Social Media Ad Performance Prediction 📈

Data: Social Media Ad Performance datasets (Source: I created my own data set).
This dataset will include features such as ad budget, audience size, ad duration, target age group, platform, and visual type, and we'll use these features to predict Conversions.

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Context

Many businesses use social media platforms like Facebook, Instagram, Twitter, and TikTok to reach target audiences and drive engagement or conversions through paid ads. Understanding what factors contribute to ad performance is crucial for maximizing return on investment (ROI).
Goal: Predict the number of conversions (click-throughs, sign-ups, etc.) on social media ads.

Objective

This analysis aims to predict the number of conversions (such as clicks, sign-ups, or purchases) based on various factors related to each ad. By identifying which variables impact performance, businesses can allocate ad budgets more effectively and improve targeting.

Data Structure

Ad Budget: Random float values representing the budget for each ad.
Audience Size: Random float values representing the size of the targeted audience.
Ad Duration: Random integer values for the number of days each ad runs.
Target Age Group: Randomly chosen median age groups (18, 25, 35, 45, 55).
Platform and Visual Type: Categorical variables encoded using dummy variables.
Conversions: Simulated as a combination of the features plus some noise for realism.

Introduction

Multiple linear regression model has the following structure:
y = β1x1 + β2x2 + ⋯ + βnxn + β0

where
y: response variable
n: number of features
xn: n-th feature
βn: regression coefficient (weight) of the n-th feature
β0: y-intercept

Retrieving Data

In [1]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
import seaborn as sns

# Load the data
df = pd.read_csv("File Dirr/social_media_ad_performance.csv")
```

```python
# Display the first few rows of the dataset
df.head()
```

Out[1]:

	Ad Budget	Audience Size	Ad Duration	Target Age Group	Platform_Facebook	Platform_Instagram	Platform_Twitter	Platform_T
0	1935.246582	70118.009688	15	18	False	False	True	
1	4758.500101	54073.540268	12	45	True	False	False	
2	3686.770315	31643.234012	16	18	False	True	False	
3	3033.426573	81565.706951	24	45	False	True	False	
4	864.491338	68788.386083	19	45	False	True	False	

Data Exploration and Preprocessing

In [2]:

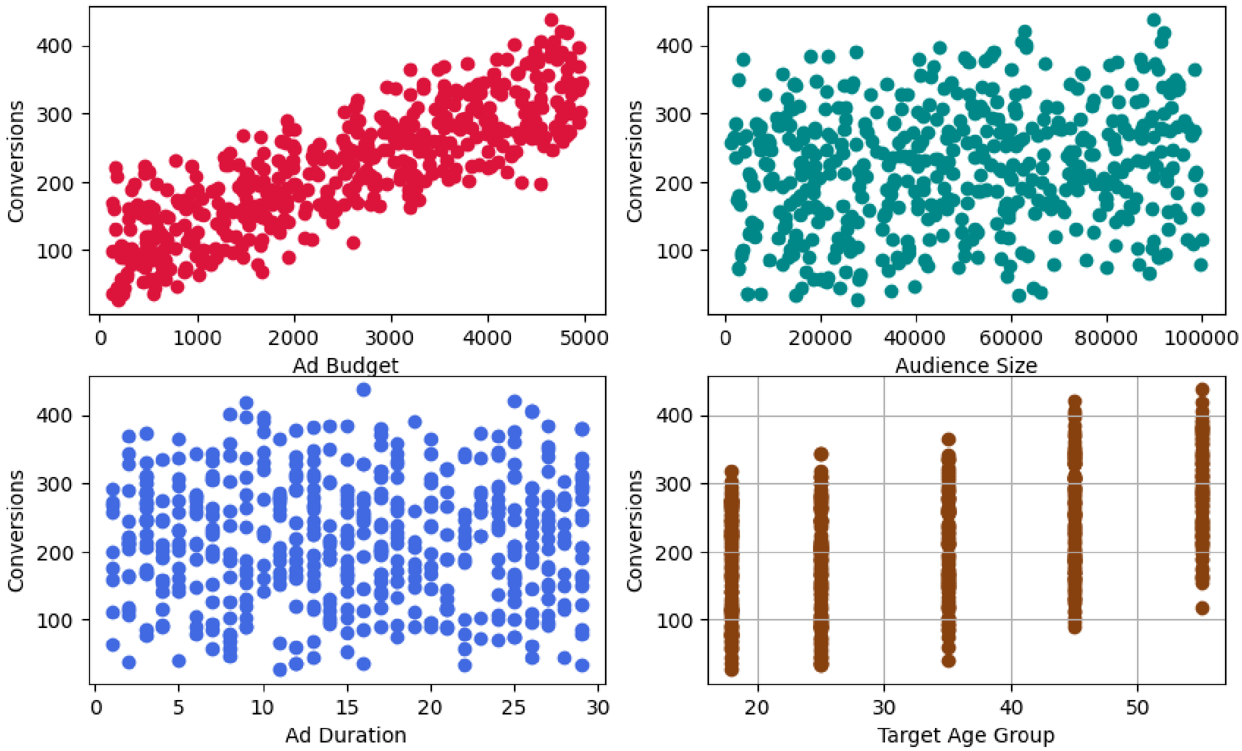
```python
# Display column names and data types
print(df.info())

# Basic statistics on the dataset
print(df.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Ad Budget           500 non-null    float64
 1   Audience Size       500 non-null    float64
 2   Ad Duration         500 non-null    int64  
 3   Target Age Group    500 non-null    int64  
 4   Platform_Facebook   500 non-null    bool   
 5   Platform_Instagram  500 non-null    bool   
 6   Platform_Twitter    500 non-null    bool   
 7   Platform_TikTok     500 non-null    bool   
 8   Visual_Image        500 non-null    bool   
 9   Visual_Video        500 non-null    bool   
 10  Conversions         500 non-null    float64
dtypes: bool(6), float64(3), int64(2)
memory usage: 22.6 KB
None
         Ad Budget  Audience Size  Ad Duration  Target Age Group  Conversions
count   500.000000     500.000000   500.000000        500.000000   500.000000
mean   2542.952390   48713.188046    15.448000         35.594000   219.688704
std    1463.573201   28263.852232     8.374698         13.432424    88.809447
min     124.801761    1458.570277     1.000000         18.000000    27.666693
25%    1282.270485   23680.825532     8.000000         25.000000   156.151314
50%    2614.502367   47710.335116    15.000000         35.000000   223.064555
75%    3805.011919   72907.345214    23.000000         45.000000   280.709974
max    4965.527501   99972.049655    29.000000         55.000000   437.184924
```

In [3]:

```python
# Pair plot of numerical features
plt.rcParams["figure.figsize"] = (10,6)

plt.subplot(2,2,1)
plt.scatter(df['Ad Budget'], df['Conversions'], c='#DC143C')
plt.xlabel("Ad Budget")
plt.ylabel("Conversions")

plt.subplot(2,2,2)
plt.scatter(df['Audience Size'], df['Conversions'], c='#008B8B')
plt.xlabel("Audience Size")
plt.ylabel("Conversions")
```

```
plt.subplot(2,2,3)
plt.scatter(df['Ad Duration'], df['Conversions'], c='#4169E1')
plt.xlabel("Ad Duration")
plt.ylabel("Conversions")

plt.subplot(2,2,4)
plt.scatter(df['Target Age Group'], df['Conversions'], c='#8B4513')
plt.xlabel("Target Age Group")
plt.ylabel("Conversions")
plt.grid()
```



Feature Selection and Engineering

In [4]:
```
# Selecting relevant features
features = ['Ad Budget', 'Audience Size', 'Ad Duration', 'Target Age Group',
            'Platform_Facebook', 'Platform_Instagram', 'Platform_Twitter', 'Platform_TikTok',
            'Visual_Image', 'Visual_Video']

# Filter the dataset for selected features and target variable
df = df.reindex(columns=features + ['Conversions'])

# Drop rows with missing values for simplicity
df = df.dropna()
df.head()
```

Out[4]:

	Ad Budget	Audience Size	Ad Duration	Target Age Group	Platform_Facebook	Platform_Instagram	Platform_Twitter	Platform_T
0	1935.246582	70118.009688	15	18	False	False	True	
1	4758.500101	54073.540268	12	45	True	False	False	
2	3686.770315	31643.234012	16	18	False	True	False	
3	3033.426573	81565.706951	24	45	False	True	False	
4	864.491338	68788.386083	19	45	False	True	False	

Feature Encoding

In [5]:
```
new_df = pd.DataFrame(df, columns=features + ['Conversions'])

from sklearn.preprocessing import LabelEncoder

# Fit and transform the categorical data
le = LabelEncoder()
new_df['Platform_Facebook'] = le.fit_transform(df['Platform_Facebook'])
new_df['Platform_Instagram'] = le.fit_transform(df['Platform_Instagram'])
new_df['Platform_Twitter'] = le.fit_transform(df['Platform_Twitter'])
new_df['Platform_TikTok'] = le.fit_transform(df['Platform_TikTok'])
new_df['Visual_Image'] = le.fit_transform(df['Visual_Image'])
new_df['Visual_Video'] = le.fit_transform(df['Visual_Video'])
```

In [6]:
```
new_df.head()
```

Out[6]:

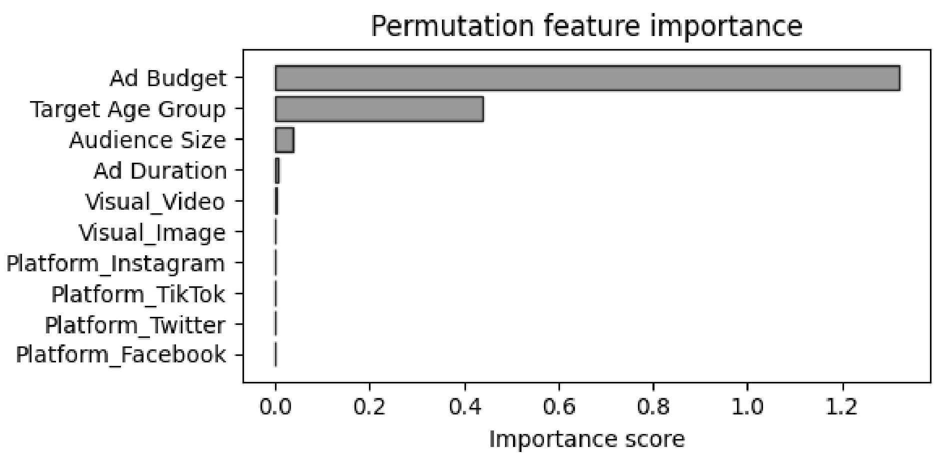
	Ad Budget	Audience Size	Ad Duration	Target Age Group	Platform_Facebook	Platform_Instagram	Platform_Twitter	Platform_T
0	1935.246582	70118.009688	15	18	0	0	1	
1	4758.500101	54073.540268	12	45	1	0	0	
2	3686.770315	31643.234012	16	18	0	1	0	
3	3033.426573	81565.706951	24	45	0	1	0	
4	864.491338	68788.386083	19	45	0	1	0	

- Permutation Feature Importances -

We have ten features (Ad Budget, Audience Size, Ad Duration, Target Age Group, Platform_Facebook, Platform_Instagram, Platform_Twitter, Platform_TikTok, Visual_Image, Visual_Video) to predict the response variable (Conversions). Based on the permutation feature importances shown in figure below, 'Ad Budget' is the most important feature, and 'Target Age Group' is the second most important feature".
Feature importances are obtained with rfpimp python library.

In [7]:
```
import rfpimp
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split

# Train/test split
df_train, df_test = train_test_split(new_df, test_size=0.20)

X_train, y_train = df_train.drop('Conversions',axis=1), df_train['Conversions']
X_test, y_test = df_test.drop('Conversions',axis=1), df_test['Conversions']
```

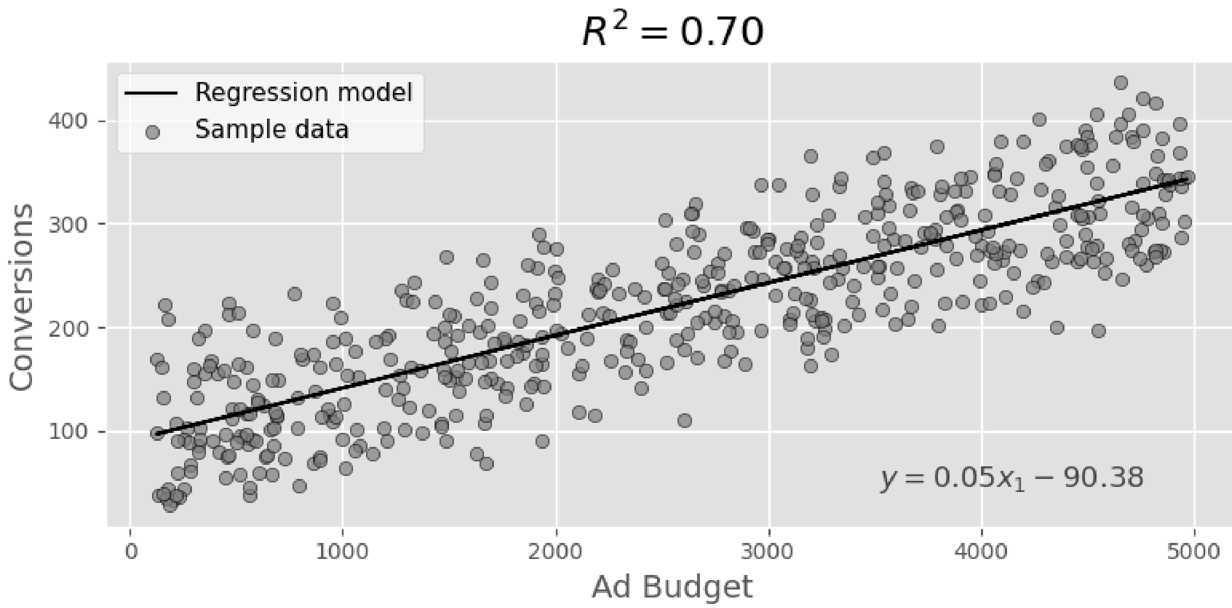
```
# Train
rf = RandomForestRegressor(n_estimators=100, n_jobs=-1)
rf.fit(X_train, y_train)

# Permutation feature importance
imp = rfpimp.importances(rf, X_test, y_test)

# Plot
fig, ax = plt.subplots(figsize=(6, 3))

ax.barh(imp.index, imp['Importance'], height=0.8, facecolor='grey', alpha=0.8, edgecolor='k')
ax.set_xlabel('Importance score')
ax.set_title('Permutation feature importance')
ax.text(0.8, 0.15, '', fontsize=12, ha='center', va='center', transform=ax.transAxes, color='grey', alpha=0
plt.gca().invert_yaxis()

fig.tight_layout()
```



- Visualize 2D bivariate linear regression model -

First, let's visualize 2D bivariate linear regression model, using 'Ad Budget' as a single feature. Although 'Ad Budget' is the most important feature regarding 'Conversions', 'Ad Budget' alone captured only 70% of variance of the data.

In [8]:
```
from sklearn import linear_model

X = new_df['Ad Budget'].values.reshape(-1,1)
y = new_df['Conversions'].values

ols = linear_model.LinearRegression()
model = ols.fit(X, y)
response = model.predict(X)

r2 = model.score(X, y)

plt.style.use('default')
plt.style.use('ggplot')

fig, ax = plt.subplots(figsize=(8, 4))

ax.plot(X, response, color='k', label='Regression model')
ax.scatter(X, y, edgecolor='k', facecolor='grey', alpha=0.7, label='Sample data')
ax.set_ylabel('Conversions', fontsize=14)
ax.set_xlabel('Ad Budget', fontsize=14)
ax.text(0.8, 0.1, '$y = %.2f x_1 - %.2f $' % (model.coef_[0], abs(model.intercept_)), fontsize=13, ha='cent
         transform=ax.transAxes, color='k', alpha=0.7)
ax.legend(facecolor='white', fontsize=11)
ax.set_title('$R^2= %.2f$' % r2, fontsize=18)

fig.tight_layout()
```

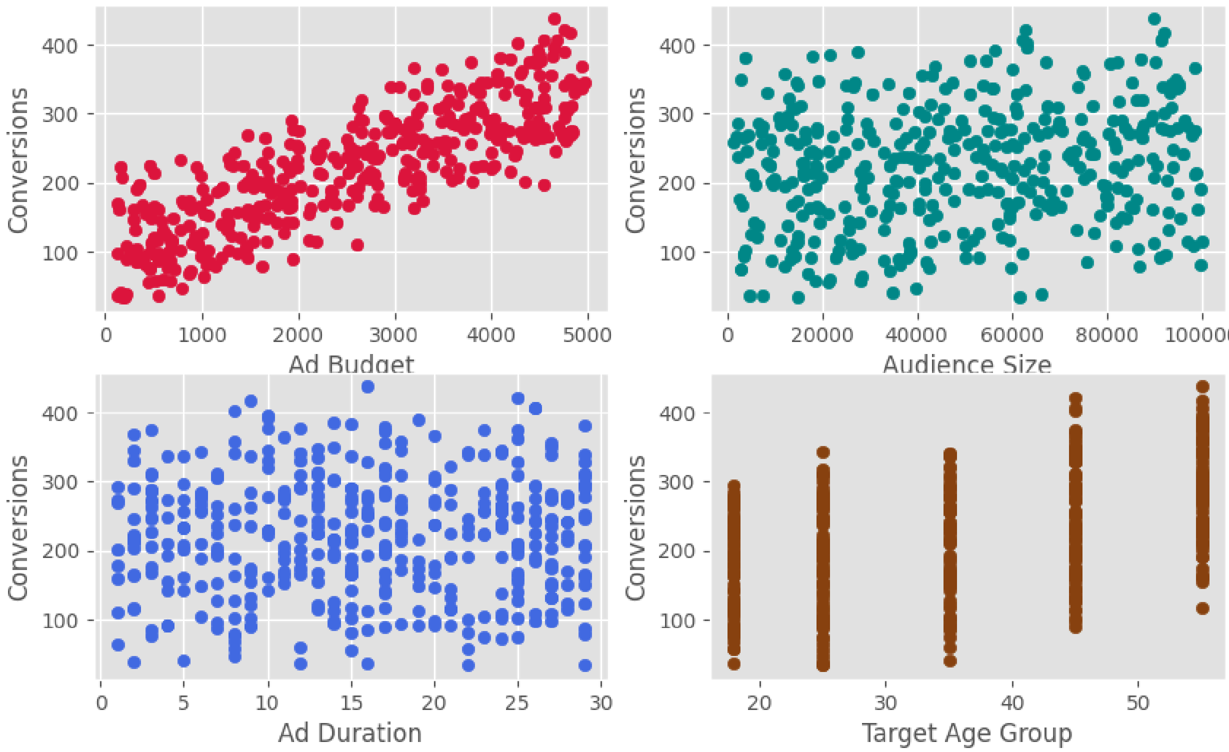


Creating Train and Test Dataset

In [9]:
```
import numpy as np
msk = np.random.rand(len(new_df)) < 0.8
train = new_df[msk]
test = new_df[~msk]
```

Train data distribution

In [10]:
```
plt.rcParams["figure.figsize"] = (10,6)

plt.subplot(2,2,1)
plt.scatter(train['Ad Budget'], train['Conversions'], c='#DC143C')
plt.xlabel("Ad Budget")
plt.ylabel("Conversions")

plt.subplot(2,2,2)
plt.scatter(train['Audience Size'], train['Conversions'], c='#008B8B')
plt.xlabel("Audience Size")
plt.ylabel("Conversions")

plt.subplot(2,2,3)
plt.scatter(train['Ad Duration'], train['Conversions'], c='#4169E1')
plt.xlabel("Ad Duration")
plt.ylabel("Conversions")

plt.subplot(2,2,4)
plt.scatter(train['Target Age Group'], train['Conversions'], c='#8B4513')
plt.xlabel("Target Age Group")
plt.ylabel("Conversions")
plt.grid()
```



Multiple Regression Model

In reality, there are multiple variables that impact the Coefficients. When more than one independent variable is present, the process is called multiple linear regression.
We will declare six features: features = ['Ad Budget', 'Audience Size', 'Ad Duration', 'Target Age Group', 'Visual_Image', 'Visual_Video'].

In [11]:
```
from sklearn import linear_model
regr = linear_model.LinearRegression()
features = ['Ad Budget', 'Audience Size', 'Ad Duration', 'Target Age Group',
            'Visual_Image', 'Visual_Video']
x = np.asanyarray(train[features])
y = np.asanyarray(train[['Conversions']])
regr.fit (x, y)
# The coefficients & intercept
print ('Coefficients: ', np.round(regr.coef_, 3))
print ('Intercept: ', np.round(regr.intercept_,3))
```

```
Coefficients:  [[ 5.000e-02  1.000e-03  6.660e-01  3.042e+00  8.927e+00 -8.927e+00]]
Intercept:  [-49.914]
```

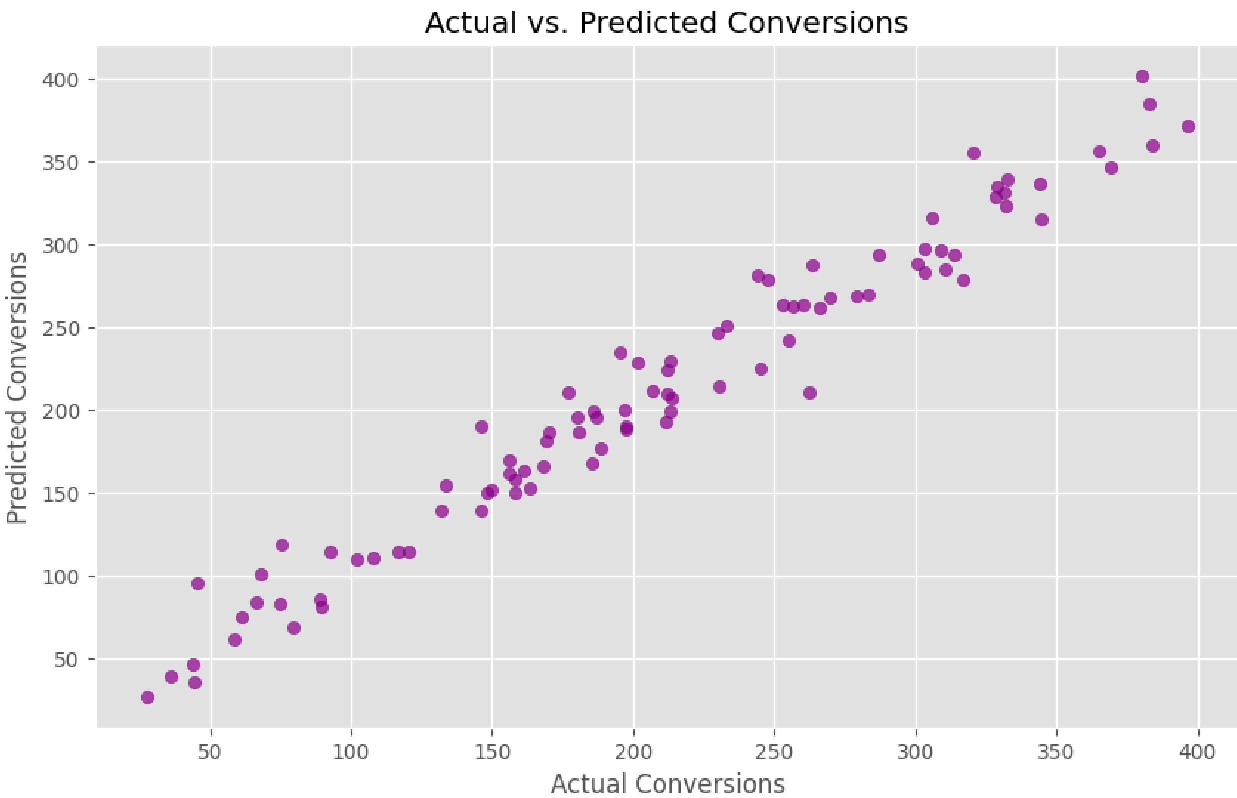
Prediction

In [12]:
```
x_test = np.asanyarray(test[features])
y_test = np.asanyarray(test[['Conversions']])
y_hat = regr.predict(x_test)

mse = mean_squared_error(y_test, y_hat)
r2 = r2_score(y_test, y_hat)

print("Mean Squared Error:", mse)
print("R-squared:", r2)

# Explained variance score: 1 is perfect prediction
print('Variance score: %.5f' % regr.score(x, y))
```

```
Mean Squared Error: 338.35502453037617
R-squared: 0.9626568028218273
Variance score: 0.94380
```

Visualize the Results

In [13]:
```python
plt.figure(figsize=(10, 6))
plt.scatter(x=y_test, y=y_hat, c ="#8B008B", alpha=0.7)
plt.xlabel("Actual Conversions")
plt.ylabel("Predicted Conversions")
plt.title("Actual vs. Predicted Conversions")
plt.show()
```



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