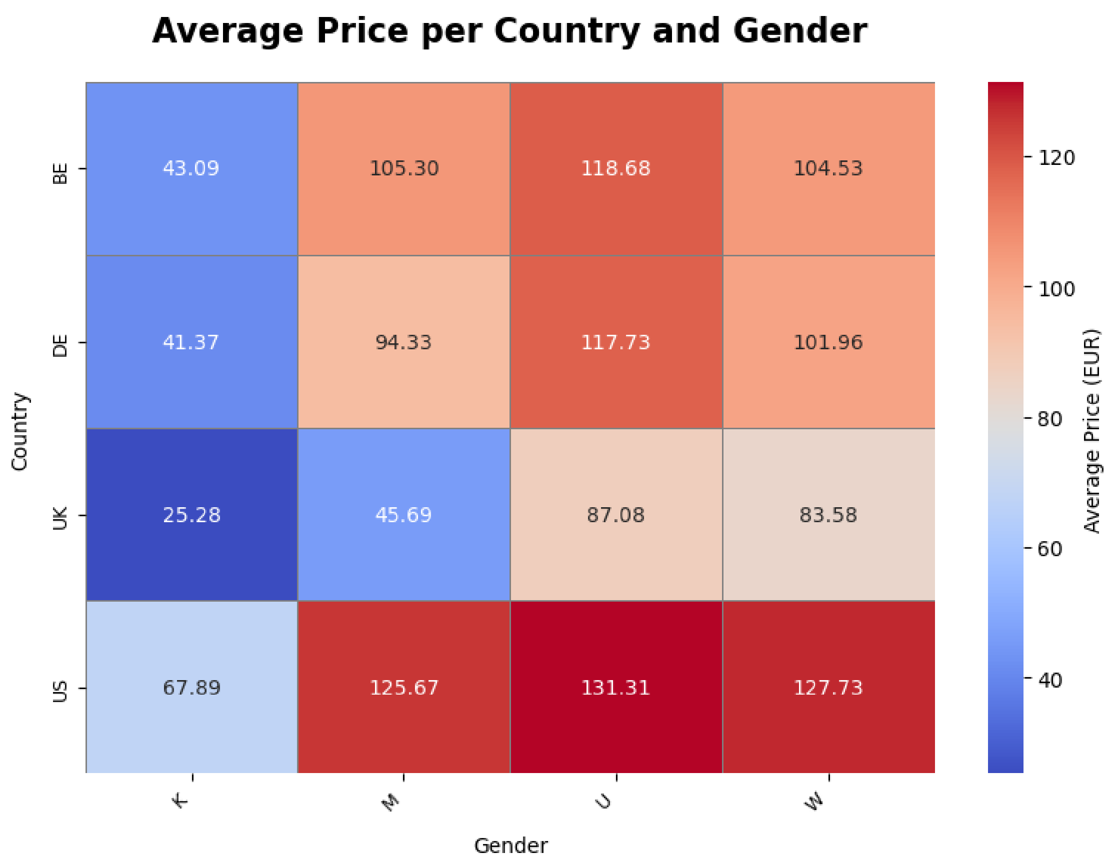


It is interesting to note that prices tend to be higher in the Unisex Gender particularly for football shoes.

[41]:
```
country_gender_prices = adidas_shoes_df.groupby(['country', 'gender'])['Prices␣
↪in Euros'].mean().unstack()

plt.figure(figsize=(8, 6))
sns.heatmap(
    country_gender_prices,
    annot=True,
    fmt=".2f",
    cmap="coolwarm",
    cbar=True,
```

```
    linewidths=0.5,
    linecolor='gray',
    cbar_kws={'label': 'Average Price (EUR)'}
)
plt.title('Average Price per Country and Gender', fontsize=16, weight='bold',␣
 ↪pad=20)
plt.xlabel('Gender', fontsize=10, labelpad=10)
plt.ylabel('Country', fontsize=10, labelpad=10)
plt.xticks(rotation=45, ha='right', fontsize=9)
plt.yticks(fontsize=9)
plt.tight_layout()
plt.show()
```



It is interesting to note that prices tend to be higher in the United States compared to European countries for all the Gender category.

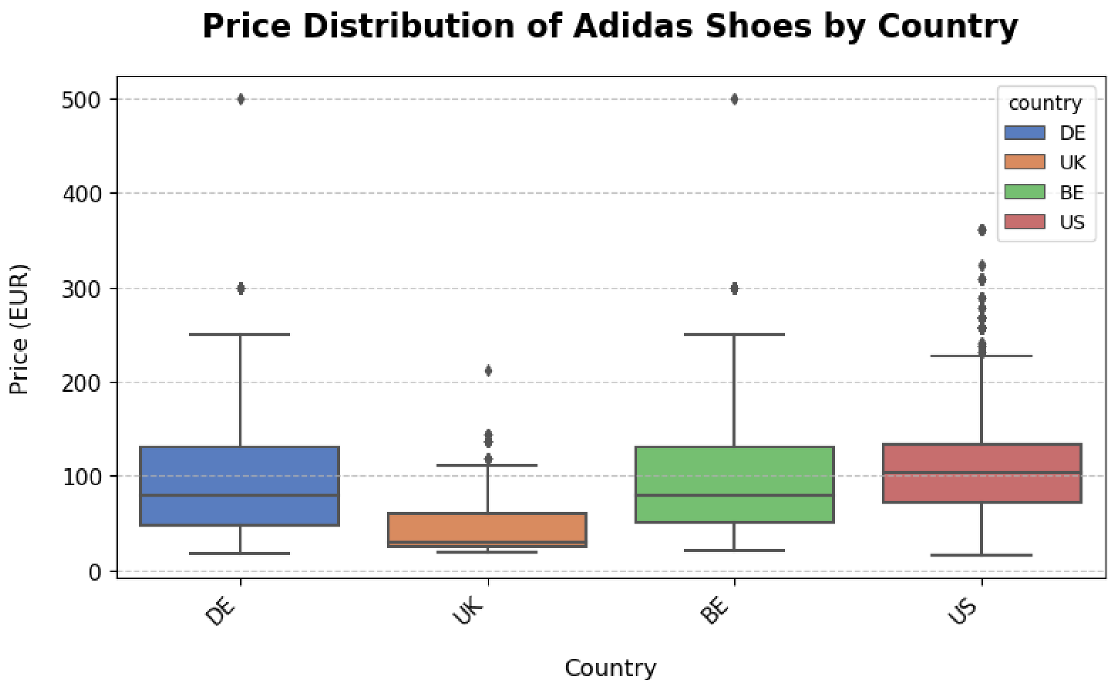
[42]:
```
plt.figure(figsize=(8, 5))

sns.boxplot(
    x='country',
```

```
    y='Prices in Euros',
    data=adidas_shoes_df,
    palette="muted",
    hue='country',
    linewidth=1.5,
    dodge=False,
    fliersize=4
)

plt.title(
    'Price Distribution of Adidas Shoes by Country',
    fontsize=16,
    weight='bold',
    pad=20
)

plt.xlabel('Country', fontsize=12, labelpad=15)
plt.ylabel('Price (EUR)', fontsize=12, labelpad=15)
plt.xticks(rotation=45, ha='right', fontsize=11)
plt.yticks(fontsize=11)
plt.grid(True, axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



At first glance, it appears that shoe prices in the US tend to be higher compared to other overseas countries. Notably, the UK includes only one category of shoes, namely 'sneaker shoes.' Meanwhile, BE and DE exhibit a similar pricing pattern, with outliers distributed relatively homogeneously within their respective trends.

In order to test these hypothesis we can conduct the ANOVA Analysis.

2.4 ANOVA Analysis - To test the prices of shoes based on the countries in the above graph

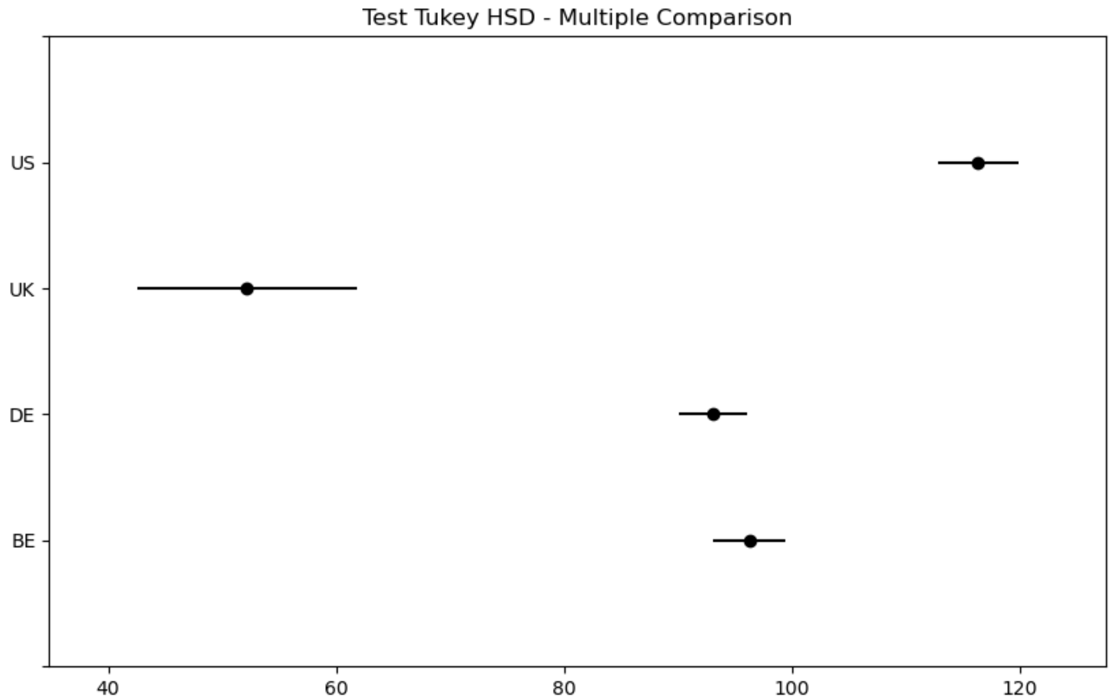
The ANOVA (Analysis of Variance) test compares the variability within each group (country) to the variability between the groups. ANOVA will be used to determine whether there are statistically significant differences in the mean shoe prices among the four countries. If the p-value is below a chosen significance level (0.05), it indicates that at least one country has a mean price that significantly differs from the others. However, it does not specify which countries differ; to see that additional post-hoc will provide for that.

[43]:
```
from scipy.stats import f_oneway
from statsmodels.stats.multicomp import pairwise_tukeyhsd

# ANOVA
groups = [group['Prices in Euros'].values for _, group in adidas_shoes_df.
 ↪groupby('country')]
anova_result = f_oneway(*groups)
print(f"F-statistic: {anova_result.statistic:.2f}")
print(f"P-value: {anova_result.pvalue:.4f}")

# Test Tukey HSD
tukey = pairwise_tukeyhsd(endog=adidas_shoes_df['Prices in Euros'],␣
 ↪groups=adidas_shoes_df['country'], alpha=0.05)
print(tukey)
tukey.plot_simultaneous()
plt.title("Test Tukey HSD - Multiple Comparison")
plt.show()
```

```
F-statistic: 63.70
P-value: 0.0000
 Multiple Comparison of Means - Tukey HSD, FWER=0.05
======================================================
group1 group2 meandiff p-adj   lower    upper   reject
------------------------------------------------------
    BE     DE  -3.2258 0.5133  -9.2429   2.7913  False
    BE     UK  -44.083    0.0 -56.9167 -31.2493   True
    BE     US  20.0258    0.0  13.2418  26.8099   True
    DE     UK -40.8572    0.0 -53.5546 -28.1599   True
    DE     US  23.2516    0.0  16.7292   29.774   True
    UK     US  64.1089    0.0  51.0307  77.1871   True
------------------------------------------------------
```



Based on the ANOVA test and, subsequently, the Tukey HSD test, no significant differences were found between BE and DE, both of which exhibit similar prices across the reported categories. This is not the case for the US, which, as shown in the graph and indicated by the p-value from the test, has a higher average shoe price compared to the other countries. The analysis also reveals statistically significant differences between most group pairs except BE vs DE, where their mean difference is not significant. This suggests that most groups have distinct mean values, except for BE and DE, which are similar.