PakWheels Price Check: Unveiling the Pakistani Used Car Market

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importing libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.ticker import FuncFormatter
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', None)
```

loading data

In [2]:
```
used_car_data = pd.read_csv('/kaggle/input/pakistan-used-car-prices-2023/pakwheels_used_car_data_v02.csv')
```

first few rows of dataframe

In [3]:
```
used_car_data.head()
```

Out[3]:

	addref	city	assembly	body	make	model	year	engine	transmission	fuel	color	registered	mileage	pric
0	7943732	Peshawar	NaN	Sedan	Toyota	Corolla	2013.0	1300.0	Manual	Petrol	Silver Metallic	Lahore	145000	2870000.
1	7730314	Lahore	NaN	Sedan	Honda	City	2000.0	1300.0	Manual	Petrol	Blue	Lahore	230000	995000.
2	7943737	Lahore	NaN	Sedan	Toyota	Yaris	2021.0	1300.0	Manual	Petrol	Super White	Punjab	60500	3585000.
3	7943733	Lahore	NaN	Hatchback	Suzuki	Swift	2017.0	1300.0	Manual	Petrol	Grey	Islamabad	87000	2250000.
4	7923484	Lahore	NaN	Sedan	Honda	Civic	2017.0	1800.0	Automatic	Petrol	Grey	Lahore	86000	4850000.

few random data sample

In [4]:
```
used_car_data.sample(5)
```

Out[4]:

	addref	city	assembly	body	make	model	year	engine	transmission	fuel	color	registered	mileage	
76644	7776836	Islamabad	NaN	Sedan	Toyota	Yaris	2022.0	1300.0	Manual	Petrol	Silver	Islamabad	1200	45
11068	7933537	Chakwal	NaN	SUV	KIA	Sportage	NaN	1999.0	Automatic	Petrol	White	Islamabad	9600	88
48177	7865193	Mian	NaN	Sedan	Honda	Civic	2020.0	1500.0	Automatic	Petrol	Crystal Black Pearl	Punjab	66000	70
5644	7939050	Karachi	NaN	Sedan	Toyota	Corolla	2010.0	1800.0	Manual	Petrol	NaN	Karachi	89000	25
45161	7872778	Lahore	NaN	Hatchback	Suzuki	Alto	2021.0	660.0	Manual	Petrol	White	Lahore	38000	23

let's exlpore metadata

In [5]:
```
used_car_data.shape
```

Out[5]:
```
(77878, 14)
```

In [6]:
```
used_car_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 77878 entries, 0 to 77877
Data columns (total 14 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   addref        77878 non-null  int64
 1   city          77878 non-null  object
 2   assembly      24189 non-null  object
 3   body          68974 non-null  object
 4   make          77878 non-null  object
 5   model         77878 non-null  object
 6   year          73099 non-null  float64
 7   engine        77875 non-null  float64
 8   transmission  77878 non-null  object
 9   fuel          76972 non-null  object
 10  color         76398 non-null  object
 11  registered    77878 non-null  object
 12  mileage       77878 non-null  int64
 13  price         77295 non-null  float64
dtypes: float64(3), int64(2), object(9)
memory usage: 8.3+ MB
```

summary statistics of all columns

In [7]:
```
used_car_data.describe(include='all')
```

Out[7]:

	addref	city	assembly	body	make	model	year	engine	transmission	fuel	color	registered	
count	7.787800e+04	77878	24189	68974	77878	77878	73099.000000	77875.000000	77878	76972	76398	77878	
unique	NaN	297	1	21	68	435	NaN	NaN	2	3	396	121	
top	NaN	Lahore	Imported	Sedan	Toyota	Corolla	NaN	NaN	Automatic	Petrol	White	Islamabad	
freq	NaN	16674	24189	30193	24910	12871	NaN	NaN	42763	70620	21444	18942	
mean	7.809878e+06	NaN	NaN	NaN	NaN	NaN	2012.812610	1408.072550	NaN	NaN	NaN	NaN	
std	2.599523e+05	NaN	NaN	NaN	NaN	NaN	7.516685	704.459947	NaN	NaN	NaN	NaN	
min	2.748970e+05	NaN	NaN	NaN	NaN	NaN	1990.000000	3.000000	NaN	NaN	NaN	NaN	
25%	7.805760e+06	NaN	NaN	NaN	NaN	NaN	2007.000000	1000.000000	NaN	NaN	NaN	NaN	
50%	7.865805e+06	NaN	NaN	NaN	NaN	NaN	2015.000000	1300.000000	NaN	NaN	NaN	NaN	
75%	7.910334e+06	NaN	NaN	NaN	NaN	NaN	2019.000000	1600.000000	NaN	NaN	NaN	NaN	1
max	7.943741e+06	NaN	NaN	NaN	NaN	NaN	2022.000000	15000.000000	NaN	NaN	NaN	NaN	10

checking duplicate data

In [8]:
```
used_car_data[used_car_data.duplicated()]
```

Out[8]:

addref	city	assembly	body	make	model	year	engine	transmission	fuel	color	registered	mileage	price

the data have 100% unqiue rows.

let's work with missing values

In [9]:
```
used_car_data.isna().sum()
```

Out[9]:
```
addref              0
city                0
assembly        53689
body             8904
make                0
model               0
year             4779
engine              3
transmission        0
fuel              906
color            1480
registered          0
mileage             0
price             583
dtype: int64
```

7 out of 14 columns have some missing values. Out of these 7 columns having missing values, 3 columns have less than 1% missing values while column 'assembly' have 70% missing values. let's investigate these columns one by one

In [10]:
```python
used_car_data['assembly'].value_counts()
```

Out[10]:
```
assembly
Imported    24189
Name: count, dtype: int64
```

if the DataFrame only contains the value "Imported" for assembly, then any missing values in the assembly column must be "Local". This is because there are no other possible values for assembly according to original data source. Therefore, we will replace all NaN values in the assembly column with "Local"

In [11]:
```python
used_car_data['assembly'] = used_car_data['assembly'].fillna('Local')
assert used_car_data['assembly'].isna().sum() == 0
```

In [12]:
```python
used_car_data['body'].value_counts()
```

Out[12]:
```
body
Sedan                  30193
Hatchback              25014
SUV                     5087
Crossover               2156
Mini Van                1337
Compact sedan            793
MPV                      786
Double Cabin             779
Van                      716
Micro Van                539
Pick Up                  521
Compact SUV              476
Station Wagon            230
Coupe                     90
Truck                     86
High Roof                 74
Convertible               47
Single Cabin              26
Off-Road Vehicles         12
Mini Vehicles              8
Compact hatchback          4
Name: count, dtype: int64
```

In [13]:
```python
used_car_data[used_car_data['body'].isna()].head(10)
```

Out[13]:

	addref	city	assembly	body	make	model	year	engine	transmission	fuel	color	registered	mileage	price
30	7896546	Lahore	Imported	NaN	Toyota	Yaris	2020.0	1000.0	Automatic	Petrol	White	Un-Registered	32745	5390000.0
34	7933596	Lahore	Imported	NaN	Toyota	Yaris	2021.0	1500.0	Automatic	Hybrid	White	Un-Registered	17449	10800000.0
49	7943719	Karachi	Imported	NaN	Nissan	Dayz	2014.0	660.0	Automatic	Petrol	Black	Karachi	93000	2250000.0
58	7943688	Islamabad	Imported	NaN	Suzuki	Alto	2009.0	660.0	Automatic	Petrol	White	Islamabad	123	1550000.0
61	7943694	Islamabad	Imported	NaN	Honda	Vezel	2014.0	1500.0	Automatic	Hybrid	White	Islamabad	110000	4740000.0
82	7943660	Hyderabad	Local	NaN	Adam	Revo	2022.0	2800.0	Automatic	Diesel	Black	Sindh	15000	15000000.0
92	7943684	Gujranwala	Local	NaN	Suzuki	Baleno	2005.0	1500.0	Automatic	Petrol	Beige	Lahore	137000	1600000.0
94	7764607	Karachi	Imported	NaN	Nissan	Sunny	1991.0	1000.0	Manual	NaN	White	Karachi	200000	400000.0
106	7926462	Karachi	Imported	NaN	Toyota	Corolla	2020.0	1500.0	Automatic	Hybrid	White	Sindh	4000	9000000.0
114	7943640	Lahore	Local	NaN	Suzuki	Cultus	2018.0	1000.0	Automatic	Petrol	Silver	Punjab	65000	2870000.0

The 'body' column initially had 8,904 missing values, accounting for approx 11% of our total data. To address this, I used a technique that replaced the missing 'body' values with the most frequent 'body' type for the same 'model'. I applied this technique specifically to the 'model' with the highest number of missing values. As a result, the number of missing 'body' values was reduced from 8904 to 2197. I chose not to run this algorithm on the entire dataset to maintain data quality. The 2197 data points that are still missing constituted only about 3% of our data, so dropping them would'nt significantly impact our overall dataset.

In [14]:
```python
model_list = pd.DataFrame(used_car_data[used_car_data['body'].isna()]['model'].value_counts().head(50)).index
print('No of missing values before replacing', used_car_data['body'].isna().sum())
model_body = {}
for model in model_list:
    model_body[model] = used_car_data[used_car_data['model']==model]['body'].value_counts().idxmax()
used_car_data['body'] = used_car_data['body'].fillna(used_car_data['model'].map(model_body))
print('No of missing values after replacing', used_car_data['body'].isna().sum())
```

```
No of missing values before replacing 8904
No of missing values after replacing 2197
```

"year" column have about 6% missing values at random so we will drop rows having missing values.

In [15]:
```python
used_car_data = used_car_data[~used_car_data['year'].isna()]
assert used_car_data['year'].isna().sum() == 0
```

In [16]:
```
print(used_car_data[(used_car_data['model']=='Passo') & (used_car_data['year']==2017) & (used_car_data['transm
print(used_car_data[(used_car_data['model']=='Passo') & (used_car_data['year']==2018) & (used_car_data['transm
```

```
engine
1000.0    48
996.0      2
100.0      1
Name: count, dtype: int64
engine
1000.0    77
996.0      7
Name: count, dtype: int64
```

We have only 2 missing values in the 'engine' column. Upon examining the rows with missing data, we found that both cars share similar characteristics, differing only in their year of manufacture by one year. Further exploration revealed that other cars with similar specifications in the dataset have a 1000cc engine. Therefore, we will replace the NaN values in the 'engine' column with 1000.

In [17]:
```
used_car_data['engine'] = used_car_data['engine'].fillna(1000)
```

Now we are left with three columns: fuel, color, and price. These three columns have very few missing values, and we can't replace them using the mean/median technique otherwise, the data quality will be ruined. Therefore, it would be better to simply drop these rows, as they will not significantly affect our analysis.

In [18]:
```
used_car_data = used_car_data.dropna()
```

In [19]:
```
used_car_data.shape
```

Out[19]:
```
(68758, 14)
```

In [20]:
```
used_car_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 68758 entries, 0 to 77877
Data columns (total 14 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   addref        68758 non-null  int64
 1   city          68758 non-null  object
 2   assembly      68758 non-null  object
 3   body          68758 non-null  object
 4   make          68758 non-null  object
 5   model         68758 non-null  object
 6   year          68758 non-null  float64
 7   engine        68758 non-null  float64
 8   transmission  68758 non-null  object
 9   fuel          68758 non-null  object
 10  color         68758 non-null  object
 11  registered    68758 non-null  object
 12  mileage       68758 non-null  int64
 13  price         68758 non-null  float64
dtypes: float64(3), int64(2), object(9)
memory usage: 7.9+ MB
```

Finally, our dataset is free from all missing values and rows reduces from 77878 to 68758. It implies that we still have more than 88% of our original dataset for further data analysis.

Changing Data Types

In [21]:
```
new_used_car_data = used_car_data.astype({'year':'int16', 'engine':'int16', 'price':'int64'})
new_used_car_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 68758 entries, 0 to 77877
Data columns (total 14 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   addref        68758 non-null  int64
 1   city          68758 non-null  object
 2   assembly      68758 non-null  object
 3   body          68758 non-null  object
 4   make          68758 non-null  object
 5   model         68758 non-null  object
 6   year          68758 non-null  int16
 7   engine        68758 non-null  int16
 8   transmission  68758 non-null  object
 9   fuel          68758 non-null  object
 10  color         68758 non-null  object
 11  registered    68758 non-null  object
 12  mileage       68758 non-null  int64
 13  price         68758 non-null  int64
dtypes: int16(2), int64(3), object(9)
memory usage: 7.1+ MB
```

Exploratory Data Analysis

In [22]:
```
used_car_data.sample(5)
```

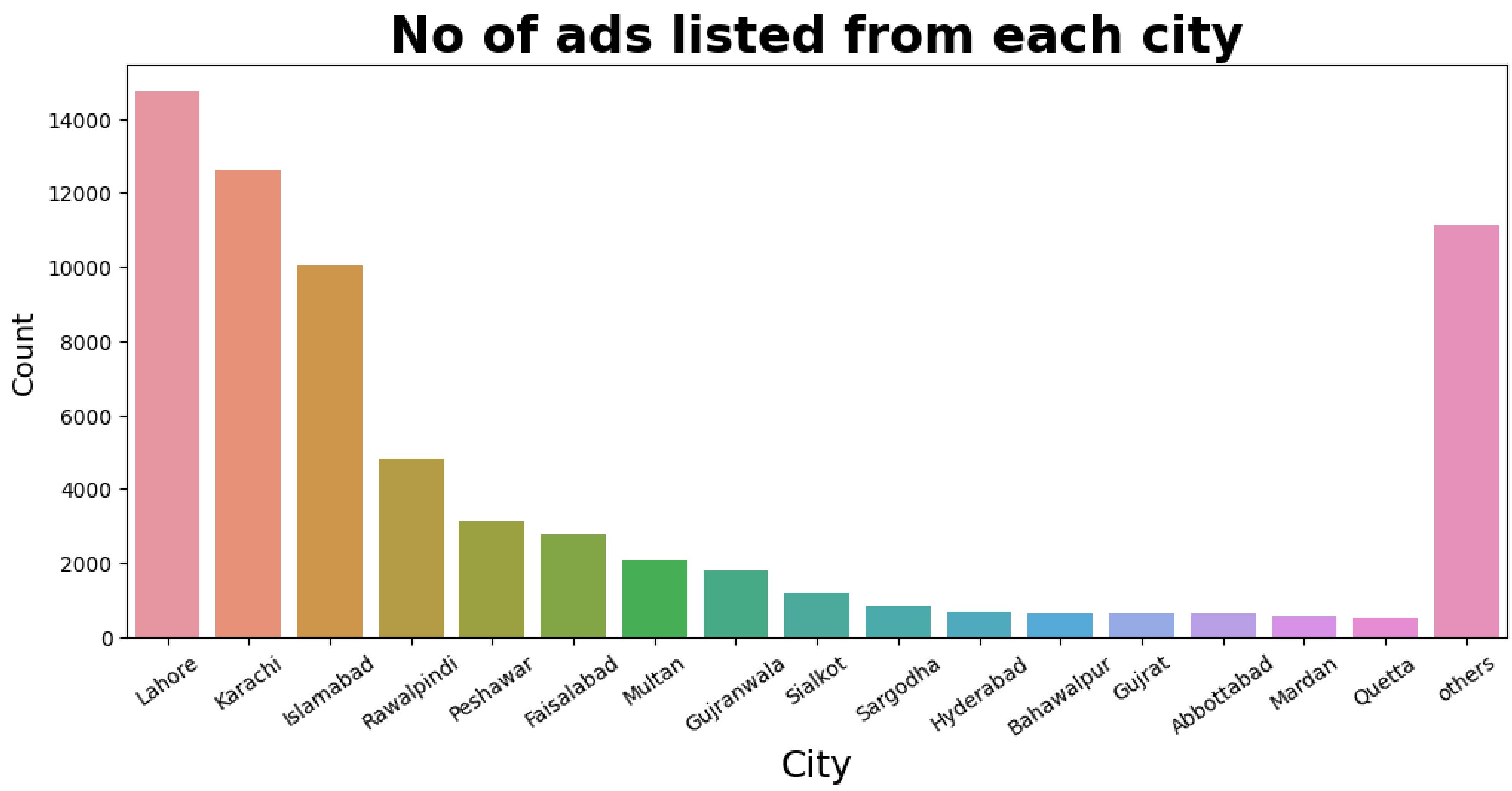
Out[22]:

	addref	city	assembly	body	make	model	year	engine	transmission	fuel	color	registered	mileage	
42774	7878258	Lahore	Local	Sedan	Honda	Civic	2003.0	1600.0	Automatic	Petrol	Brown	Sindh	7000	165
75816	7780255	Lahore	Local	Hatchback	Suzuki	Mehran	1993.0	800.0	Manual	Petrol	Snow White Pearl	Karachi	30000	45
35135	7894945	Rawalpindi	Local	Sedan	Suzuki	Liana	2007.0	1300.0	Manual	Petrol	Pearl Black	Rawalpindi	95000	112
67096	7628932	Rawalpindi	Local	Hatchback	Suzuki	Mehran	2011.0	800.0	Manual	Petrol	Blue	Islamabad	70000	89
2974	7940867	Lahore	Local	SUV	KIA	Sportage	2020.0	1999.0	Automatic	Petrol	White	Punjab	38000	719

City wise trend of car sales

In [23]:
```
city_counts = used_car_data['city'].value_counts().head(16)
cities_list = {'city': city_counts.index.tolist(), 'ads': city_counts.values.tolist()}
cities_list['city'].append('others')
cities_list['ads'].append(used_car_data.shape[0] - np.array(cities_list['ads']).sum())
```

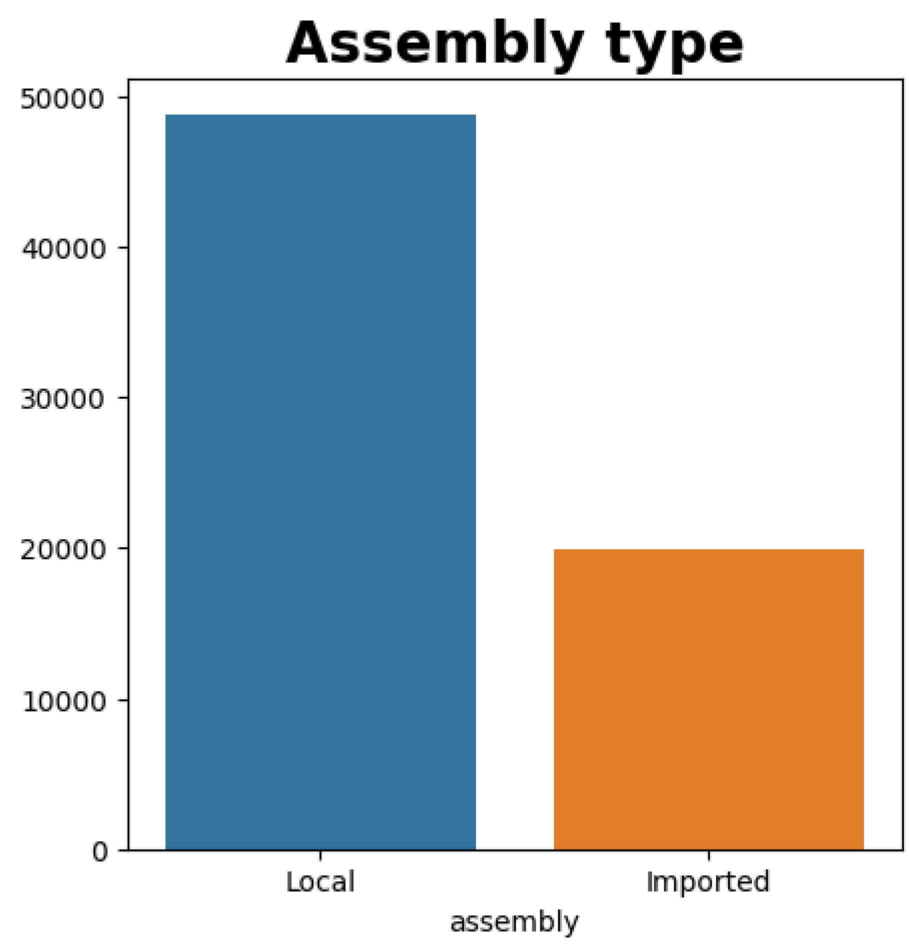
In [24]:
```
plt.figure(figsize=(12,5))
sns.barplot(y=cities_list['ads'], x = cities_list['city'])
plt.title('No of ads listed from each city', fontdict ={'fontweight':'bold','fontsize':24})
plt.xticks(rotation=35)
plt.xlabel('City', fontdict ={'fontsize':18})
plt.ylabel('Count', fontdict ={'fontsize':14})
plt.show()
```



Observation: The majority of the vehicles listed on PakWheels originate from capital cities, with over 50% of them coming from the Punjab region.

Assembly of cars

In [25]:
```
plt.figure(figsize=(5,5))
sns.barplot(x=used_car_data['assembly'].value_counts().index, y=used_car_data['assembly'].value_counts().value
plt.title('Assembly type', fontdict ={'fontweight':'bold','fontsize':20})
plt.show()
```

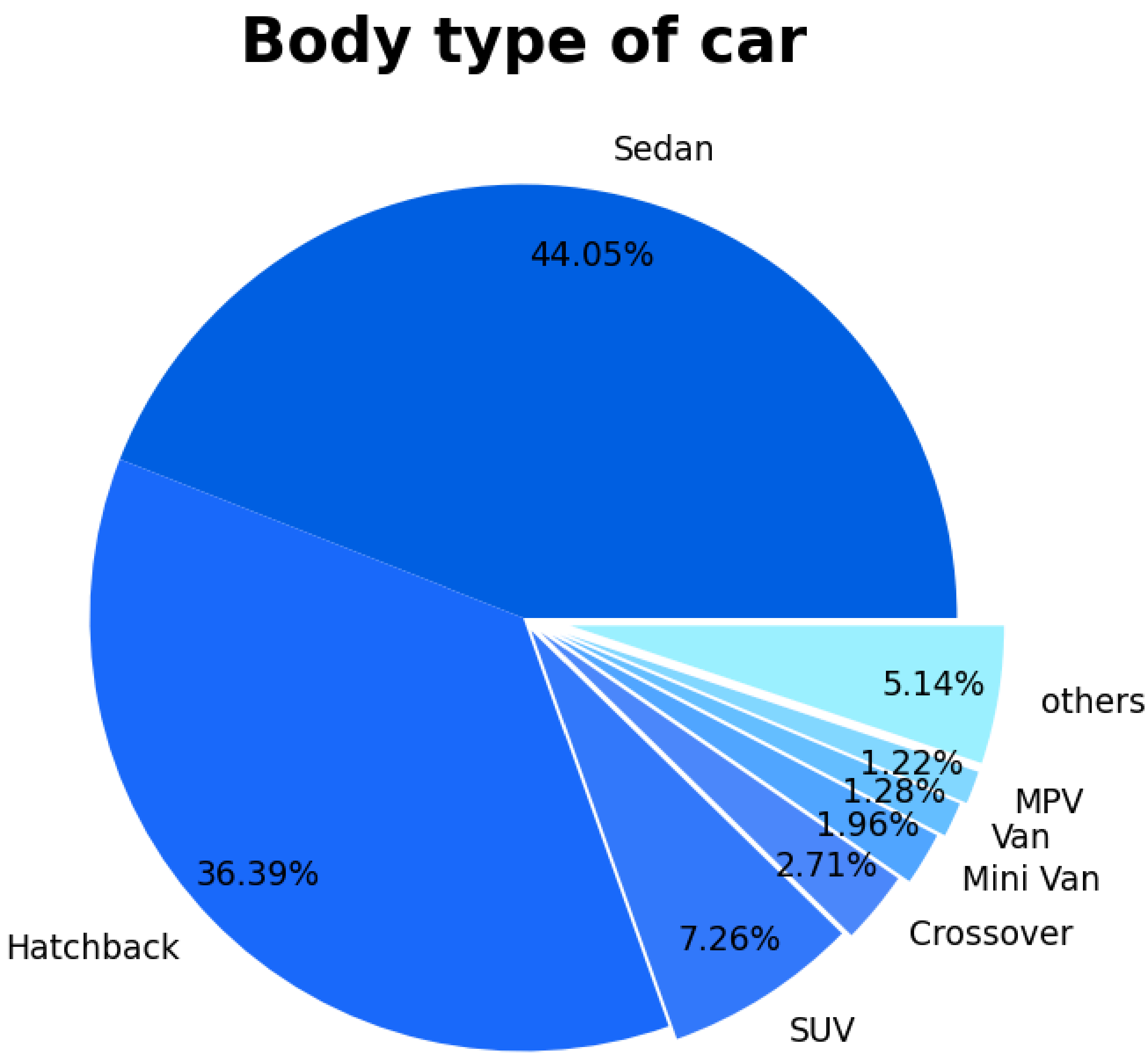


Observation: There are twice as many locally assembled cars as there are imported ones.

Most popular car body type

In [26]:
```
body_counts = used_car_data['body'].value_counts().head(7)
body_list = {'body_type': body_counts.index.tolist(), 'ads': body_counts.values.tolist()}
body_list['body_type'].append('others')
body_list['ads'].append(used_car_data.shape[0] - np.array(body_list['ads']).sum())
```

In [27]:
```
plt.figure(figsize=(8,8))
explode = (0,0,0.035,0.053,0.078, 0.094, 0.108, 0.11)
color = ['#0360e3', '#1c6afc', '#357afd', '#4f8bfd', '#50a6ff', '#64bfff', '#82d8ff', '#9cf2ff', '#9abdfe']
plt.pie(body_list['ads'], labels=body_list['body_type'], explode=explode, autopct='%.2f%%', pctdistance=.85, c
plt.title('Body type of car', fontdict ={'fontweight':'bold','fontsize':25})
plt.show()
```

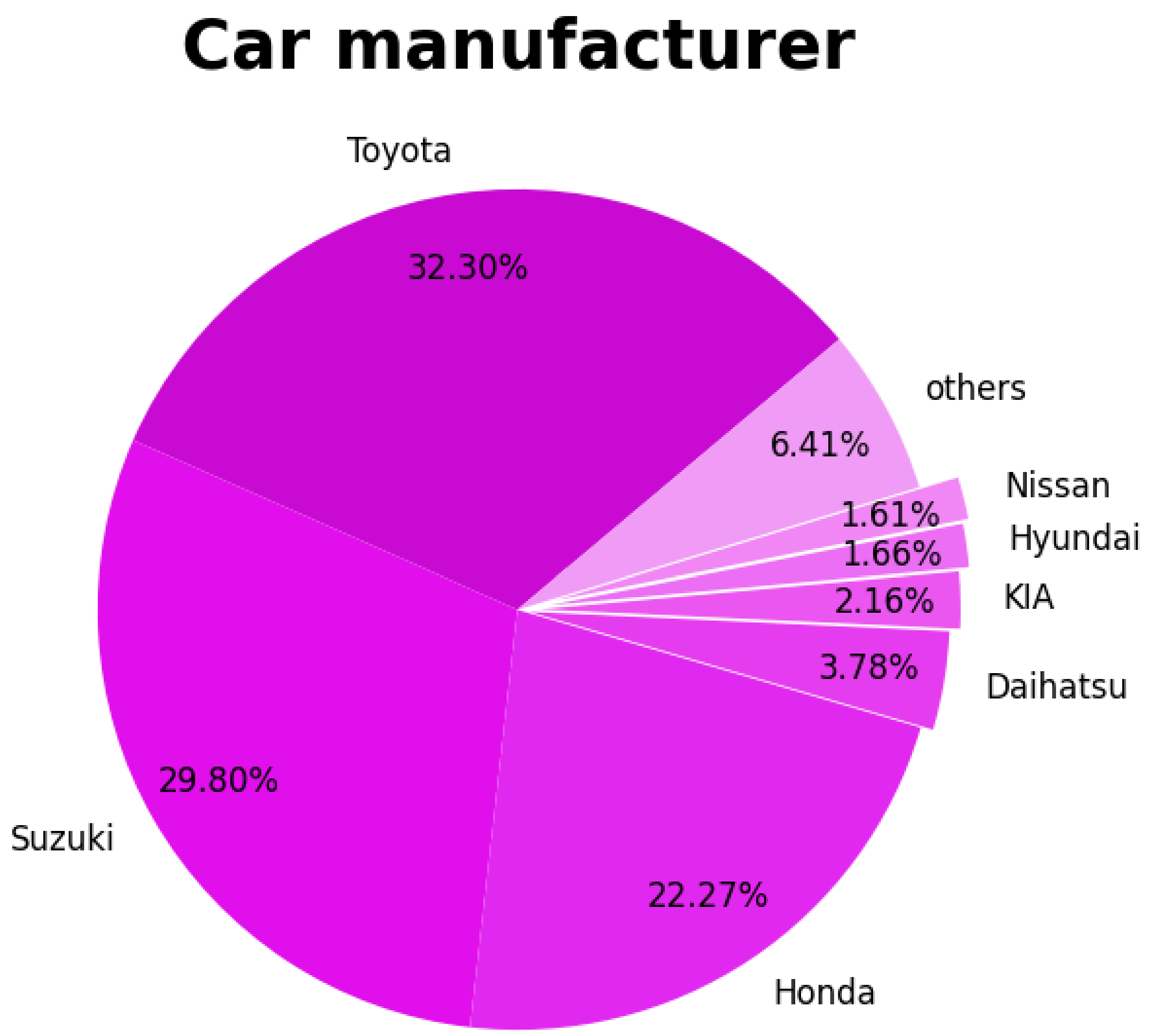


Observation: Sedan, hatchback and SUV holds more than 85% shares in Pakistani car industry

Major Car manufacturers

In [28]:
```
make_counts = used_car_data['make'].value_counts().head(7)
make_list = {'maker': make_counts.index.tolist(), 'count': make_counts.values.tolist()}
make_list['maker'].append('others')
make_list['count'].append(used_car_data.shape[0] - np.array(make_list['count']).sum())
```

In [29]:
```
plt.figure(figsize=(7,7))
explode = (0,0,0,0.03,0.055, 0.08, 0.095, 0)
color = ['#cb0ed6', '#e210ee', '#e528f0', '#e840f1', '#eb58f3', '#ee70f5', '#f188f7', '#f39ff8']
plt.pie(make_list['count'], labels=make_list['maker'], explode=explode, autopct='%.2f%%', startangle=40,  pctc
plt.title('Car manufacturer', fontdict ={'fontweight':'bold','fontsize':25})
plt.show()
```



Observation: As per given dataset, Toyota, Suzuki, and Honda collectively dominate the market, accounting for 84% of the cars listed for sale on PakWheels.

Models by each manufacturer

In [30]:
```
model_per_make = used_car_data.groupby('make').agg(model_make_count=('model','nunique'), body_make_count=('boc
model_per_make.head(9)
```

Out[30]:

	make	model_make_count	body_make_count
0	Toyota	59	17
1	Suzuki	32	13
2	Honda	28	11
3	Nissan	24	10
4	Daihatsu	19	9
5	Hyundai	13	8
6	Mitsubishi	12	6
7	KIA	11	8
8	Audi	10	4

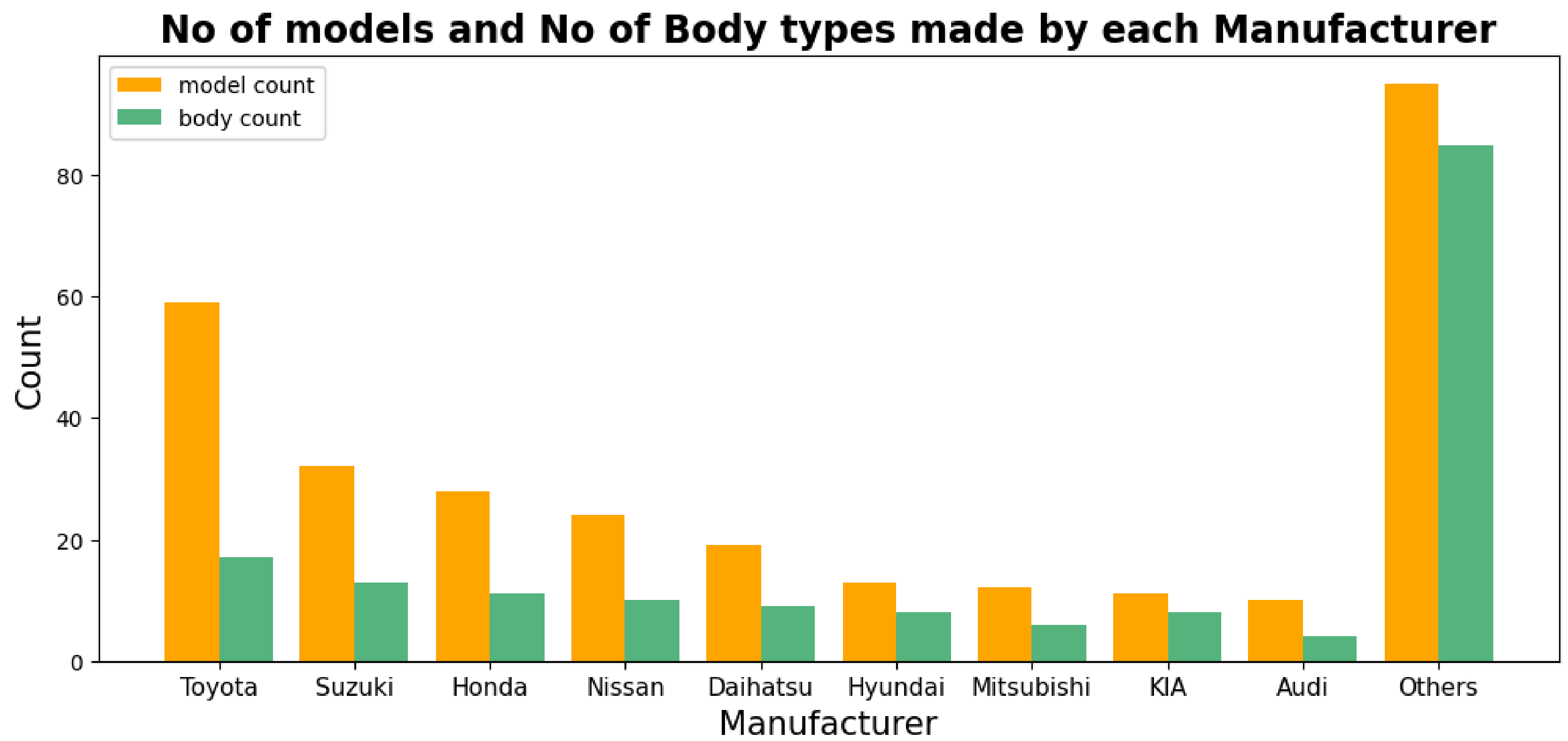
first consider 9 major manufacturers only and replace other by a single row for better data visualization

In [31]:
```
print(model_per_make['model_make_count'].sum() - model_per_make['model_make_count'].head(9).sum())
print(model_per_make['body_make_count'].sum() - model_per_make['body_make_count'].head(9).sum())
```

```
95
85
```

In [32]:
```
new_row = pd.DataFrame({'make':'Others', 'model_make_count':95, 'body_make_count':85}, index=[0])
model_per_make = model_per_make.head(9)
model_per_make = pd.concat([model_per_make, new_row], ignore_index=True)
```

In [33]:
```
plt.figure(figsize=(12,5))
x_axis = np.arange(len(model_per_make['make']))
plt.bar(x_axis-.2, model_per_make['model_make_count'], .4, label = 'model count', color = '#ffa500')
plt.bar(x_axis+.2, model_per_make['body_make_count'], .4, label = 'body count', color = '#56b47e')
plt.xlabel('Manufacturer', fontdict={'fontsize':15})
plt.ylabel('Count', fontdict={'fontsize':15})
plt.xticks(x_axis, model_per_make['make'], fontsize=11)
plt.title('No of models and No of Body types made by each Manufacturer', fontdict={'weight':'bold', 'fontsize'
plt.legend()
plt.show()
```



Observation: Looks like Toyota is the market Gaint followed by Suzuki, Honda, Nissan and Daihatsu

Feature Extraction

The 'year' column contains values ranging from 1990 to 2022. To process further, let's create a new categorical column 'year_range' from existing 'year' column.

In [34]:
```
def year_category(year):
    if year < 1995:
        return '1990-1994'
    elif year < 2000:
        return '1995-1999'
    elif year < 2005:
        return '2000-2004'
    elif year < 2010:
        return '2005-2009'
    elif year < 2015:
        return '2010-2014'
    elif year < 2020:
        return '2015-2019'
    else:
        return '2020-2024'
```

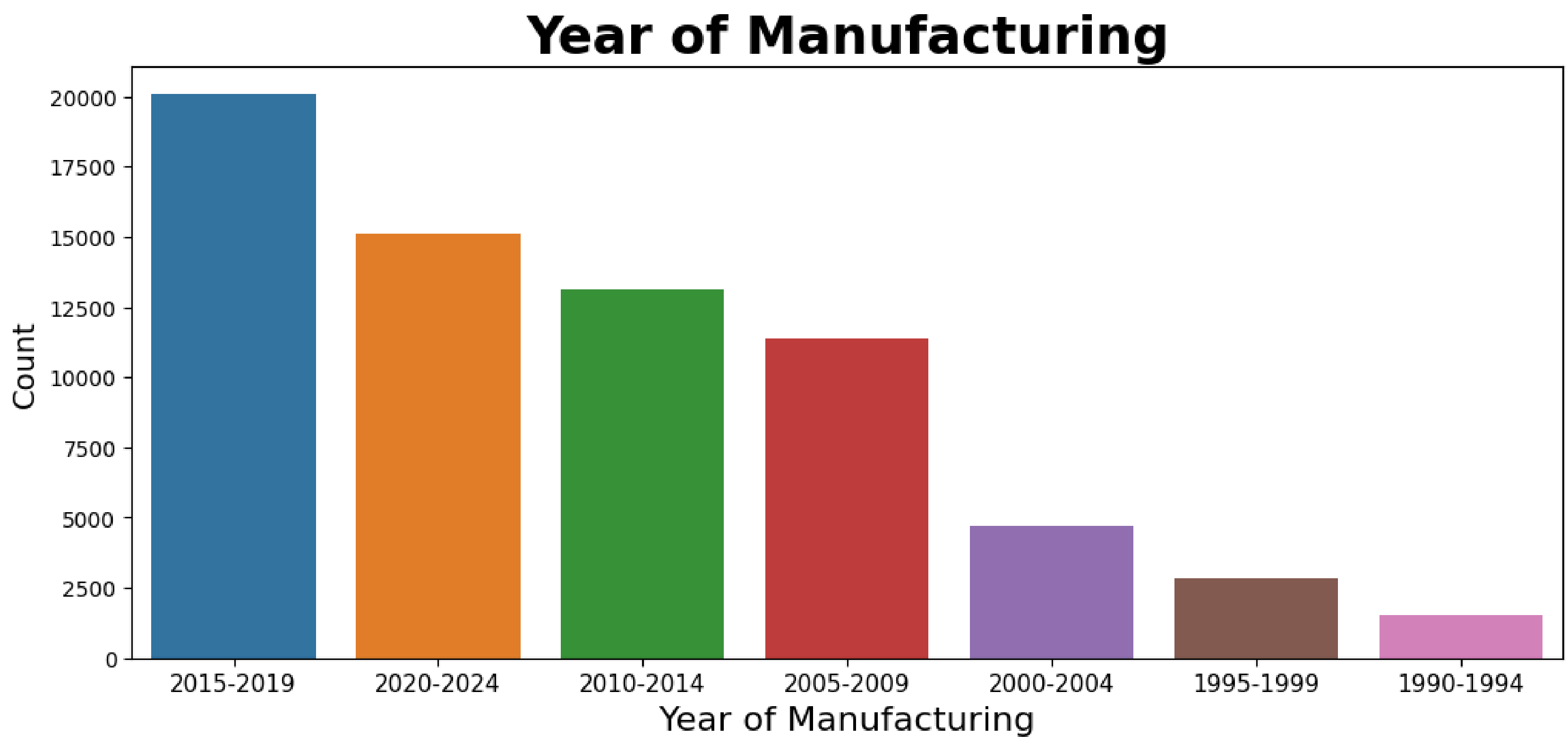
In [35]:
```
used_car_data['year_range'] = used_car_data['year'].apply(lambda x: year_category(x))
used_car_data.sample(3)
```

Out[35]:

	addref	city	assembly	body	make	model	year	engine	transmission	fuel	color	registered	mileage	p
53328	7853095	Lahore	Local	Mini Van	Suzuki	Bolan	2021.0	800.0	Manual	Petrol	Solid White	Lahore	38000	16500
16656	7539142	Lahore	Local	Hatchback	Suzuki	Cultus	2021.0	1000.0	Manual	Petrol	Grey	Lahore	24438	34800
64018	7802557	Faisalabad	Local	Hatchback	Suzuki	Cultus	2004.0	1000.0	Manual	Petrol	White	Faisalabad	94137	7300

Are there more old cars for sale than new ones?

In [36]:
```
plt.figure(figsize=(12,5))
sns.barplot(x=used_car_data['year_range'].value_counts().index, y = used_car_data['year_range'].value_counts()
plt.title('Year of Manufacturing', fontdict ={'fontweight':'bold','fontsize':24})
plt.xlabel('Year of Manufacturing', fontdict ={'fontsize':16})
plt.ylabel('Count', fontdict ={'fontsize':14})
plt.xticks(fontsize=11)
plt.show()
```



Observations: It appears that there is a direct correlation between the manufacturing year and the number of ads. Fewer cars listed on PakWheels have older manufacturing years.

Most popular car model by top 10 manufacturer

In [37]:
```
used_car_data.groupby(['make', 'model'])[['make', 'model']].size().reset_index().sort_values(by=[0, 'model'],
```

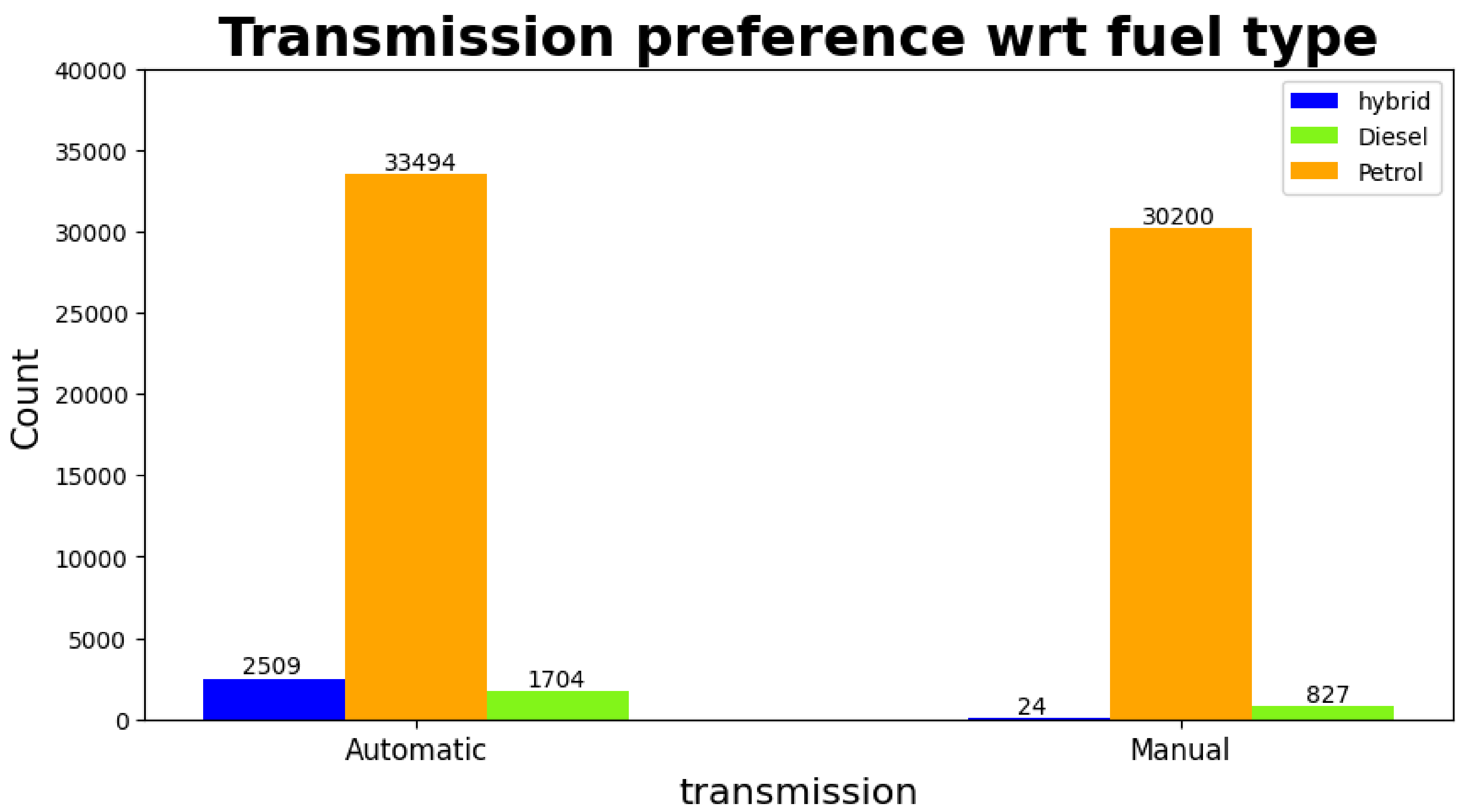
Out[37]:

	make	most popular model	count
251	Toyota	Corolla	11713
83	Honda	Civic	7870
227	Suzuki	Mehran	4379
132	KIA	Sportage	883
54	Daihatsu	Mira	860
150	Mercedes	Benz	536
110	Hyundai	Santro	516
169	Nissan	Dayz	397
139	MG	HS	358
25	Changan	Alsvin	355

Transmission preference wrt fuel type

In [38]:
```
transmissio_fuel_data = used_car_data.groupby(['transmission', 'fuel'])[['transmission', 'fuel']].size().reset
```

In [39]:
```
plt.figure(figsize=(10,5))
x_axis = np.array([0,.7])
plt.bar(x_axis-.13, transmissio_fuel_data[transmissio_fuel_data['fuel']=='Hybrid']['count'], .13, label = 'hyb
plt.bar(x_axis+.13, transmissio_fuel_data[transmissio_fuel_data['fuel']=='Diesel']['count'], .13, label = 'Die
plt.bar(x_axis, transmissio_fuel_data[transmissio_fuel_data['fuel']=='Petrol']['count'], .13, label = 'Petrol'
plt.xlabel('transmission', fontdict={'fontsize':16})
plt.ylabel('Count', fontdict={'fontsize':15})
plt.xticks(x_axis, ['Automatic', 'Manual'], fontsize=12)
plt.title('Transmission preference wrt fuel type', fontdict={'weight':'bold', 'fontsize':23})
plt.yticks(np.arange(0,41000,5000))
plt.legend()
plt.annotate('2509', (-0.16,2800))
plt.annotate('33494', (-0.03,33800))
plt.annotate('1704', (0.10,2000))
plt.annotate('24', (.55,320))
plt.annotate('827', (.815,1100))
plt.annotate('30200', (.665,30500))
plt.show()
```



Observation: People show a preference for automatic hybrid cars over manual hybrid cars. The ratio of automatic petrol cars to manual petrol cars is approximately 1.1:1. In the case of diesel cars, there are twice as many automatic cars as there are manual ones.

Feature Simplification

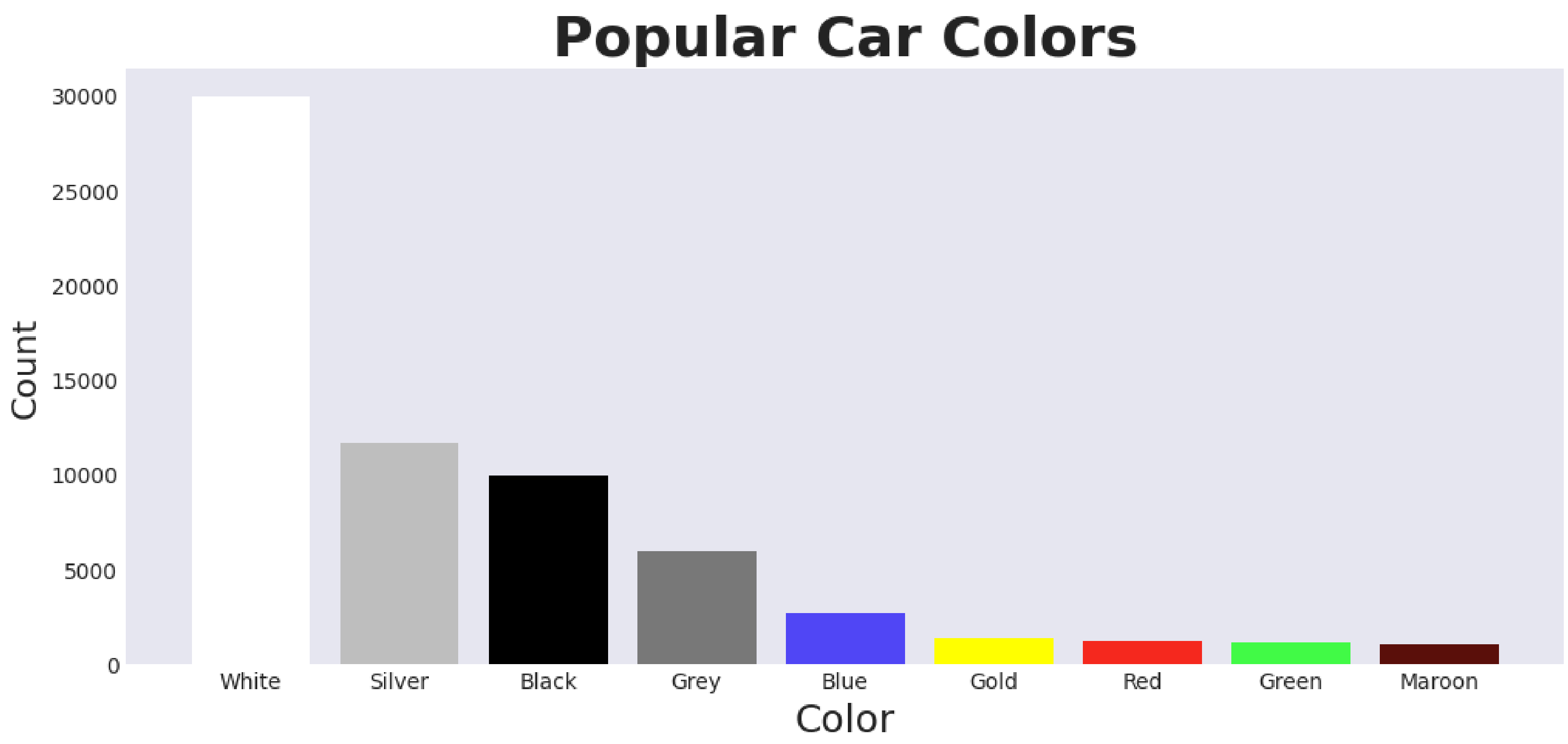
The following block of code maps 381 colors to 45 colors, greatly improving the data quality so that we can visualize it better.

In [40]:
```
color = ["white", "black", "gray", "grey", "silver", "red", "blue", "green", "brown", "yellow", "orange", "gol
def color_change(color_row):
    for col in color:
        if col in color_row.lower():
            return col.capitalize()
    return color_row.capitalize()
used_car_data['color'] = used_car_data['color'].apply(lambda x: color_change(x))
used_car_data['color'] = used_car_data['color'].replace(['Night blacl', 'Timeless back', 'Galaxy balck'], 'Bla
used_car_data['color'] = used_car_data['color'].replace(['Gray', 'Gun metallic'], 'Grey')
used_car_data['color'] = used_car_data['color'].replace('Rio tomato', 'Red')
used_car_data['color'] = used_car_data['color'].replace('Yellow', 'Gold')
used_car_data['color'] = used_car_data['color'].replace(['Alpine whire', 'Whitw', 'Precious wite pearl', 'Moor
used_car_data['color'].nunique()
```

Out[40]: 45

Popular Car Color

In [41]:
```
plt.figure(figsize=(12,5))
colors = ['White', '#C0C0C0', 'Black', '#7C7C7C', '#504AF7', 'yellow', '#F92C22', '#41FD49', '#5E0F0B']
plt.style.use('seaborn-dark')
plt.bar(x=used_car_data['color'].value_counts().head(9).index, height=used_car_data['color'].value_counts().he
plt.title('Popular Car Colors', fontdict ={'fontweight':'bold','fontsize':26})
plt.xlabel('Color', fontdict ={'fontsize':18})
plt.ylabel('Count', fontdict ={'fontsize':16})
plt.show()
```

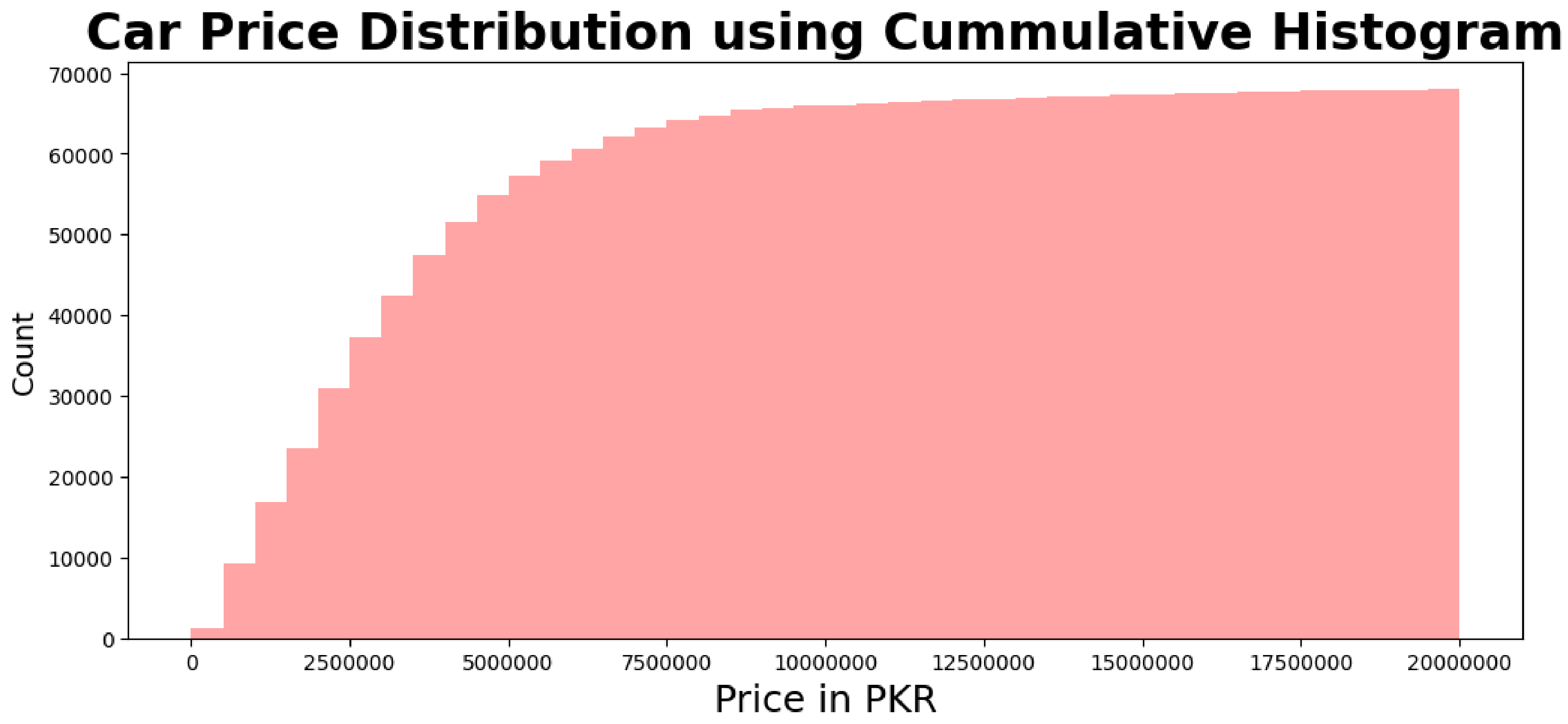


Observation: White remains the most popular car color followed by silver, black and grey

Car Price Distribution

In [42]:
```
def format_ticks(value, tick_number):
    return int(value)
```

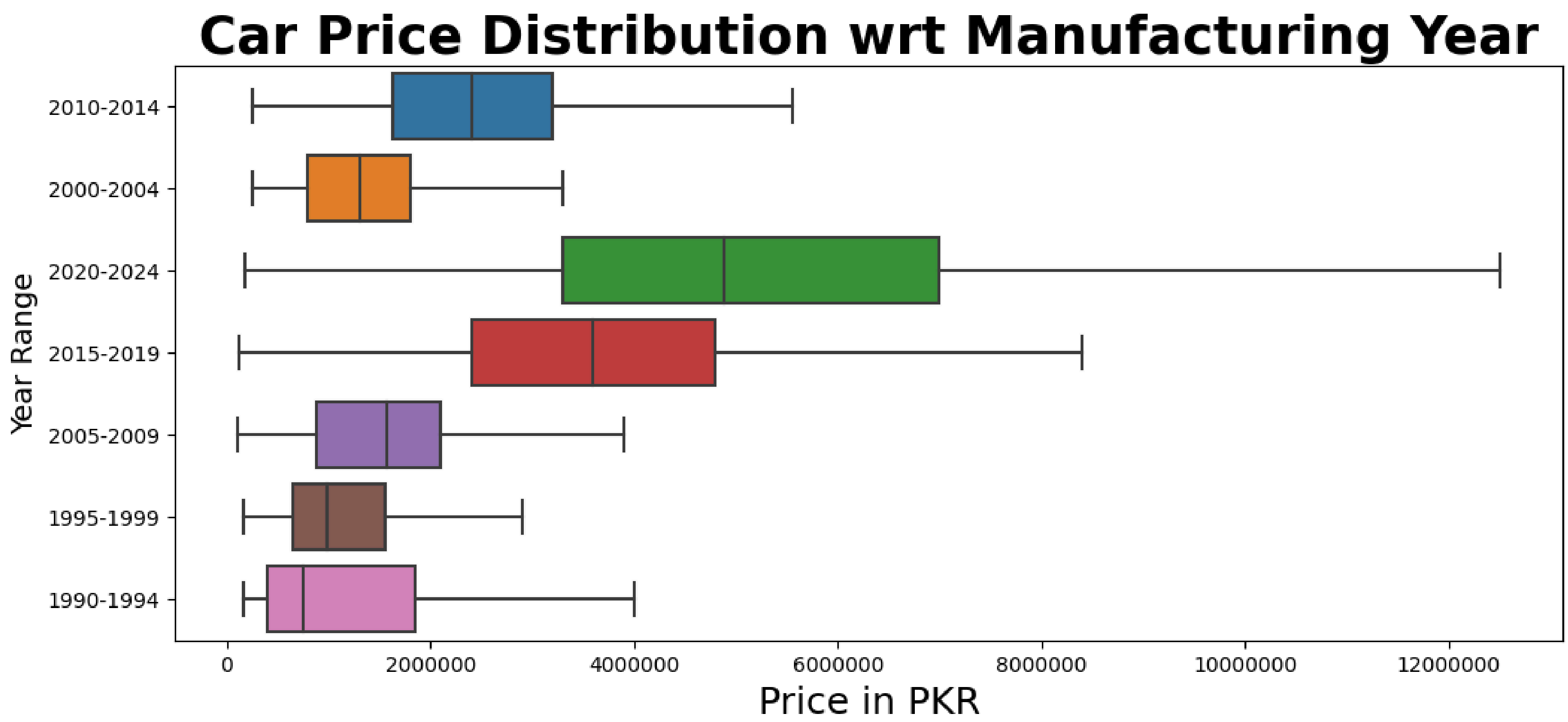
In [43]:
```
plt.figure(figsize=(12, 5))
plt.style.use('default')
plt.hist(used_car_data['price'], bins=40, cumulative=True, range=(0, 20000000), color=['red'], alpha=.35)
plt.title('Car Price Distribution using Cummulative Histogram', fontdict ={'fontweight':'bold','fontsize':24})
plt.xlabel('Price in PKR', fontdict ={'fontsize':18})
plt.ylabel('Count', fontdict ={'fontsize':14})
plt.gca().xaxis.set_major_formatter(FuncFormatter(format_ticks))
plt.show()
```



Observation: More than 75% car have values under 5000000 PKR. The count of cars decrease as the price goes up.

Car Price Distribution with respect to Manufacturing Year

In [44]:
```
plt.figure(figsize=(12,5))
sns.boxplot(data=used_car_data, x="price", y="year_range", showfliers=False)
plt.gca().xaxis.set_major_formatter(FuncFormatter(format_ticks))
plt.title('Car Price Distribution wrt Manufacturing Year', fontdict ={'fontweight':'bold','fontsize':25})
plt.xlabel('Price in PKR', fontdict ={'fontsize':18})
plt.ylabel('Year Range', fontdict ={'fontsize':14})
plt.show()
```



Observation: It appears that the price is directly proportional to the car's manufacturing year, with newer cars having higher prices.

Is there any car which is registered in a city but listed for sale in another city?

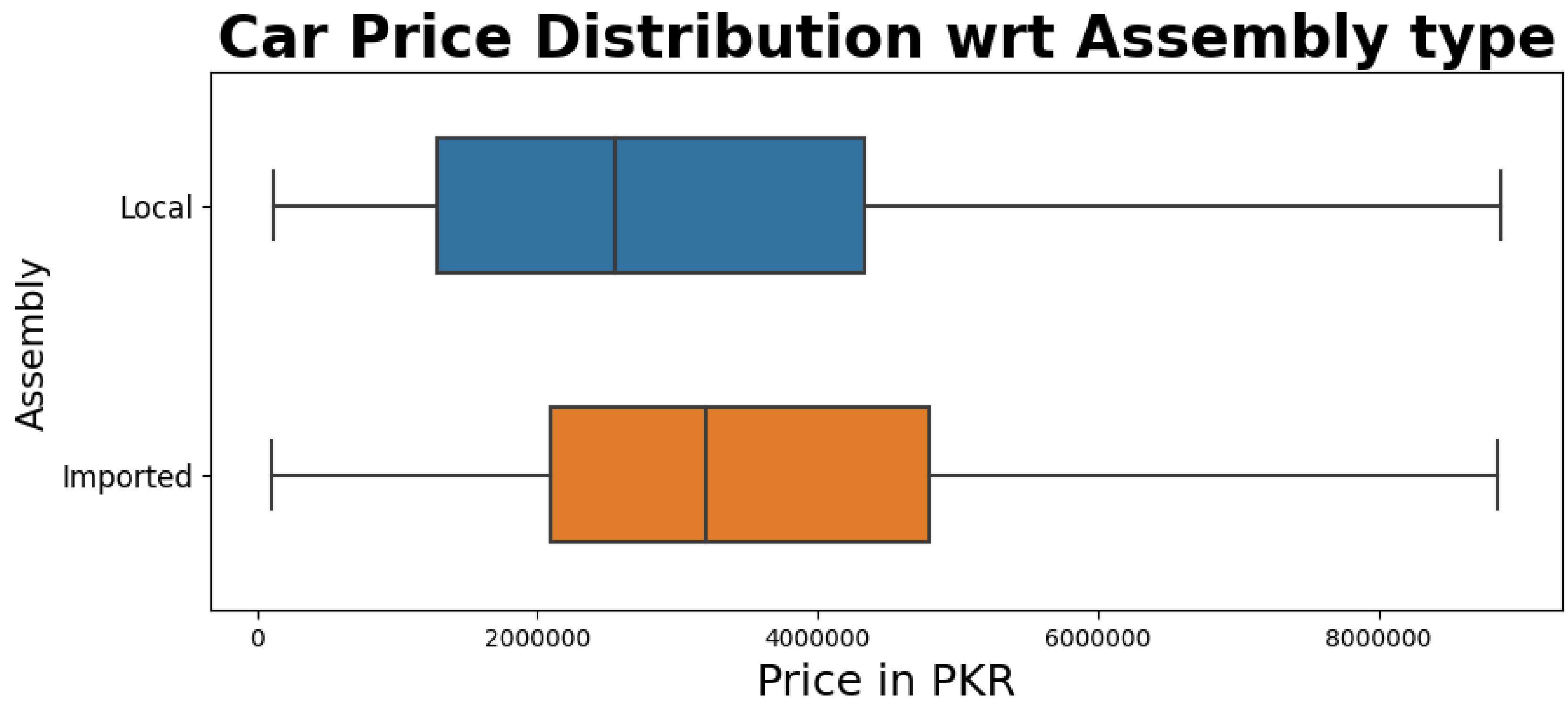
In [45]:
```
used_car_data['same_city_sale'] = used_car_data['city']==used_car_data['registered']
used_car_data['same_city_sale'].value_counts()
```

Out[45]:
```
same_city_sale
False    46424
True     22334
Name: count, dtype: int64
```

Observation: There are twice as many cars listed for sale in a city are registered in a different city.

Car Price Distribution wrt Assembly type

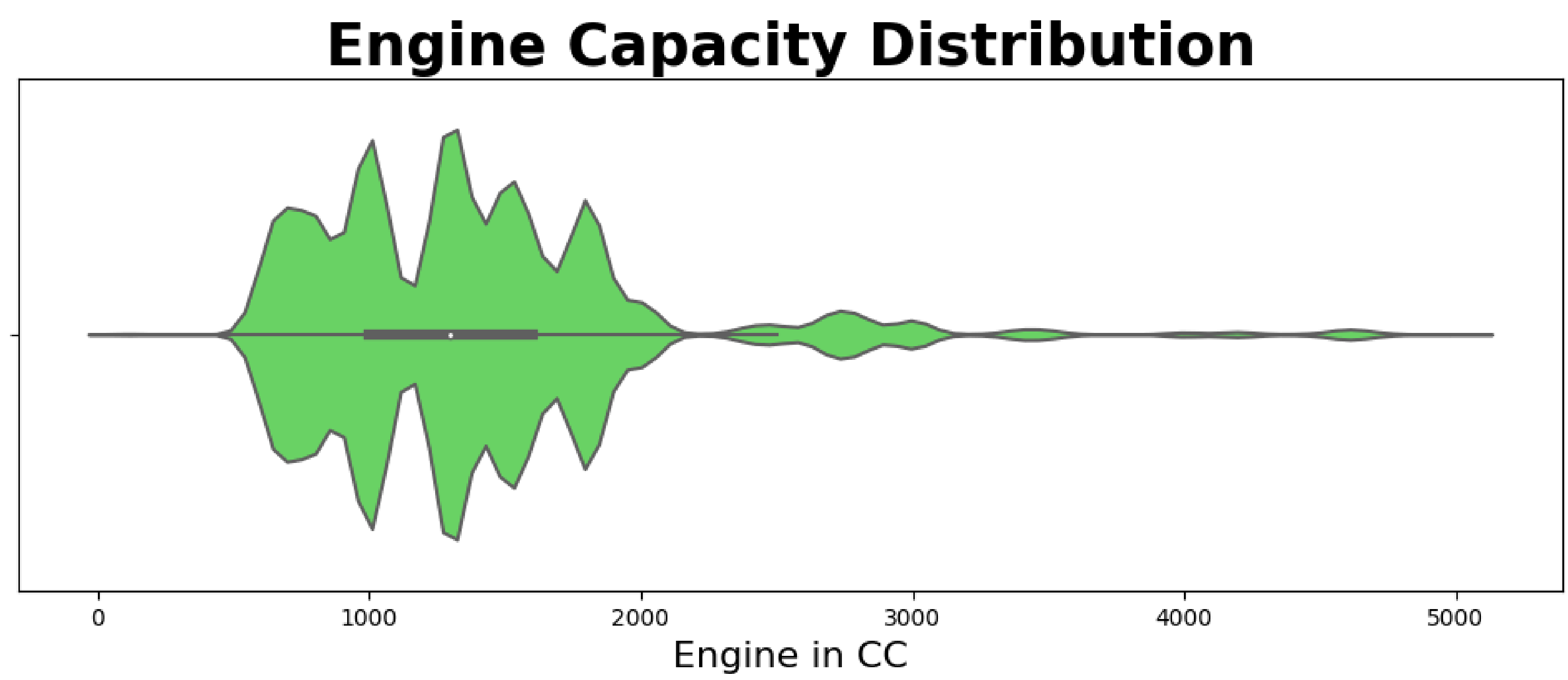
In [46]:
```
plt.figure(figsize=(10,4))
sns.boxplot(data=used_car_data, x="price", y="assembly", showfliers=False, width=.5)
plt.gca().xaxis.set_major_formatter(FuncFormatter(format_ticks))
plt.title('Car Price Distribution wrt Assembly type', fontdict ={'fontweight':'bold','fontsize':24})
plt.xlabel('Price in PKR', fontdict ={'fontsize':18})
plt.ylabel('Assembly', fontdict ={'fontsize':15})
plt.yticks(fontsize=12)
plt.show()
```



Observation: Locally assembled cars are cheaper than imported ones

Engine Capacity Distribution

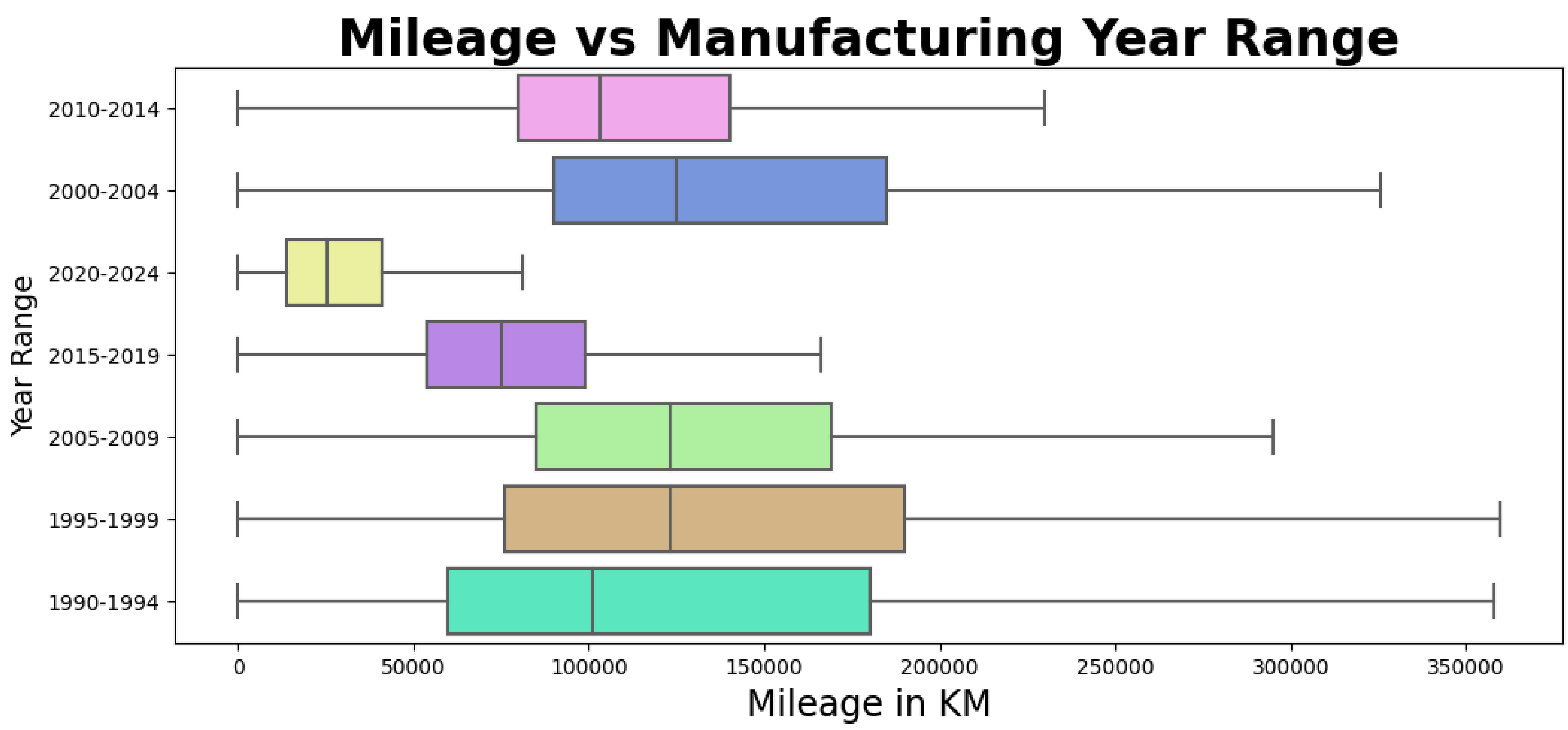
In [47]:
```
plt.figure(figsize=(12,4))
sns.violinplot(data=used_car_data[(used_car_data['engine']>00)&(used_car_data['engine']<5000)], x='engine', sh
plt.gca().xaxis.set_major_formatter(FuncFormatter(format_ticks))
plt.title('Engine Capacity Distribution', fontdict ={'fontweight':'bold','fontsize':25})
plt.xlabel('Engine in CC', fontdict ={'fontsize':16})
plt.show()
```



Observation: The majority of cars have engines ranging from 600 CC to 2000 CC.

Do old cars have more mileage than new ones?

In [48]:
```
plt.figure(figsize=(12,5))
sns.boxplot(data=used_car_data, x="mileage", y="year_range", showfliers=False, palette=["#FFA1F5", "#688EF1",
plt.gca().xaxis.set_major_formatter(FuncFormatter(format_ticks))
plt.title('Mileage vs Manufacturing Year Range', fontdict ={'fontweight':'bold','fontsize':24})
plt.xlabel('Mileage in KM', fontdict ={'fontsize':17})
plt.ylabel('Year Range', fontdict ={'fontsize':14})
plt.show()
```



Observation: If we look at the chart above, we can observe that the most recent years, i.e., 2020-2024, have the lowest mileage represented by a smaller whisker-box, whereas years before 2010 have significantly larger whisker-boxes, indicating higher mileage. Therefore, it implies that old cars have more mileage than new ones.

Predicting used car price

In [49]:
```
used_car_data = pd.read_csv('/kaggle/input/pakistan-used-car-prices-2023/pakwheels_used_car_data_v02.csv')
```

Have a look at metadata

In [50]:
```
used_car_data.describe(include='all')
```

Out[50]:

	addref	city	assembly	body	make	model	year	engine	transmission	fuel	color	registered	
count	7.787800e+04	77878	24189	68974	77878	77878	73099.000000	77875.000000	77878	76972	76398	77878	
unique	NaN	297	1	21	68	435	NaN	NaN	2	3	396	121	
top	NaN	Lahore	Imported	Sedan	Toyota	Corolla	NaN	NaN	Automatic	Petrol	White	Islamabad	
freq	NaN	16674	24189	30193	24910	12871	NaN	NaN	42763	70620	21444	18942	
mean	7.809878e+06	NaN	NaN	NaN	NaN	NaN	2012.812610	1408.072550	NaN	NaN	NaN	NaN	
std	2.599523e+05	NaN	NaN	NaN	NaN	NaN	7.516685	704.459947	NaN	NaN	NaN	NaN	
min	2.748970e+05	NaN	NaN	NaN	NaN	NaN	1990.000000	3.000000	NaN	NaN	NaN	NaN	
25%	7.805760e+06	NaN	NaN	NaN	NaN	NaN	2007.000000	1000.000000	NaN	NaN	NaN	NaN	
50%	7.865805e+06	NaN	NaN	NaN	NaN	NaN	2015.000000	1300.000000	NaN	NaN	NaN	NaN	
75%	7.910334e+06	NaN	NaN	NaN	NaN	NaN	2019.000000	1600.000000	NaN	NaN	NaN	NaN	1
max	7.943741e+06	NaN	NaN	NaN	NaN	NaN	2022.000000	15000.000000	NaN	NaN	NaN	NaN	10

Do we have missing values

In [51]:
```
used_car_data.isna().sum()
```

Out[51]:
```
addref              0
city                0
assembly        53689
body             8904
make                0
model               0
year             4779
engine              3
transmission        0
fuel              906
color            1480
registered          0
mileage             0
price             583
dtype: int64
```

In [52]:
```
used_car_data['assembly'] = used_car_data['assembly'].fillna('Local')
assert used_car_data['assembly'].isna().sum() == 0
```

In [53]:
```
used_car_data[used_car_data['body'].isna()]['model'].value_counts().head(80)
```

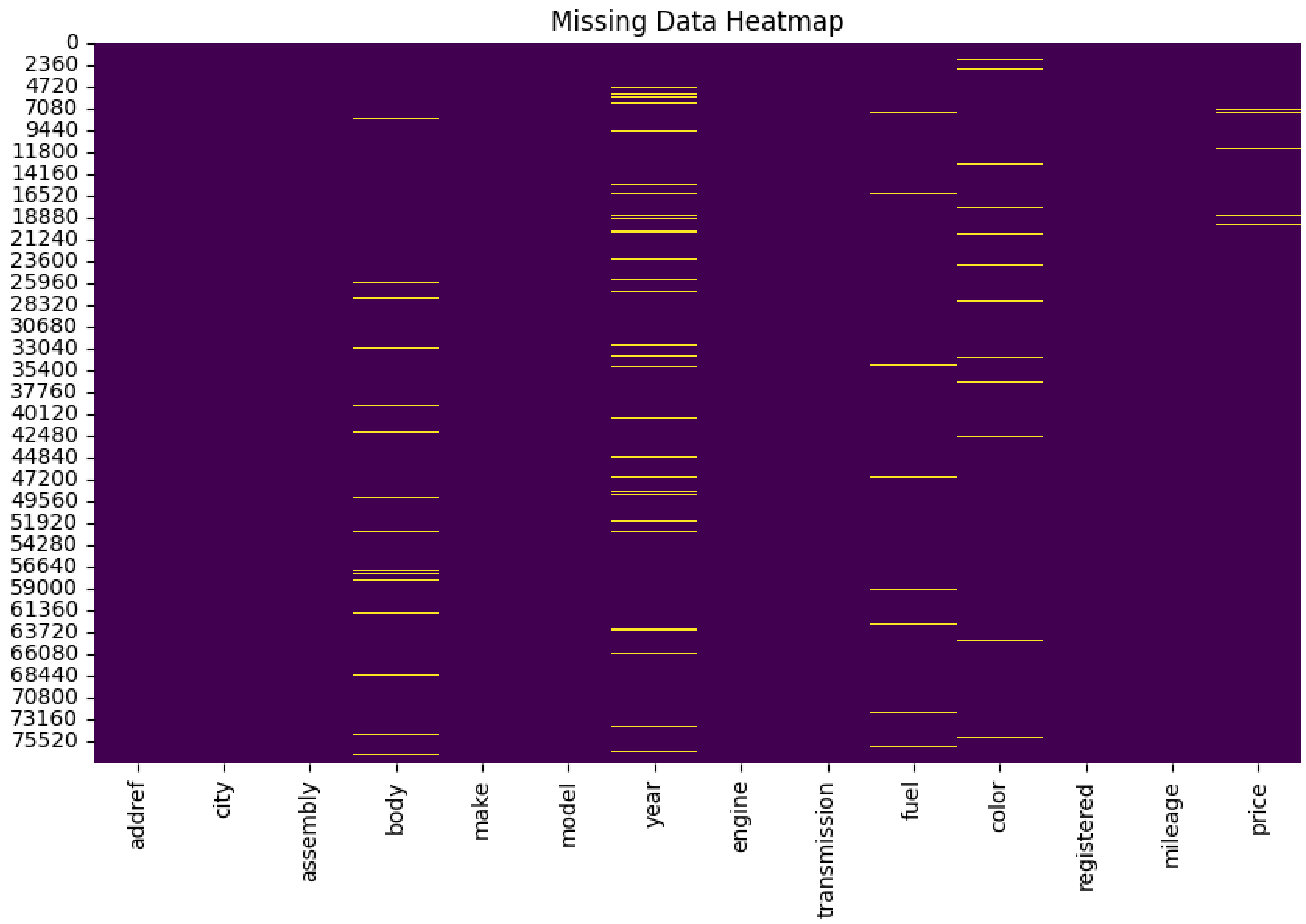
Out[53]:
```
model
Corolla    714
Civic      399
Alto       307
Prius      243
Land       240
          ...
Acty        20
Rav4        20
Pearl       19
Town        19
Patrol      18
Name: count, Length: 80, dtype: int64
```

In [54]:
```
model_list = pd.DataFrame(used_car_data[used_car_data['body'].isna()]['model'].value_counts().head(50)).index
print('No of missing values before replacing', used_car_data['body'].isna().sum())
model_body = {}
for model in model_list:
    model_body[model] = used_car_data[used_car_data['model']==model]['body'].value_counts().idxmax()
used_car_data['body'] = used_car_data['body'].fillna(used_car_data['model'].map(model_body))
print('No of missing values after replacing', used_car_data['body'].isna().sum())
```

```
No of missing values before replacing 8904
No of missing values after replacing 2197
```

Is it missing at random?

In [55]:
```
plt.figure(figsize=(10, 6))
sns.heatmap(used_car_data.isnull(), cbar=False, cmap='viridis')
plt.title('Missing Data Heatmap')
plt.show()
```



The plot shows that the data is missing at random so let work on these

In [56]:
```
round(used_car_data[(~used_car_data.isnull())].drop(columns=['body']).isnull().any(axis=1).sum()/used_car_data
```

Out[56]: 9.37

we are going to lose approx 9.37% data if we drop rows having missing values

Drop rows having missing data points

In [57]:
```
used_car_data = used_car_data.dropna()
```

In [58]:
```
used_car_data.shape
```

Out[58]: (68756, 14)

feature engineering

In [59]:
```
color = ["white", "black", "gray", "grey", "silver", "red", "blue", "green", "brown", "yellow", "orange", "gol
def color_change(color_row):
    for col in color:
        if col in color_row.lower():
            return col.capitalize()
    return color_row.capitalize()
used_car_data['color'] = used_car_data['color'].apply(lambda x: color_change(x))
used_car_data['color'] = used_car_data['color'].replace(['Night blacl', 'Timeless back', 'Galaxy balck'], 'Bla
used_car_data['color'] = used_car_data['color'].replace(['Gray', 'Gun metallic'], 'Grey')
used_car_data['color'] = used_car_data['color'].replace('Rio tomato', 'Red')
used_car_data['color'] = used_car_data['color'].replace('Yellow', 'Gold')
used_car_data['color'] = used_car_data['color'].replace(['Alpine whire', 'Whitw', 'Precious wite pearl', 'Moor
used_car_data['color'].nunique()
```

Out[59]: 45

In [60]:
```python
used_car_data['year_range'] = used_car_data['year'].apply(lambda x: year_category(x))
used_car_data.sample(3)
```

Out[60]:

	addref	city	assembly	body	make	model	year	engine	transmission	fuel	color	registered	mileage	
31700	7902102	Islamabad	Imported	Hatchback	Suzuki	Wagon	2020.0	660.0	Automatic	Hybrid	Beige	Un-Registered	13000	3675
14420	7929979	Rawalpindi	Imported	Crossover	Honda	Vezel	2016.0	1500.0	Automatic	Petrol	Silver	Islamabad	34540	6900
33973	7897549	Karachi	Imported	SUV	Toyota	Prado	1997.0	3000.0	Automatic	Diesel	Beige	Karachi	116000	4500

Removing outliers and unimportant features

In [61]:
```python
ambigous_index = list(used_car_data[(used_car_data['mileage']<10000)&(used_car_data['year']<2000)].index)
ind = list(used_car_data[(used_car_data['engine']<600)|(used_car_data['engine']>6600)].index)
ambigous_index = ambigous_index + ind + [17405, 46696, 210, 2113, 197, 1649, 646, 4071, 56430]
```

In [62]:
```python
ambigous_index = np.array(ambigous_index).ravel().reshape(552,)
ambigous_index.shape
```

Out[62]: (552,)

In [63]:
```python
to_be_dropped = used_car_data.loc[ambigous_index]
```

In [64]:
```python
used_car_data = used_car_data[~used_car_data['addref'].isin(to_be_dropped['addref'])]
```

In [65]:
```python
used_car_data = used_car_data.drop(columns=['addref', 'city', 'year', 'body'])
used_car_data.head()
```

Out[65]:

	assembly	make	model	engine	transmission	fuel	color	registered	mileage	price	year_range
0	Local	Toyota	Corolla	1300.0	Manual	Petrol	Silver	Lahore	145000	2870000.0	2010-2014
1	Local	Honda	City	1300.0	Manual	Petrol	Blue	Lahore	230000	995000.0	2000-2004
2	Local	Toyota	Yaris	1300.0	Manual	Petrol	White	Punjab	60500	3585000.0	2020-2024
3	Local	Suzuki	Swift	1300.0	Manual	Petrol	Grey	Islamabad	87000	2250000.0	2015-2019
4	Local	Honda	Civic	1800.0	Automatic	Petrol	Grey	Lahore	86000	4850000.0	2015-2019

In [66]:
```python
used_car_data.shape
```

Out[66]: (68210, 11)

Importing python packages for ML

In [67]:
```python
import xgboost as xgb
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from math import sqrt
```

Label encoding of categorical variables

In [68]:
```python
categorical_columns = ['assembly', 'make', 'model', 'transmission', 'fuel', 'color', 'registered', 'year_range
label_encoder = LabelEncoder()
for col in categorical_columns:
    used_car_data[col] = label_encoder.fit_transform(used_car_data[col])
```

In [69]:
```python
used_car_data.sample(4)
```

Out[69]:

	assembly	make	model	engine	transmission	fuel	color	registered	mileage	price	year_range
29874	1	45	76	1300.0	1	2	6	90	90000	2395000.0	4
36027	0	45	196	1800.0	0	1	43	53	197100	4500000.0	4
66659	1	45	76	1800.0	0	2	43	90	49000	6450000.0	6
18187	1	19	67	1600.0	1	2	18	90	123456	1050000.0	1

Train Test Split

In [70]:
```
X = used_car_data.drop(columns=['price'])
y = used_car_data['price']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

Linear Regression

In [71]:
```
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print("Mean Squared root Error:", sqrt(mse))
print("R-squared:", round(r2*100,4))
```

```
Mean Squared root Error: 3353663.098983003
R-squared: 52.5384
```

high msqe and low r2 score indicates that linear regresssion is not feasible for this dataset

Random forest

In [72]:
```
rf_model = RandomForestRegressor()
param_grid = {
    'n_estimators': [50], #we will use large number of tress after findin optimal parameters to minimize runti
    'max_depth': [6, 12, 15],
    'min_samples_split': [2, 4, 6],
    'min_samples_leaf': [1, 2, 3]
}

# Create the GridSearchCV object
grid_search = GridSearchCV(estimator=rf_model, param_grid=param_grid, cv=5, scoring='neg_mean_squared_error')

# Perform the grid search
grid_search.fit(X_train, y_train)

# Print the best parameters and best score
print("Best Parameters: ", grid_search.best_params_)
print("Best Score (Neg Mean Squared Error): ", -grid_search.best_score_)
```

```
Best Parameters:  {'max_depth': 12, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 50}
Best Score (Neg Mean Squared Error):  1800273452674.884
```

In [73]:
```
y_pred = grid_search.predict(X_test)
r2 = r2_score(y_test, y_pred)
r2*100
```

Out[73]:
```
93.85880360097023
```

In [74]:
```
cv_results = grid_search.cv_results_

# Extract and print the evaluation scores for each run
mean_test_scores = cv_results['mean_test_score']
std_test_scores = cv_results['std_test_score']

for mean_score, std_score, params in zip(mean_test_scores, std_test_scores, cv_results['params']):
    print(f"Parameters: {params}")
    print(f"Mean Test Score: {mean_score}")
    print(f"Standard Deviation: {std_score}")
    print("=" * 80)
```

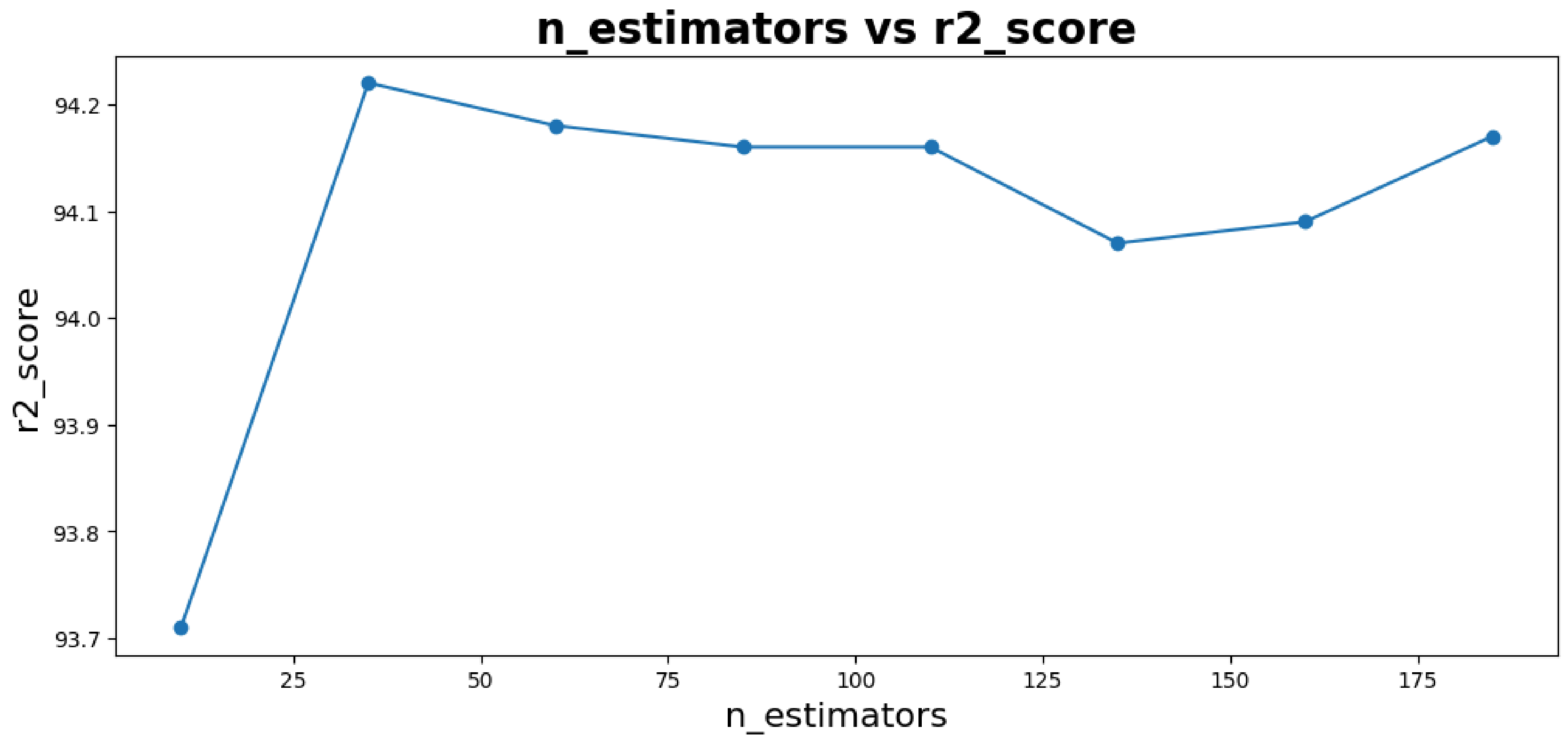
```
Parameters: {'max_depth': 6, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 50}
Mean Test Score: -3782826400318.957
Standard Deviation: 685680934843.1815
================================================================================
Parameters: {'max_depth': 6, 'min_samples_leaf': 1, 'min_samples_split': 4, 'n_estimators': 50}
Mean Test Score: -3743249906938.12
Standard Deviation: 711946671611.2451
================================================================================
Parameters: {'max_depth': 6, 'min_samples_leaf': 1, 'min_samples_split': 6, 'n_estimators': 50}
Mean Test Score: -3856174735893.626
Standard Deviation: 829464057889.5496
================================================================================
Parameters: {'max_depth': 6, 'min_samples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 50}
Mean Test Score: -3816739679331.539
Standard Deviation: 743913421685.5349
================================================================================
Parameters: {'max_depth': 6, 'min_samples_leaf': 2, 'min_samples_split': 4, 'n_estimators': 50}
Mean Test Score: -3886154632902.4893
Standard Deviation: 744028269756.4966
```

Finding optimal value of n_estimators

In [75]:
```
r2_rf = []
mse_rf = []
for i in np.arange(10,200,25):
    random_forest_model = RandomForestRegressor(n_estimators=i, max_depth=15, min_samples_leaf=1, min_samples_
    random_forest_model.fit(X_train, y_train)
    y_pred = random_forest_model.predict(X_test)
    mse_rf.append(round(mean_squared_error(y_test, y_pred)))
    r2_rf.append(round(r2_score(y_test, y_pred)*100,2))
print("Random Forest Metrics:")
print("Mean Squared Error:", mse_rf)
print("R-squared:", (r2_rf))
```

```
Random Forest Metrics:
Mean Squared Error: [1491459048908, 1369725588584, 1378668588794, 1384239085963, 1382857416397, 140626424465
7, 1399962639753, 1380453295811]
R-squared: [93.71, 94.22, 94.18, 94.16, 94.16, 94.07, 94.09, 94.17]
```

In [76]:
```
plt.figure(figsize=(12,5))
plt.plot(np.arange(10,200,25), r2_rf, marker='o')
plt.title("n_estimators vs r2_score", fontdict={'fontsize':20, 'weight':'bold'})
plt.xlabel("n_estimators", fontdict={'fontsize':16})
plt.ylabel("r2_score", fontdict={'fontsize':16})
plt.show()
```

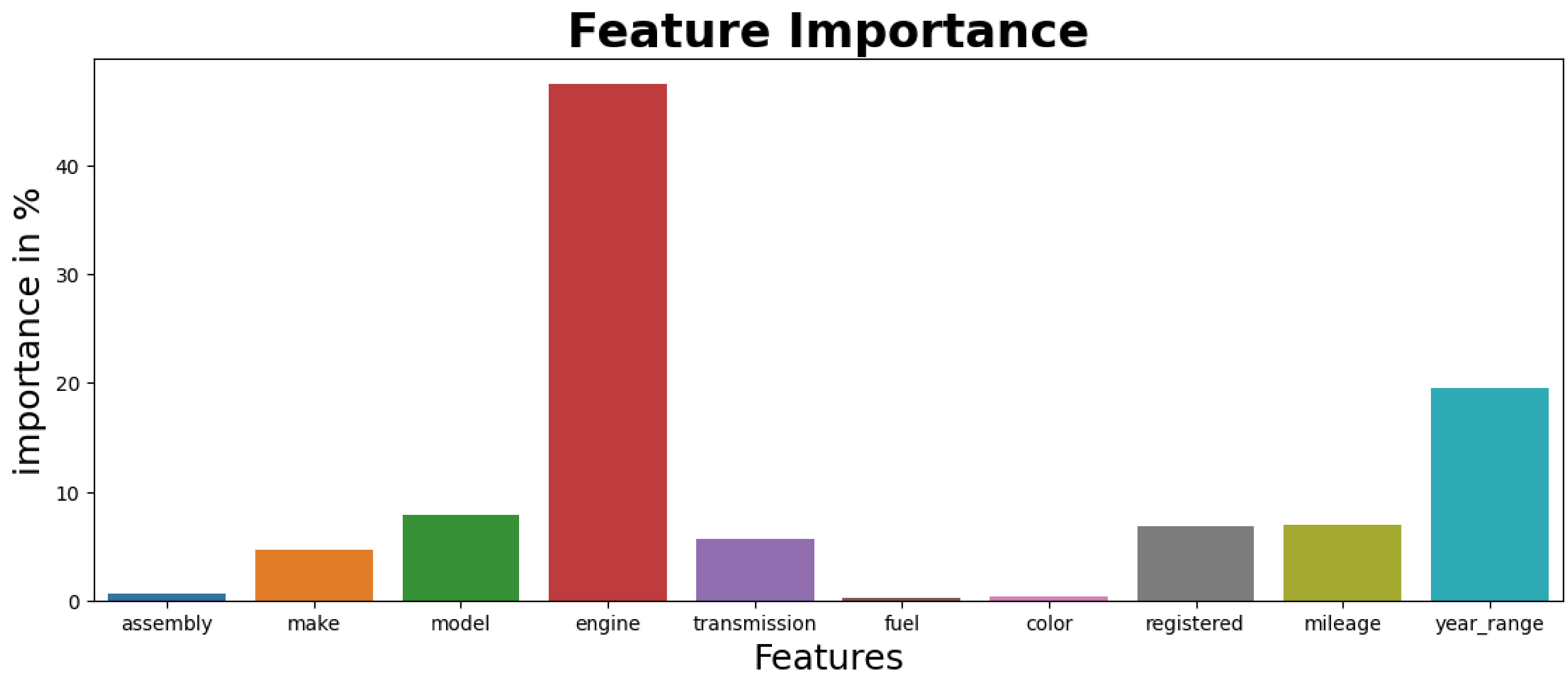


n_estimators = 35 gives the best r2_score

In [77]:
```
random_forest_model = RandomForestRegressor(n_estimators=35, max_depth=15, min_samples_leaf=1, min_samples_spl
random_forest_model.fit(X_train, y_train)
y_pred = random_forest_model.predict(X_test)
mse_rf = mean_squared_error(y_test, y_pred)
r2_rf = r2_score(y_test, y_pred)
print("Random Forest Metrics:")
print("Mean Squared Error:", mse_rf)
print("R-squared:", round(r2_rf*100, 2))
```

```
Random Forest Metrics:
Mean Squared Error: 1369725588583.8298
R-squared: 94.22
```

In [78]:
```python
feature_importances = random_forest_model.feature_importances_
plt.figure(figsize=(13.5,5))
sns.barplot(x=X.columns, y=(feature_importances*100))
plt.xlabel("Features", fontdict={'fontsize':18})
plt.ylabel("importance in %", fontdict={'fontsize':18})
plt.title("Feature Importance", fontdict={'fontsize':24, 'weight':'bold'})
plt.show()
```



XGBoost Regressor

In [79]:
```python
xgb_regressor = xgb.XGBRegressor()

param_grid = {
    'n_estimators': [50],
    'max_depth': [4, 5, 6],
    'learning_rate': [.05, 0.1, 0.5],
    'min_child_weight': [2,3,4]
}

grid_search = GridSearchCV(estimator=xgb_regressor, param_grid=param_grid, cv=5, scoring='neg_mean_squared_err

grid_search.fit(X_train, y_train)

print("Best Parameters: ", grid_search.best_params_)
print("Best Score (Neg Mean Squared Error): ", -grid_search.best_score_)
```

```
Best Parameters:  {'learning_rate': 0.5, 'max_depth': 6, 'min_child_weight': 3, 'n_estimators': 50}
Best Score (Neg Mean Squared Error):  1948773761641.3413
```

In [80]:
```python
y_pred = grid_search.predict(X_test)
r2 = r2_score(y_test, y_pred)
print(round(r2*100,2))
```

```
93.5
```

random forest regressor performs much better than xgboost regressor.

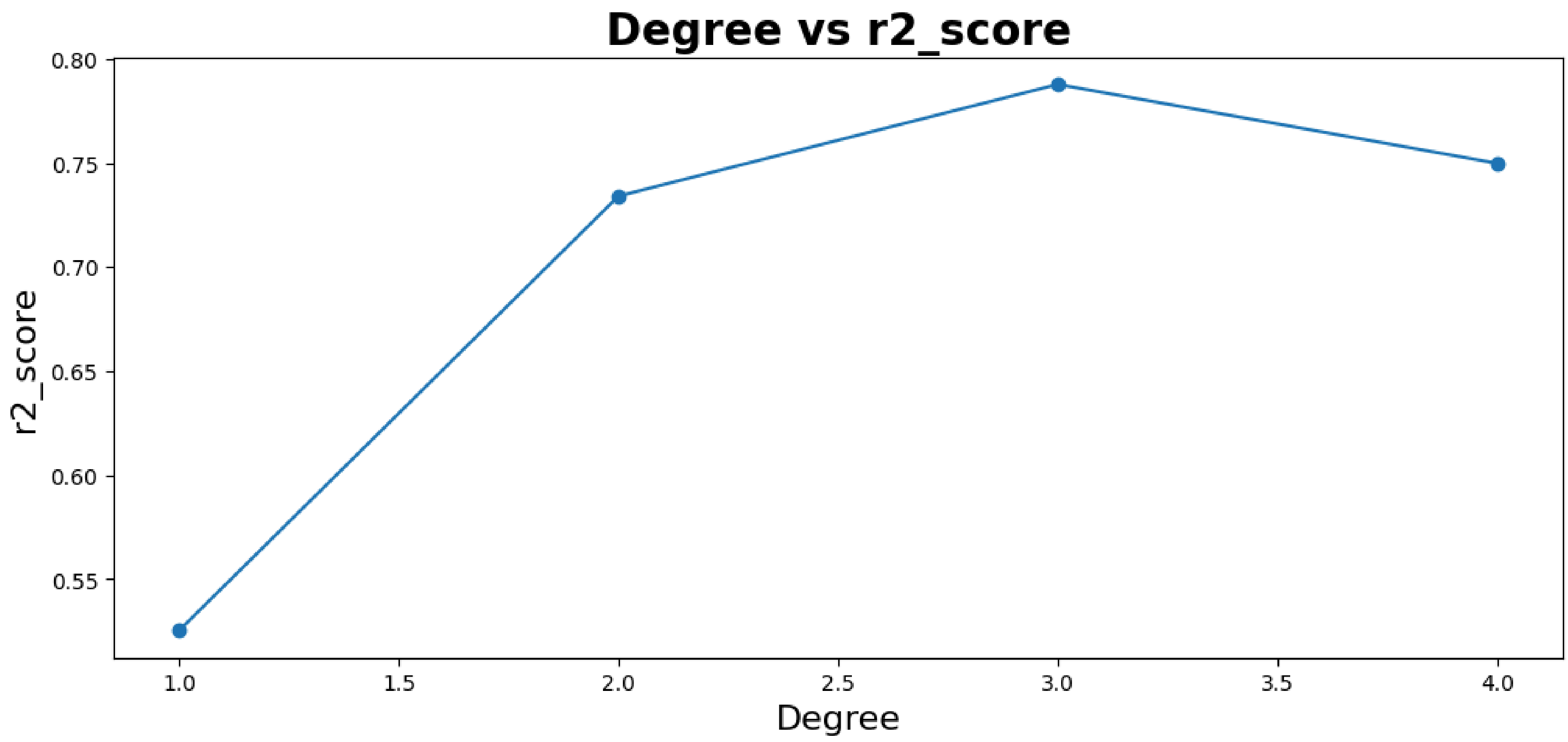
Polynomial Regression

In [81]:
```python
from sklearn.preprocessing import PolynomialFeatures
mse = []
r2 = []
for i in np.arange(1,5,1):
    poly_features = PolynomialFeatures(degree=i)
    X_train_poly = poly_features.fit_transform(X_train)
    model = LinearRegression()
    model.fit(X_train_poly, y_train)
    X_test_poly = poly_features.transform(X_test)
    y_pred = model.predict(X_test_poly)
    mse.append(mean_squared_error(y_test, y_pred))
    r2.append(r2_score(y_test, y_pred))
```

In [82]:
```python
print("Mean squared root error: ", np.sqrt(mse))
print("r2_score: ", r2)
```

```
Mean squared root error:  [3353663.09898308 2510020.0644155  2242254.61440862 2434503.86508727]
r2_score:  [0.5253840346873337, 0.7341370221748821, 0.7878352004194986, 0.7498938244659688]
```

In [83]:
```
plt.figure(figsize=(12,5))
plt.plot(np.arange(1,5,1), r2, marker='o')
plt.title("Degree vs r2_score", fontdict={'fontsize':20, 'weight':'bold'})
plt.xlabel("Degree", fontdict={'fontsize':16})
plt.ylabel("r2_score", fontdict={'fontsize':16})
plt.show()
```



3rd degree polynomial regression performs the best but its still worse than the random forest model.

Visualizing performance of various predicting models

In [84]:
```
plt.style.use('classic')
categories = ['Random Forest', 'XGBoost', 'LR', '2nd Degree PR', '3rd Degree PR', '4th Degree PR']
r2_score = [94.22, 93.5, 52.54, 73.41, 78.78, 74.99]
custom_colors = ["#e60049", "#0bb4ff", "#50e991", "#e6d800", "#9b19f5", "#dc0ab4"]
plt.figure(figsize=(12,5))
sns.barplot(x = r2_score, y=categories, palette=custom_colors)
plt.title('R2 score of various models', fontdict={'fontsize':22, 'weight':'bold'})
plt.xlabel('R2 score', fontdict={'fontsize':16})
plt.xticks(fontsize=14)
plt.yticks(fontsize=13)
plt.show()
```