In [1]:

```
# Created by: Michael Cullen
# 19/11/2024
# https://zenodo.org/records/10457828
# https://www.kaggle.com/datasets/syedanwarafridi/vehicle-sales-data/data
```

In [2]:

```
import pandas as pd
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, r2_score
```

In [3]:

```
# made by chatgpt to install csv as file is to big to commit to github

import kagglehub
import shutil
import os

# Define the current working directory
current_directory = os.getcwd()

# Check if the CSV file already exists in the current directory
csv_exists = any(file.endswith(".csv") for file in os.listdir(current_directory))

if not csv_exists:
    # Download the dataset using kagglehub
    default_path = kagglehub.dataset_download("syedanwarafridi/vehicle-sales-data")

    # Move all downloaded CSV files to the current directory
    for file_name in os.listdir(default_path):
        if file_name.endswith(".csv"):
            shutil.move(os.path.join(default_path, file_name), os.path.join(current

    # Delete the downloaded folder after moving the files
    shutil.rmtree(default_path)

    print("Dataset files moved to:", current_directory)
    print(f"Deleted temporary folder: {default_path}")
else:
    print("CSV file already exists in the current directory.")
```

```
CSV file already exists in the current directory.
```

In [4]:

```
df = pd.read_csv('car_prices.csv')

df.head()
```

Out[4]:

| | year | make | model | trim | body | transmission | vin | state | condition |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 2015 | Kia | Sorento | LX | SUV | automatic | 5xyktca69fg566472 | ca | 5.0 |
| **1** | 2015 | Kia | Sorento | LX | SUV | automatic | 5xyktca69fg561319 | ca | 5.0 |
| **2** | 2014 | BMW | 3 Series | 328i SULEV | Sedan | automatic | wba3c1c51ek116351 | ca | 45.0 |
| **3** | 2015 | Volvo | S60 | T5 | Sedan | automatic | yv1612tb4f1310987 | ca | 41.0 |
| **4** | 2014 | BMW | 6 Series Gran Coupe | 650i | Sedan | automatic | wba6b2c57ed129731 | ca | 43.0 |

In [5]:

```
print("Amount of columns: ", df.shape[0])
```

```
Amount of columns:  558837
```

In [6]:

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

Out[6]:

```
year                0
make            10301
model           10399
trim            10651
body            13195
transmission    65352
vin                 4
state               0
condition       11820
odometer           94
color             749
interior          749
seller              0
mmr                38
sellingprice       12
saledate           12
dtype: int64
```

In [7]:

```
# Drop not needed columns
df = df.drop(columns=['trim','vin','state','interior','seller','saledate'], errors=

# Remove rows with missing data
df = df.dropna()


df.head(20)
```

Out[7]:

| | year | make | model | body | transmission | condition | odometer | color | mm |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 2015 | Kia | Sorento | SUV | automatic | 5.0 | 16639.0 | white | 20500. |
| **1** | 2015 | Kia | Sorento | SUV | automatic | 5.0 | 9393.0 | white | 20800. |
| **2** | 2014 | BMW | 3 Series | Sedan | automatic | 45.0 | 1331.0 | gray | 31900. |
| **3** | 2015 | Volvo | S60 | Sedan | automatic | 41.0 | 14282.0 | white | 27500. |
| **4** | 2014 | BMW | 6 Series Gran Coupe | Sedan | automatic | 43.0 | 2641.0 | gray | 66000. |
| **5** | 2015 | Nissan | Altima | Sedan | automatic | 1.0 | 5554.0 | gray | 15350. |
| **6** | 2014 | BMW | M5 | Sedan | automatic | 34.0 | 14943.0 | black | 69000. |
| **7** | 2014 | Chevrolet | Cruze | Sedan | automatic | 2.0 | 28617.0 | black | 11900. |
| **8** | 2014 | Audi | A4 | Sedan | automatic | 42.0 | 9557.0 | white | 32100. |
| **9** | 2014 | Chevrolet | Camaro | Convertible | automatic | 3.0 | 4809.0 | red | 26300. |
| **10** | 2014 | Audi | A6 | Sedan | automatic | 48.0 | 14414.0 | black | 47300. |
| **11** | 2015 | Kia | Optima | Sedan | automatic | 48.0 | 2034.0 | red | 15150. |
| **12** | 2015 | Ford | Fusion | Sedan | automatic | 2.0 | 5559.0 | white | 15350. |
| **13** | 2015 | Kia | Sorento | SUV | automatic | 5.0 | 14634.0 | silver | 20600. |
| **15** | 2015 | Nissan | Altima | Sedan | automatic | 2.0 | 11398.0 | black | 14750. |
| **17** | 2014 | Audi | Q5 | SUV | automatic | 49.0 | 7983.0 | white | 37100. |
| **18** | 2014 | Chevrolet | Camaro | Coupe | automatic | 17.0 | 13441.0 | black | 17750. |
| **19** | 2014 | BMW | 6 Series | Convertible | automatic | 34.0 | 8819.0 | black | 68000. |
| **20** | 2015 | Chevrolet | Impala | Sedan | automatic | 19.0 | 14538.0 | silver | 24300. |
| **21** | 2014 | BMW | 5 Series | Sedan | automatic | 29.0 | 25969.0 | black | 34200. |

In [8]:

```
print(df.isnull().sum())
print("Amount of columns: ", df.shape[0])
```

```
year            0
make            0
model           0
body            0
transmission    0
condition       0
odometer        0
color           0
mmr             0
sellingprice    0
dtype: int64
Amount of columns:  472325
```

In [9]:

```python
from sklearn.preprocessing import LabelEncoder

# Convert odometer, year, and mmr to numeric
df['odometer'] = pd.to_numeric(df['odometer'], errors='coerce')
df['year'] = pd.to_numeric(df['year'], errors='coerce')
df['mmr'] = pd.to_numeric(df['mmr'], errors='coerce')

# Define the function to categorise odometer values
def categorise_odometer(odometer):  # 1 = 0-20k, 2 = 20-50k, 3 = 50-100k, 4 = 100-1
    if odometer <= 20000:
        return 1  # 0-20k
    elif odometer <= 50000:
        return 2  # 20-50k
    elif odometer <= 100000:
        return 3  # 50-100k
    elif odometer <= 150000:
        return 4  # 100-150k
    elif odometer <= 200000:
        return 5  # 150-200k
    else:
        return 6  # 200k+

# Define function to categorise year
def categorise_year(year):  # 1 = very old, 2 = old, 3 = modern, 4 = new
    if year < 1990:
        return 1  # Very old
    elif year < 2005:
        return 2  # Old
    elif year < 2015:
        return 3  # Modern
    else:
        return 4  # New

# Define function to categorise price
def categorise_price(price):  # 1 = low, 2 = medium, 3 = high, 4 = premium
    if price < 5000:
        return 1  # Low
    elif price < 20000:
        return 2  # Medium
    elif price < 40000:
        return 3  # High
    else:
        return 4  # Premium
```

```
# Define function to categorise mmr
def categorise_mmr(mmr):  # 1 = very low, 2 = low, 3 = medium, 4 = high, 5 = very h
    if mmr < 5000:
        return 1  # Very Low
    elif mmr < 15000:
        return 2  # Low
    elif mmr < 30000:
        return 3  # Medium
    elif mmr < 50000:
        return 4  # High
    else:
        return 5  # Very High


# Apply categorisation functions
df['odometer_group'] = df['odometer'].apply(categorise_odometer)
df['year_group'] = df['year'].apply(categorise_year)
df['price_group'] = df['sellingprice'].apply(categorise_price)
df['mmr_group'] = df['mmr'].apply(categorise_mmr)

# Group rare colors into 'Other' to reduce noise
if 'color' in df.columns:
    color_counts = df['color'].value_counts()
    rare_colors = color_counts[color_counts < 50].index  # Adjust threshold as need
    df['color'] = df['color'].replace(rare_colors, 'Other')

# Handle categorical features using LabelEncoder
categorical_columns = ['make', 'model', 'body', 'cylinders', 'drive', 'condition',

# Encode all categorical columns
for col in categorical_columns:
    if col in df.columns:  # Ensure the column exists in the dataset
        df[col] = LabelEncoder().fit_transform(df[col].astype(str))

# Drop the original columns
df = df.drop(columns=['odometer', 'year', 'sellingprice', 'mmr'], errors='ignore')

# Show the first 10 rows of the processed DataFrame
df.head(10)
```

Out[9]:

| | make | model | body | transmission | condition | color | odometer_group | year_group | price |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 24 | 637 | 35 | 0 | 40 | 16 | 1 | 4 | |
| **1** | 24 | 637 | 35 | 0 | 40 | 16 | 1 | 4 | |
| **2** | 3 | 8 | 36 | 0 | 35 | 8 | 1 | 3 | |
| **3** | 51 | 575 | 36 | 0 | 31 | 16 | 1 | 4 | |
| **4** | 3 | 33 | 36 | 0 | 33 | 8 | 1 | 3 | |
| **5** | 36 | 63 | 36 | 0 | 0 | 8 | 1 | 4 | |
| **6** | 3 | 406 | 36 | 0 | 24 | 2 | 1 | 3 | |
| **7** | 7 | 186 | 36 | 0 | 10 | 2 | 2 | 3 | |
| **8** | 2 | 46 | 36 | 0 | 32 | 16 | 1 | 3 | |
| **9** | 7 | 135 | 9 | 0 | 20 | 13 | 1 | 3 | |

In [10]:

```
# Define features (X) and target (y)
X = df.drop(columns='price_group')
y = df['price_group']

# Train/test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
```

In [11]:

```
from sklearn.model_selection import GridSearchCV
#https://www.kaggle.com/code/syedanwarafridi/eda-visualizaton-random-forest-on-vehi
# code to find out best parameters sourced from kaggle forum

# Random Forest hyperparameter tuning using GridSearchCV
rf_param_grid = {
    'n_estimators': [50, 100],
    'max_depth': [30, 40, 50],
    'min_samples_split': [8, 12],
    'min_samples_leaf': [4, 5]
}

# Instantiate the model using the best parameters
rf_model = RandomForestRegressor(random_state=42)
rf_best = GridSearchCV(rf_model, rf_param_grid, cv=5, scoring='neg_mean_squared_err

# Fit the model to the training data
rf_best.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 24 candidates, totalling 120 fits
c:\Users\mjcul\OneDrive\Documents\GitHub\DataScience\venv\lib\site-packages\numpy\ma
\core.py:2881: RuntimeWarning: invalid value encountered in cast
  _data = np.array(data, dtype=dtype, copy=copy,
```

Out[11]:

```
▸ GridSearchCV
▸ best_estimator_: RandomForestRegressor
    ▸ RandomForestRegressor
```

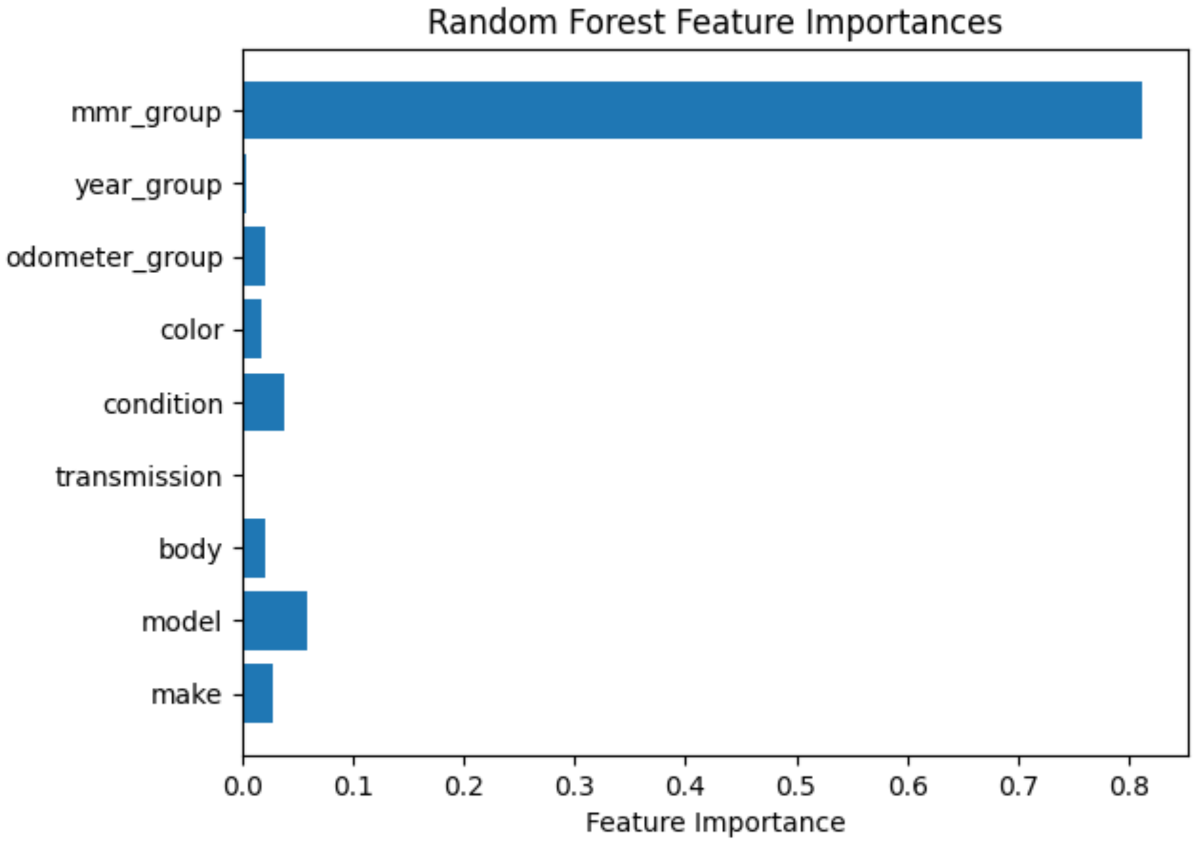
In [12]:

```python
# Make predictions
y_pred = rf_best.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print(f'Mean Squared Error: {mse:.2f}')

r2 = r2_score(y_test, y_pred)
print(f'R-squared: {r2:.2f}')
```

```
Mean Squared Error: 0.08
R-squared: 0.82
```

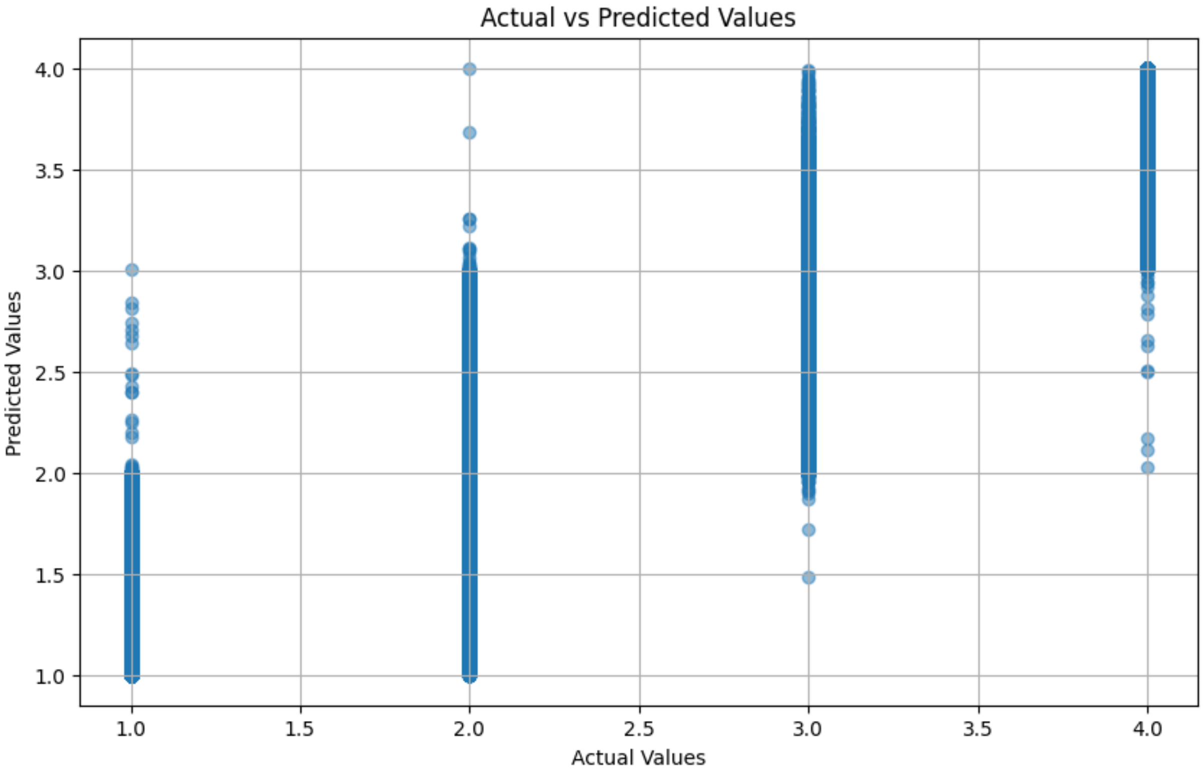
In [14]:

```python
importances = rf_best.best_estimator_.feature_importances_
plt.barh(X.columns, importances)
plt.xlabel("Feature Importance")
plt.title("Random Forest Feature Importances")
plt.show()
```



In [ ]:

```python
# Scatter plot for actual vs predicted values
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.title('Actual vs Predicted Values')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.grid(True)
plt.show()
```


Actual vs Predicted Values
Predicted Values
Actual Values