In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
sns.set_theme(color_codes=True)
```

In [2]:
```
df = pd.read_csv('pizza_v1.csv')
df.head()
```

Out[2]:

	company	price_rupiah	diameter	topping	variant	size	extra_sauce	extra_cheese
0	A	Rp235,000	22.0	chicken	double_signature	jumbo	yes	yes
1	A	Rp198,000	20.0	papperoni	double_signature	jumbo	yes	yes
2	A	Rp120,000	16.0	mushrooms	double_signature	reguler	yes	yes
3	A	Rp155,000	14.0	smoked beef	double_signature	reguler	yes	no
4	A	Rp248,000	18.0	mozzarella	double_signature	jumbo	yes	no

Data Preprocessing Part 1

In [3]:
```
# remove "Rp" and comma from "price_rupiah" column
df['price_rupiah'] = df['price_rupiah'].str.replace('Rp', '').str.replace(',', '')
```

In [4]:
```
df.head()
```

Out[4]:

	company	price_rupiah	diameter	topping	variant	size	extra_sauce	extra_cheese
0	A	235000	22.0	chicken	double_signature	jumbo	yes	yes
1	A	198000	20.0	papperoni	double_signature	jumbo	yes	yes
2	A	120000	16.0	mushrooms	double_signature	reguler	yes	yes
3	A	155000	14.0	smoked beef	double_signature	reguler	yes	no
4	A	248000	18.0	mozzarella	double_signature	jumbo	yes	no

In [5]:
```
#Check the number of unique value on object datatype
df.select_dtypes(include='object').nunique()
```

Out[5]:
```
company          5
price_rupiah    43
topping         12
variant         20
size             6
extra_sauce      2
extra_cheese     2
dtype: int64
```

In [6]:
```
# convert "Amount" column to integer
df['price_rupiah'] = df['price_rupiah'].astype(int)
```

Segment Pizza Variant

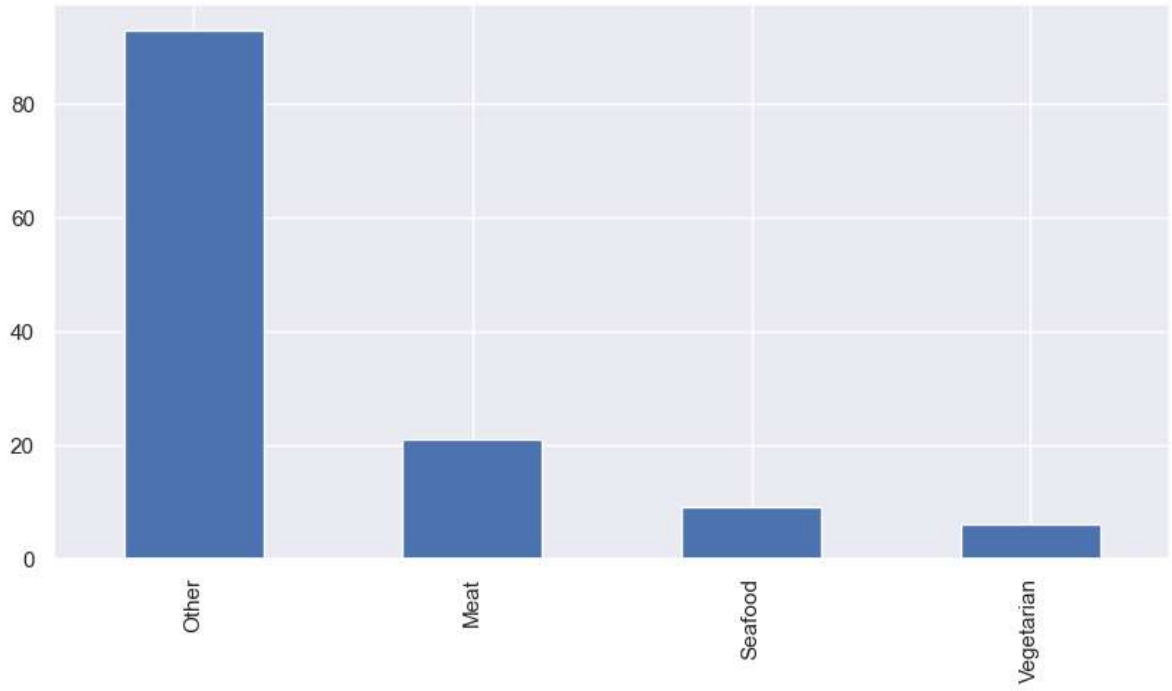
In [7]:
```
df.variant.unique()
```

Out[7]:
```
array(['double_signature', 'american_favorite', 'super_supreme',
       'meat_lovers', 'double_mix', 'classic', 'crunchy', 'new_york',
       'double_decker', 'spicy_tuna', 'BBQ_meat_fiesta', 'BBQ_sausage',
       'extravaganza', 'meat_eater', 'gournet_greek', 'italian_veggie',
       'thai_veggie', 'american_classic', 'neptune_tuna', 'spicy tuna'],
      dtype=object)
```

In [8]:
```
# define function to segment pizza names into types
def segment_variant(variant):
    if 'veggie' in variant:
        return 'Vegetarian'
    elif 'meat' in variant or 'BBQ' in variant:
        return 'Meat'
    elif 'tuna' in variant:
        return 'Seafood'
    else:
        return 'Other'

# apply function to 'Pizza Name' column to create new 'Pizza Type' column
df['variant'] = df['variant'].apply(segment_variant)
```

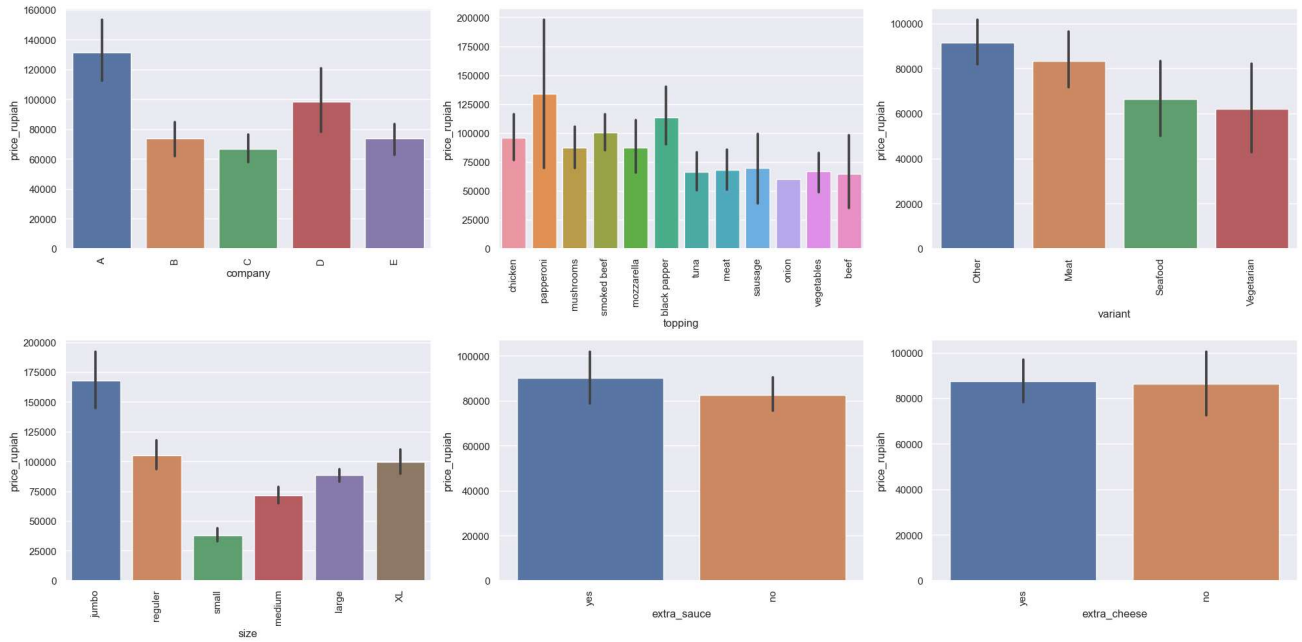
In [9]:
```
plt.figure(figsize=(10,5))
df['variant'].value_counts().plot(kind='bar')
```

Out[9]: <AxesSubplot:>



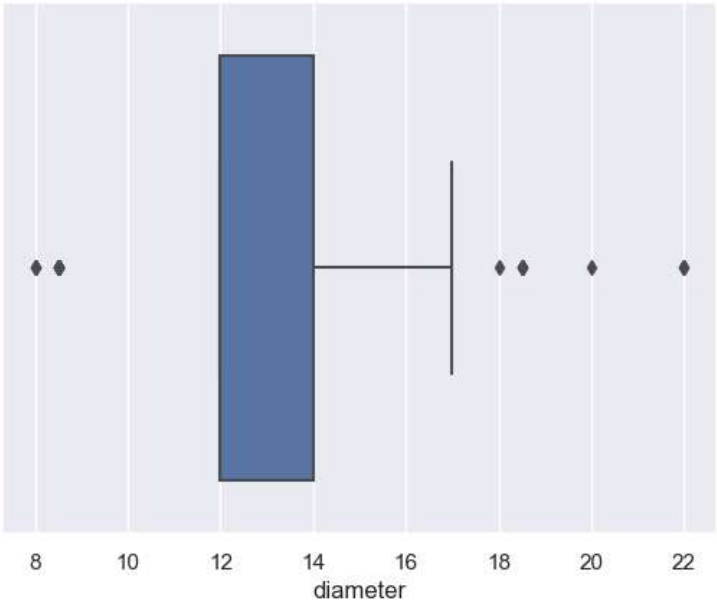
Exploratory Data Analysis

In [11]:
```
# list of categorical variables to plot
cat_vars = ['company', 'topping', 'variant', 'size', 'extra_sauce', 'extra_cheese']

# create figure with subplots
fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(20, 10))
axs = axs.ravel()

# create barplot for each categorical variable
for i, var in enumerate(cat_vars):
    sns.barplot(x=var, y='price_rupiah', data=df, ax=axs[i], estimator=np.mean)
    axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation=90)

# adjust spacing between subplots
fig.tight_layout()

# show plot
plt.show()
```



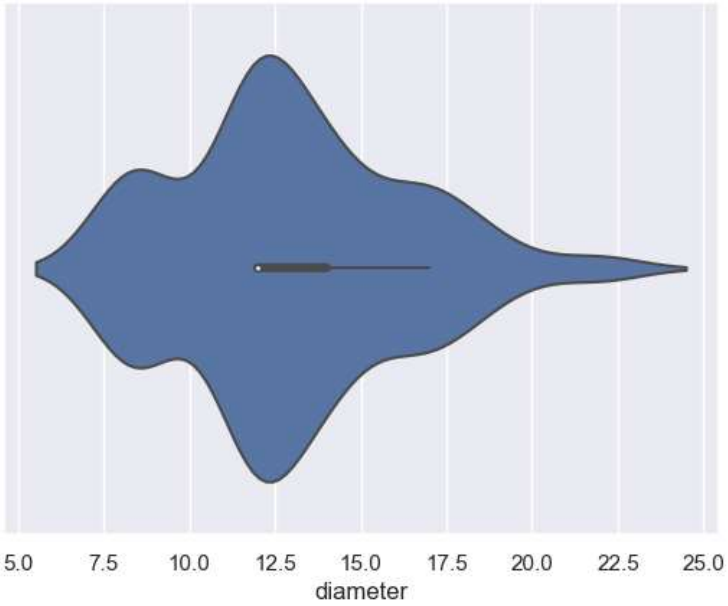
In [12]:
```
sns.boxplot(x='diameter', data=df)
```

Out[12]: <AxesSubplot:xlabel='diameter'>



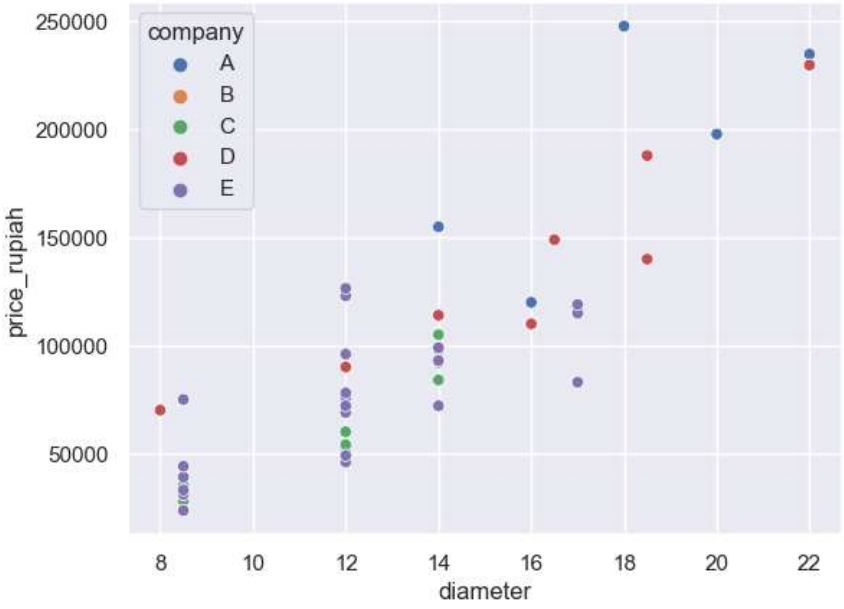
In [13]:
```
sns.violinplot(x='diameter', data=df)
```

Out[13]:
```
<AxesSubplot:xlabel='diameter'>
```



In [14]:
```
sns.scatterplot(data=df, x="diameter", y="price_rupiah", hue="company")
```

Out[14]:
```
<AxesSubplot:xlabel='diameter', ylabel='price_rupiah'>
```



Data Preprocessing Part 2

In [15]:
```
df.head()
```

Out[15]:

	company	price_rupiah	diameter	topping	variant	size	extra_sauce	extra_cheese
0	A	235000	22.0	chicken	Other	jumbo	yes	yes
1	A	198000	20.0	papperoni	Other	jumbo	yes	yes
2	A	120000	16.0	mushrooms	Other	reguler	yes	yes
3	A	155000	14.0	smoked beef	Other	reguler	yes	no
4	A	248000	18.0	mozzarella	Other	jumbo	yes	no

In [16]:
```
#Check missing value
check_missing = df.isnull().sum() * 100 / df.shape[0]
check_missing[check_missing > 0].sort_values(ascending=False)
```

Out[16]:
```
Series([], dtype: float64)
```

Label Encoding for Object datatype

In [17]:
```
# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Print the column name and the unique values
    print(f"{col}: {df[col].unique()}")
```

```
company: ['A' 'B' 'C' 'D' 'E']
topping: ['chicken' 'papperoni' 'mushrooms' 'smoked beef' 'mozzarella'
 'black papper' 'tuna' 'meat' 'sausage' 'onion' 'vegetables' 'beef']
variant: ['Other' 'Meat' 'Seafood' 'Vegetarian']
size: ['jumbo' 'reguler' 'small' 'medium' 'large' 'XL']
extra_sauce: ['yes' 'no']
extra_cheese: ['yes' 'no']
```

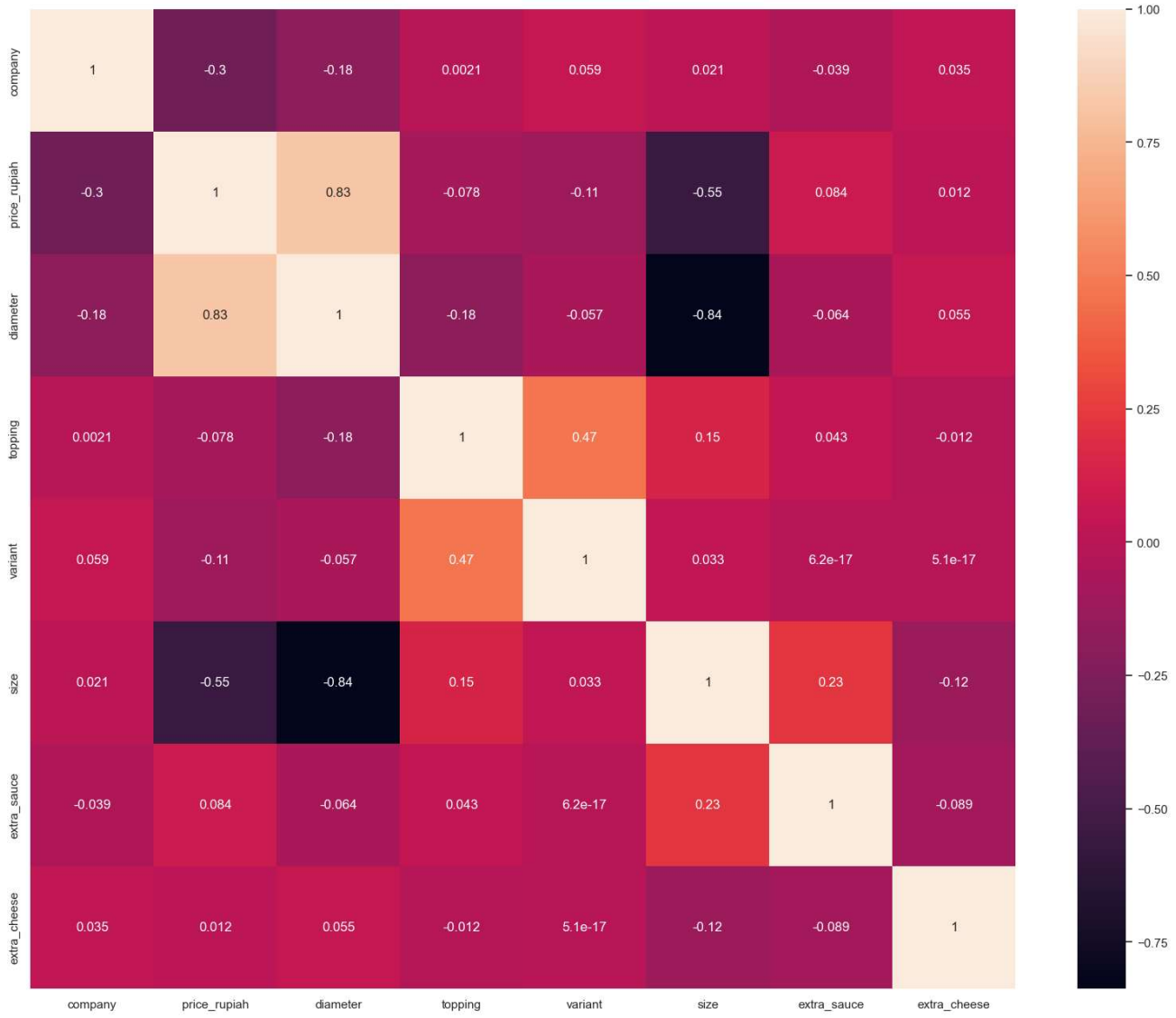
In [18]:
```
from sklearn import preprocessing

# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Initialize a LabelEncoder object
    label_encoder = preprocessing.LabelEncoder()

    # Fit the encoder to the unique values in the column
    label_encoder.fit(df[col].unique())

    # Transform the column using the encoder
    df[col] = label_encoder.transform(df[col])

    # Print the column name and the unique encoded values
    print(f"{col}: {df[col].unique()}")
```

```
company: [0 1 2 3 4]
topping: [ 2  7  5  9  4  1 10  3  8  6 11  0]
variant: [1 0 2 3]
size: [1 4 5 3 2 0]
extra_sauce: [1 0]
extra_cheese: [1 0]
```

I will not remove the outlier because the dataset is very small

In [19]:
```
#Correlation Heatmap
plt.figure(figsize=(20, 16))
sns.heatmap(df.corr(), fmt='.2g', annot=True)
```

Out[19]: <AxesSubplot:>



Train Test Split

In [20]:
```
X = df.drop('price_rupiah', axis=1)
y = df['price_rupiah']
```

In [21]:
```
#test size 20% and train size 80%
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2,random_state=0)
```

Decision Tree Regressor

In [22]:
```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.datasets import load_boston


# Create a DecisionTreeRegressor object
dtree = DecisionTreeRegressor()

# Define the hyperparameters to tune and their values
param_grid = {
    'max_depth': [2, 4, 6, 8],
    'min_samples_split': [2, 4, 6, 8],
    'min_samples_leaf': [1, 2, 3, 4],
    'max_features': ['auto', 'sqrt', 'log2']
}

# Create a GridSearchCV object
grid_search = GridSearchCV(dtree, param_grid, cv=5, scoring='neg_mean_squared_error')

# Fit the GridSearchCV object to the data
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print(grid_search.best_params_)
```

```
{'max_depth': 8, 'max_features': 'auto', 'min_samples_leaf': 1, 'min_samples_split': 2}
```

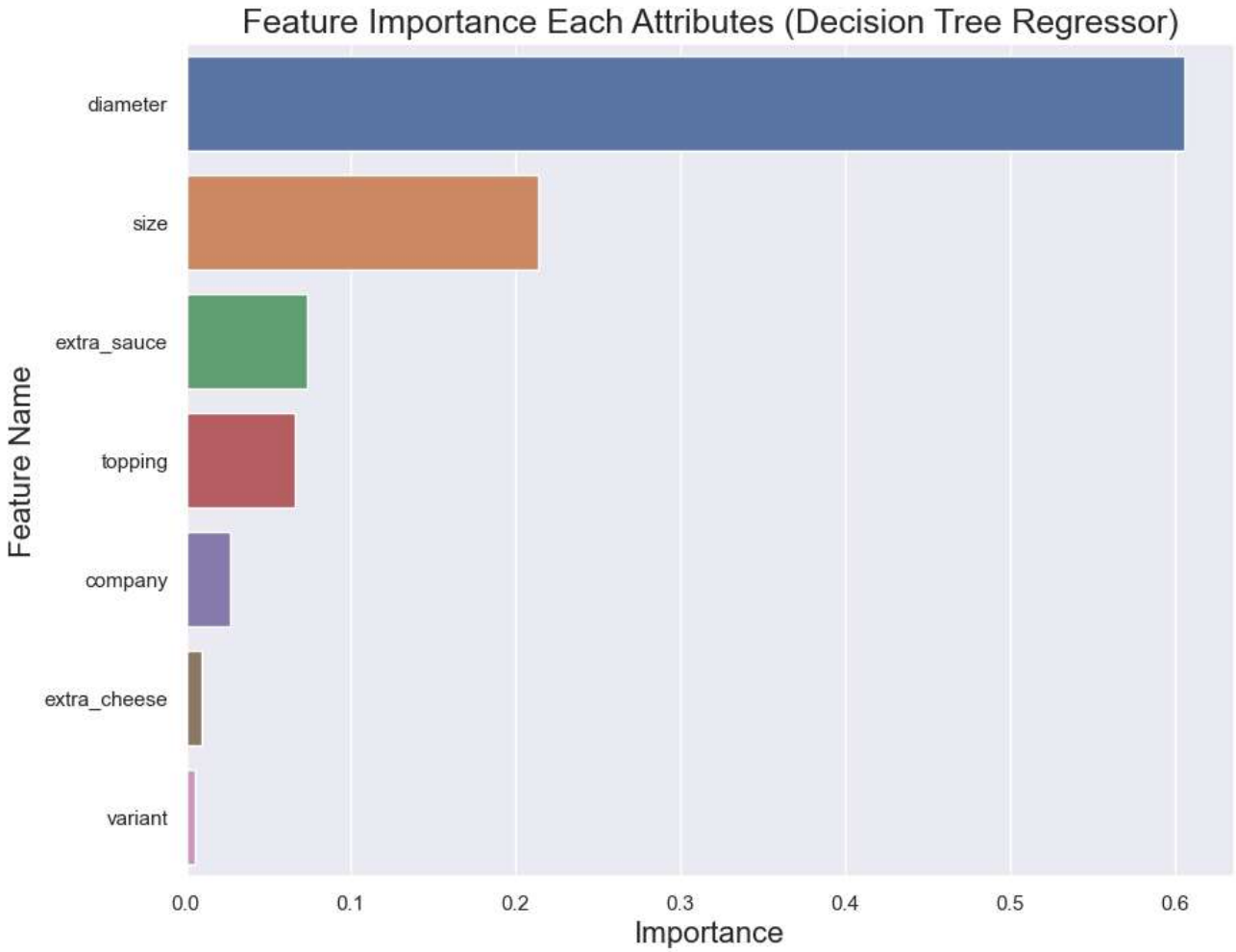
In [23]:
```
from sklearn.tree import DecisionTreeRegressor
dtree = DecisionTreeRegressor(random_state=0, max_depth=8, max_features='auto', min_samples_leaf=1, min_samples_split=
dtree.fit(X_train, y_train)
```

Out[23]:
```
DecisionTreeRegressor(max_depth=8, max_features='auto', random_state=0)
```

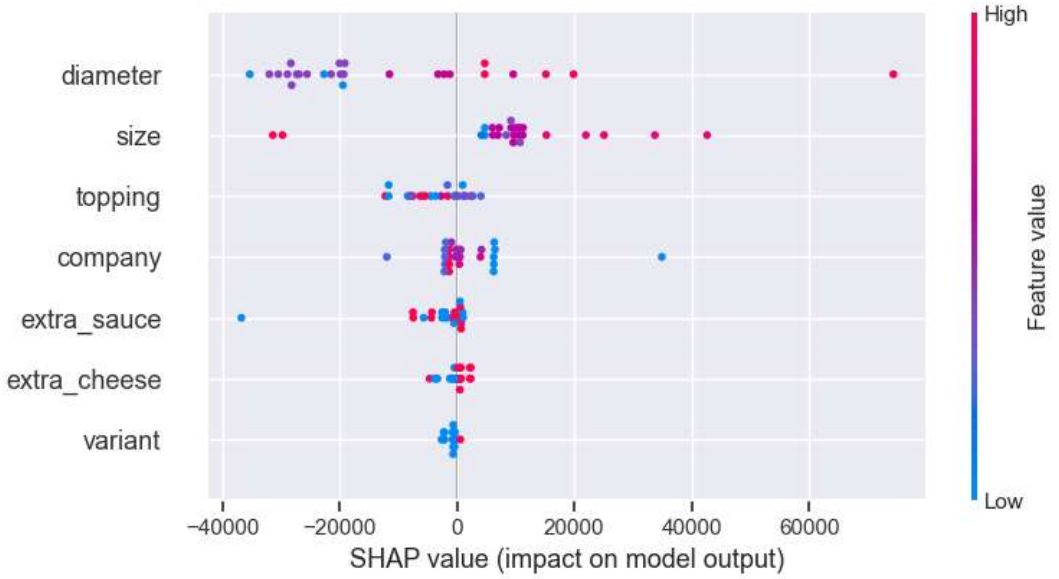
In [24]:
```
from sklearn import metrics
from sklearn.metrics import mean_absolute_percentage_error
import math
y_pred = dtree.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

print('MAE is {}'.format(mae))
print('MAPE is {}'.format(mape))
print('MSE is {}'.format(mse))
print('R2 score is {}'.format(r2))
print('RMSE score is {}'.format(rmse))
```

```
MAE is 8896.153846153846
MAPE is 0.11478195348575036
MSE is 173730965.46310833
R2 score is 0.7989720567793299
RMSE score is 13180.704285549704
```

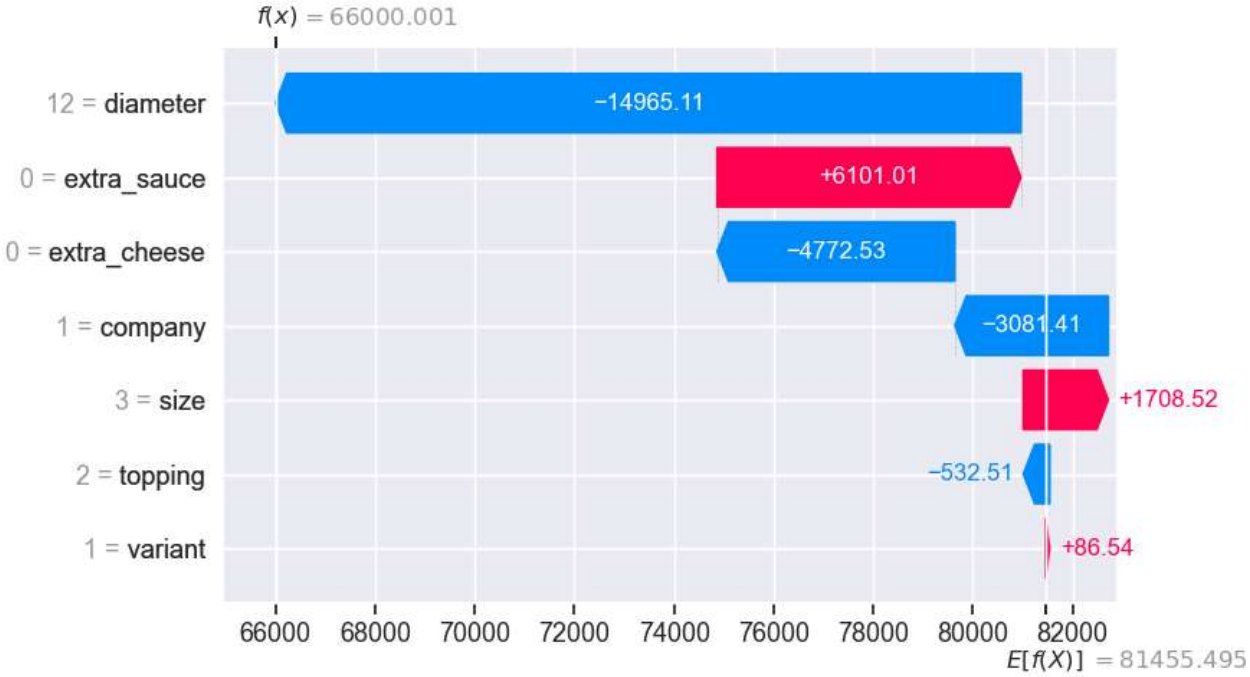
In [25]:
```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": dtree.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Feature Importance Each Attributes (Decision Tree Regressor)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



In [26]:
```
import shap
explainer = shap.TreeExplainer(dtree)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```



In [27]:
```
explainer = shap.Explainer(dtree, X_test)
shap_values = explainer(X_test)
shap.plots.waterfall(shap_values[0])
```



Random Forest Regressor

In [28]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV

# Create a Random Forest Regressor object
rf = RandomForestRegressor()

# Define the hyperparameter grid
param_grid = {
    'max_depth': [3, 5, 7, 9],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt']
}

# Create a GridSearchCV object
grid_search = GridSearchCV(rf, param_grid, cv=5, scoring='r2')

# Fit the GridSearchCV object to the training data
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print("Best hyperparameters: ", grid_search.best_params_)
```

```
Best hyperparameters:  {'max_depth': 9, 'max_features': 'auto', 'min_samples_leaf': 1, 'min_samples_split': 2}
```

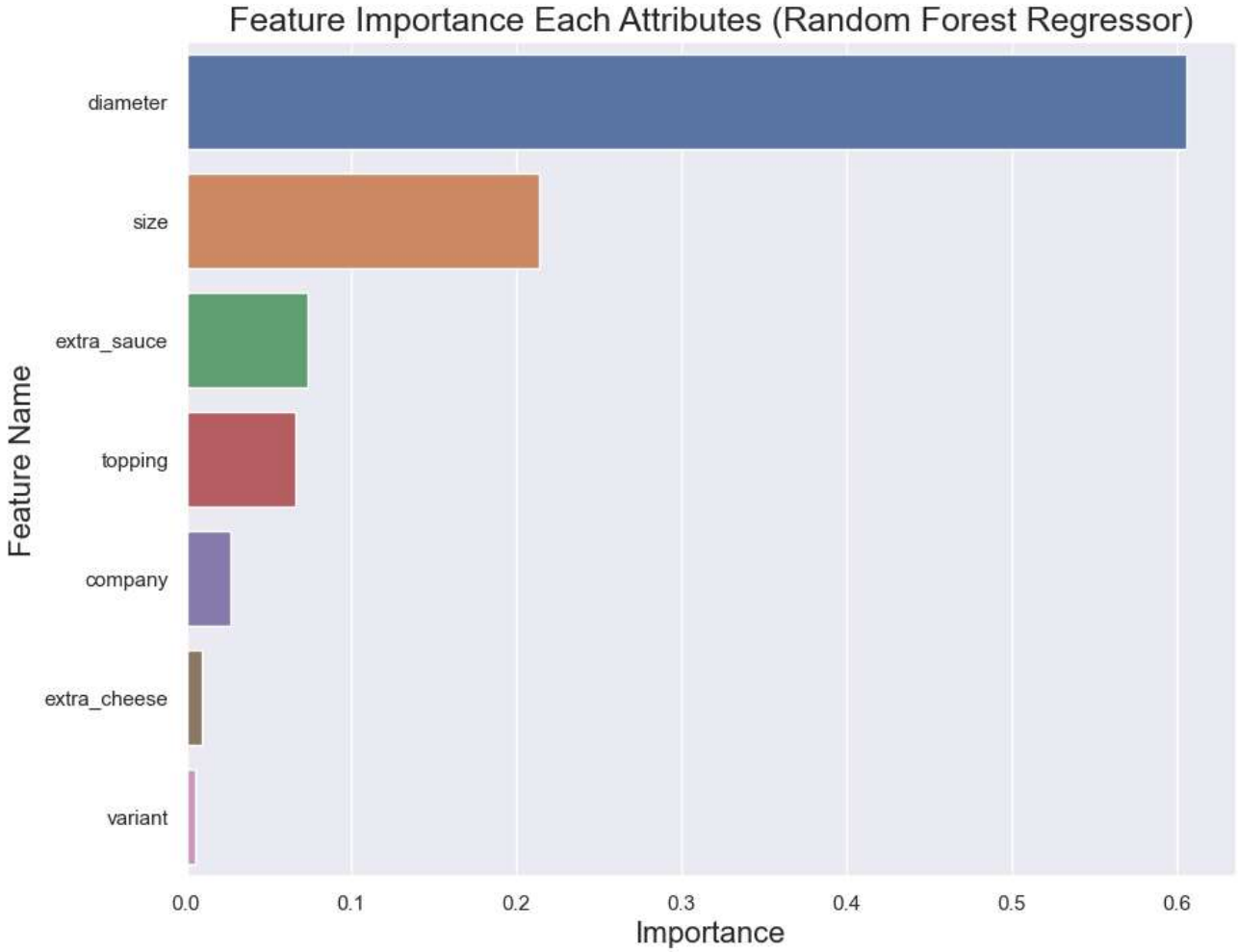
In [29]:
```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor(random_state=0, max_depth=9, min_samples_split=2, min_samples_leaf=1,
                           max_features='auto')
rf.fit(X_train, y_train)
```

Out[29]:
```
RandomForestRegressor(max_depth=9, random_state=0)
```

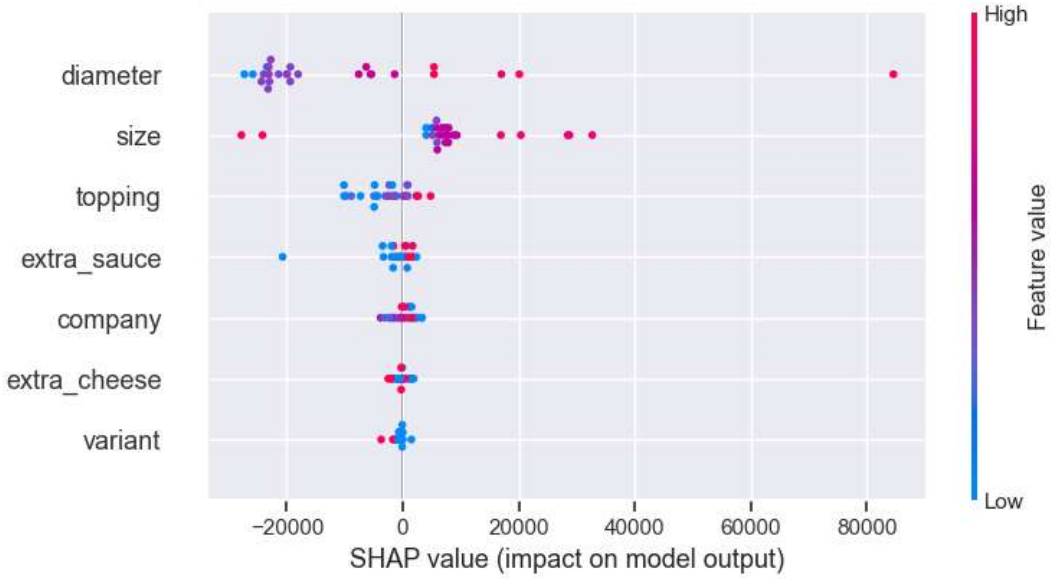
In [30]:
```
from sklearn import metrics
from sklearn.metrics import mean_absolute_percentage_error
import math
y_pred = rf.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

print('MAE is {}'.format(mae))
print('MAPE is {}'.format(mape))
print('MSE is {}'.format(mse))
print('R2 score is {}'.format(r2))
print('RMSE score is {}'.format(rmse))
```

```
MAE is 10979.558705183706
MAPE is 0.16435802453302076
MSE is 174617535.78390014
R2 score is 0.7979461866494185
RMSE score is 13214.292859774985
```

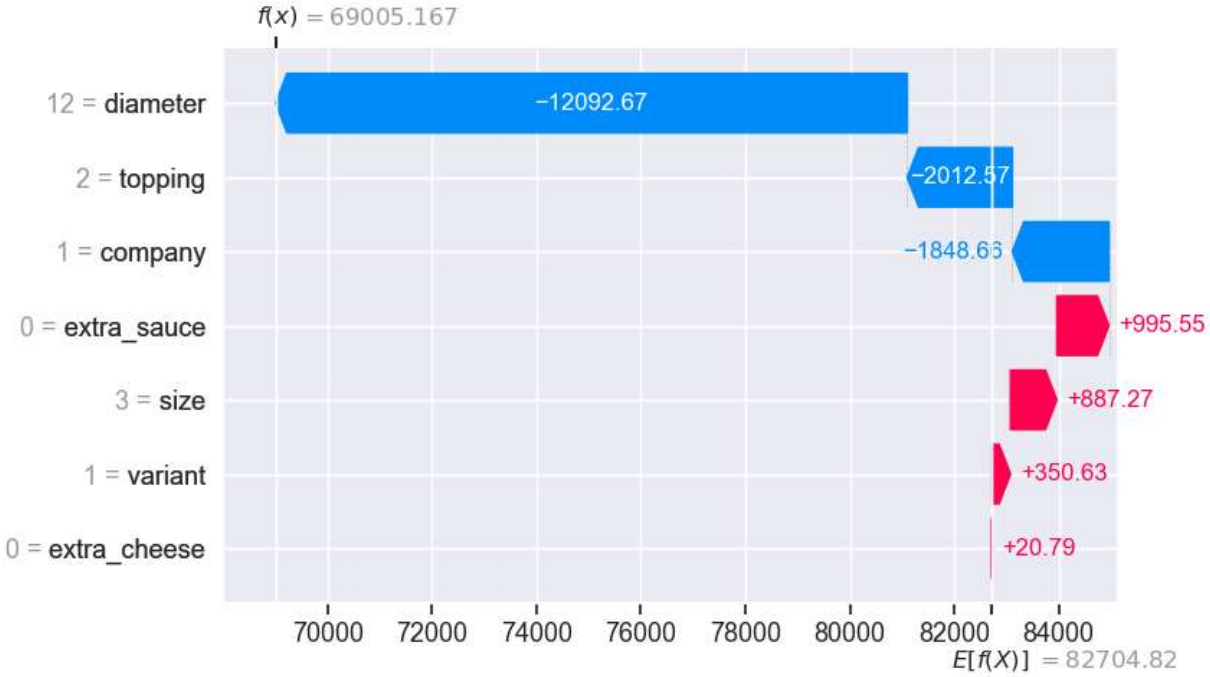
In [31]:
```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": dtree.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Feature Importance Each Attributes (Random Forest Regressor)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



In [32]:
```
import shap
explainer = shap.TreeExplainer(rf)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```



In [33]:
```
explainer = shap.Explainer(rf, X_test, check_additivity=False)
shap_values = explainer(X_test, check_additivity=False)
shap.plots.waterfall(shap_values[0])
```



AdaBoost Regressor

In [34]:
```
from sklearn.ensemble import AdaBoostRegressor
from sklearn.model_selection import GridSearchCV

# Define AdaBoostRegressor model
abr = AdaBoostRegressor()

# Define hyperparameters and possible values
params = {'n_estimators': [50, 100, 150],
          'learning_rate': [0.01, 0.1, 1, 10]}

# Perform GridSearchCV with 5-fold cross validation
grid_search = GridSearchCV(abr, param_grid=params, cv=5, scoring='neg_mean_squared_error')
grid_search.fit(X_train, y_train)

# Print best hyperparameters and corresponding score
print("Best hyperparameters: ", grid_search.best_params_)
```

```
Best hyperparameters:  {'learning_rate': 1, 'n_estimators': 50}
```

In [35]:
```
from sklearn.ensemble import RandomForestRegressor
abr = AdaBoostRegressor(random_state=0, learning_rate=1, n_estimators=50)
abr.fit(X_train, y_train)
```

Out[35]:
```
AdaBoostRegressor(learning_rate=1, random_state=0)
```

In [36]:
```
from sklearn import metrics
from sklearn.metrics import mean_absolute_percentage_error
import math
y_pred = abr.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

print('MAE is {}'.format(mae))
print('MAPE is {}'.format(mape))
print('MSE is {}'.format(mse))
print('R2 score is {}'.format(r2))
print('RMSE score is {}'.format(rmse))
```

```
MAE is 11310.953520583891
MAPE is 0.18546632912903405
MSE is 213998142.11136267
R2 score is 0.752378015933912
RMSE score is 14628.675336863645
```

In [37]:
```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": abr.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Feature Importance Each Attributes (AdaBoost Regressor)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```