1. Problem Statement In the fast-paced taxi booking sector, making the most of revenue is essential for long-term success and driver happiness. Our goal is to use data-driven insights to maximise revenue streams for taxi drivers in order to meet this need. Our research aims todetermine whether payment methods have an impact on fare pricing by focusing on the relationship between payment type and fare amount. 2. Objective This project is main goal is to run an A/B testto examine the relationship between the total fare and the method of payments.We use descriptive statistics to extract useful information that can helps texi's drivers to generates more cash.In paticular,we want to find out the big difference in the fare for those who pay who pay with credit cards versus those who pay with cash. 4. Research Question Is there a relationship between total fare amount and payment type? Can we nudge customers towards payment methods that generate higher revenue for drivers, without negatively impacting customer experience?

In [2]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as s
import warnings
import statsmodels.api as sm
warnings.filterwarnings("ignore")
```

In [4]:
```python
#load datsets
df=pd.read_csv("C:\\Users\\HP\\Downloads\\yellow_tripdata_2020-09.csv")
```

In [5]:
```python
df.head()
```

Out[5]:

	Unnamed: 0	Unnamed:_0	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_distance	RatecodeID	store_and_fwd_flag	PULocationID	DOLocationID	payment_type	fare_amount	extra	mta_tax	tip_amount	tolls_amount	improv
0	0	0	1.0	2020-09-01 07:37:32	2020-09-01 07:42:12	1.0	0.90	1.0	N	140	262	1.0	5.5	2.5	0.5	1.75	0.0	
1	1	1	2.0	2020-09-01 07:47:57	2020-09-01 07:52:30	1.0	0.87	1.0	N	48	230	1.0	5.5	0.0	0.5	1.20	0.0	
2	2	2	2.0	2020-09-01 09:02:30	2020-09-01 09:14:01	1.0	2.33	1.0	N	238	43	2.0	11.0	0.0	0.5	0.00	0.0	
3	3	3	1.0	2020-09-01 09:00:28	2020-09-01 09:07:20	1.0	1.30	1.0	N	142	163	1.0	7.0	2.5	0.5	2.00	0.0	
4	4	4	2.0	2020-09-01 10:55:27	2020-09-01 11:06:12	1.0	4.93	1.0	N	88	170	1.0	15.5	0.0	0.5	2.50	0.0	

In [6]:
```python
#Exploratray Data analysis
df.shape
```

Out[6]:
```
(998, 20)
```

In [7]:
```python
df.dtypes
```

Out[7]:
```
Unnamed: 0                  int64
Unnamed:_0                  int64
VendorID                  float64
tpep_pickup_datetime       object
tpep_dropoff_datetime      object
passenger_count           float64
trip_distance             float64
RatecodeID                float64
store_and_fwd_flag         object
PULocationID                int64
DOLocationID                int64
payment_type              float64
fare_amount               float64
extra                     float64
mta_tax                   float64
tip_amount                float64
tolls_amount              float64
improvement_surcharge     float64
total_amount              float64
congestion_surcharge      float64
dtype: object
```

In [8]:
```python
df["tpep_pickup_datetime"]=pd.to_datetime(df["tpep_pickup_datetime"])
df["tpep_dropoff_datetime"]=pd.to_datetime(df["tpep_dropoff_datetime"])
```

In [9]:
```python
df["duration"]=df["tpep_dropoff_datetime"]-df["tpep_pickup_datetime"]
df["duration"].dt.total_seconds()/60
```

Out[9]:
```
0       4.666667
1       4.550000
2      11.516667
3       6.866667
4      10.750000
         ...
993    22.000000
994    10.000000
995    -0.483333
996    25.100000
997    12.000000
Name: duration, Length: 998, dtype: float64
```

In [10]:
```python
#filtering data
df=df[["passenger_count","payment_type","fare_amount","trip_distance","duration"]]
df
```

Out[10]:

	passenger_count	payment_type	fare_amount	trip_distance	duration
0	1.0	1.0	5.50	0.90	0 days 00:04:40
1	1.0	1.0	5.50	0.87	0 days 00:04:33
2	1.0	2.0	11.00	2.33	0 days 00:11:31
3	1.0	1.0	7.00	1.30	0 days 00:06:52
4	1.0	1.0	15.50	4.93	0 days 00:10:45
...	...	...	...	...	...
993	NaN	NaN	25.98	9.54	0 days 00:22:00
994	NaN	NaN	11.45	1.35	0 days 00:10:00
995	NaN	NaN	17.02	4.04	-1 days +23:59:31
996	NaN	NaN	33.52	6.38	0 days 00:25:06
997	NaN	NaN	13.40	2.56	0 days 00:12:00

998 rows × 5 columns

In [11]:
```python
#check missing value
df.isnull().sum()
```

Out[11]:
```
passenger_count    69
payment_type       69
fare_amount         0
trip_distance       0
duration            0
dtype: int64
```

In [12]:
```python
(69/len(df)*100)
```

Out[12]:
```
6.913827655310621
```

In [13]:
```python
df.dropna(inplace=True)
df
```

Out[13]:

	passenger_count	payment_type	fare_amount	trip_distance	duration
0	1.0	1.0	5.5	0.90	0 days 00:04:40
1	1.0	1.0	5.5	0.87	0 days 00:04:33
2	1.0	2.0	11.0	2.33	0 days 00:11:31
3	1.0	1.0	7.0	1.30	0 days 00:06:52
4	1.0	1.0	15.5	4.93	0 days 00:10:45
...	...	...	...	...	...
924	4.0	2.0	12.5	3.00	0 days 00:15:17
925	1.0	2.0	8.5	1.98	0 days 00:07:35
926	1.0	1.0	5.0	0.91	0 days 00:03:42
927	1.0	1.0	11.0	3.15	0 days 00:09:27
928	1.0	2.0	9.5	2.10	0 days 00:10:13

929 rows × 5 columns

In [14]:
```python
df["passenger_count"]=df["passenger_count"].astype("int64")
df["payment_type"]=df["payment_type"].astype("int64")
```

In [15]:
```python
df[df.duplicated()]
df
```

Out[15]:

	passenger_count	payment_type	fare_amount	trip_distance	duration
0	1	1	5.5	0.90	0 days 00:04:40
1	1	1	5.5	0.87	0 days 00:04:33
2	1	2	11.0	2.33	0 days 00:11:31
3	1	1	7.0	1.30	0 days 00:06:52
4	1	1	15.5	4.93	0 days 00:10:45
...	...	...	...	...	...
924	4	2	12.5	3.00	0 days 00:15:17
925	1	2	8.5	1.98	0 days 00:07:35
926	1	1	5.0	0.91	0 days 00:03:42
927	1	1	11.0	3.15	0 days 00:09:27
928	1	2	9.5	2.10	0 days 00:10:13

929 rows × 5 columns

In [16]:
```python
df.drop_duplicates(inplace=True)
```

In [17]:
```python
#data distribution or contribution
df["passenger_count"].value_counts(normalize=True)
```

Out[17]:
```
passenger_count
1    0.750000
2    0.140086
3    0.029095
5    0.026940
4    0.020474
6    0.020474
0    0.012931
Name: proportion, dtype: float64
```

In [18]:
```python
df["payment_type"].value_counts(normalize=True)
```

Out[18]:
```
payment_type
1    0.712284
2    0.275862
3    0.008621
4    0.003233
Name: proportion, dtype: float64
```

In [19]:
```python
df=df[df["payment_type"]<3]
df=df[(df["passenger_count"]>0)&(df["passenger_count"]<6)]
```

In [20]:
```python
df.shape
```

Out[20]:
```
(887, 5)
```

In [21]:
```python
df["payment_type"].replace([1,2],['Card','Cash'], inplace = True)
```

In [22]:
```python
df.describe()
```

Out[22]:

	passenger_count	fare_amount	trip_distance	duration
count	887.000000	887.000000	887.000000	887
mean	1.379932	10.657272	2.431172	0 days 00:19:22.277339346
std	0.870227	8.501169	2.858909	0 days 01:42:20.360185295
min	1.000000	-4.000000	0.000000	0 days 00:00:00
25%	1.000000	6.000000	0.980000	0 days 00:05:41.500000
50%	1.000000	8.500000	1.600000	0 days 00:09:01
75%	1.000000	12.000000	2.700000	0 days 00:13:48
max	5.000000	100.000000	27.330000	0 days 23:38:53

In [23]:
```python
df=df[df["passenger_count"]>0]
df=df[df["fare_amount"]>0]
df=df[df["trip_distance"]>0]
df
```

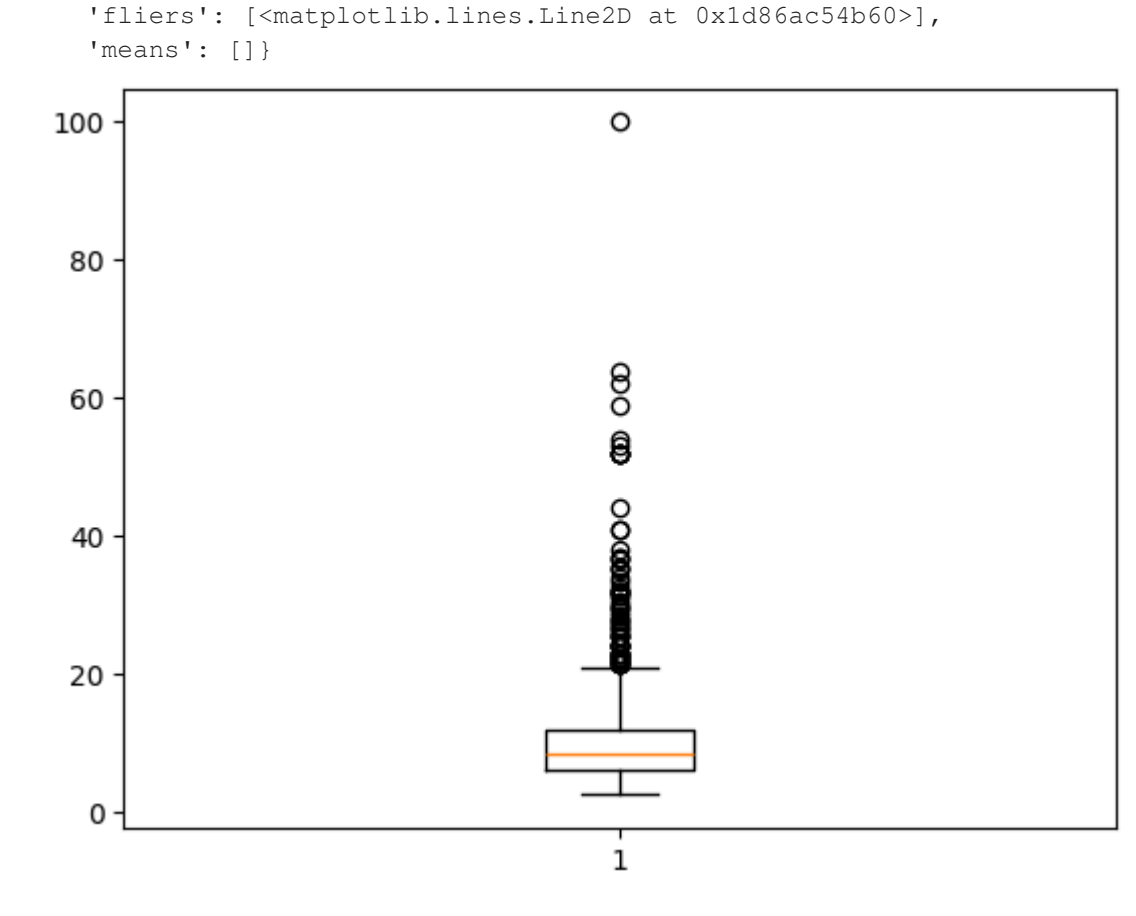
Out[23]:

	passenger_count	payment_type	fare_amount	trip_distance	duration
0	1	Card	5.5	0.90	0 days 00:04:40
1	1	Card	5.5	0.87	0 days 00:04:33
2	1	Cash	11.0	2.33	0 days 00:11:31
3	1	Card	7.0	1.30	0 days 00:06:52
4	1	Card	15.5	4.93	0 days 00:10:45
...	...	...	...	...	...
924	4	Cash	12.5	3.00	0 days 00:15:17
925	1	Cash	8.5	1.98	0 days 00:07:35
926	1	Card	5.0	0.91	0 days 00:03:42
927	1	Card	11.0	3.15	0 days 00:09:27
928	1	Cash	9.5	2.10	0 days 00:10:13

879 rows × 5 columns

In [24]:
```python
#before outliers
plt.boxplot(df["fare_amount"])
```

Out[24]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x1d86a76ecc0>,
  <matplotlib.lines.Line2D at 0x1d86ac54410>],
 'caps': [<matplotlib.lines.Line2D at 0x1d86ac545f0>,
  <matplotlib.lines.Line2D at 0x1d86ac54c20>],
 'boxes': [<matplotlib.lines.Line2D at 0x1d86ac4a1e0>],
 'medians': [<matplotlib.lines.Line2D at 0x1d86ac54dd0>],
 'fliers': [<matplotlib.lines.Line2D at 0x1d86ac54b60>],
 'means': []}
```



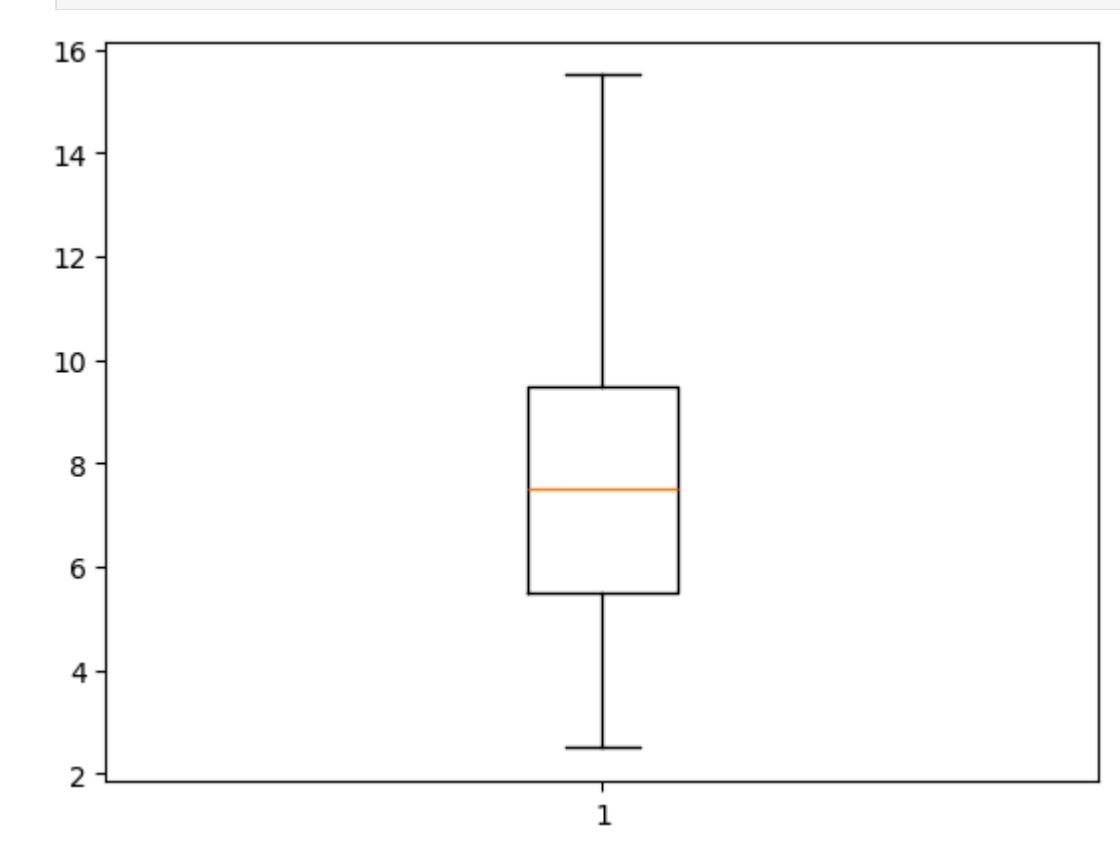
In [27]:
```python
#using IQR
for col in ['fare_amount','trip_distance','duration']:
    q1=df[col].quantile(0.25)
    q3=df[col].quantile(0.75)
    IQR=q3-q1

    lower_bound = q1-1.5*IQR
    upper_bound = q3+1.5*IQR

    df=df[(df[col]>=lower_bound)&(df[col]<=upper_bound)]

df
```

Out[27]:

	passenger_count	payment_type	fare_amount	trip_distance	duration
0	1	Card	5.5	0.90	0 days 00:04:40
1	1	Card	5.5	0.87	0 days 00:04:33
2	1	Cash	11.0	2.33	0 days 00:11:31
3	1	Card	7.0	1.30	0 days 00:06:52
5	1	Card	8.0	1.61	0 days 00:09:19
...	...	...	...	...	...
924	4	Cash	12.5	3.00	0 days 00:15:17
925	1	Cash	8.5	1.98	0 days 00:07:35
926	1	Card	5.0	0.91	0 days 00:03:42
927	1	Card	11.0	3.15	0 days 00:09:27
928	1	Cash	9.5	2.10	0 days 00:10:13

737 rows × 5 columns

In [28]:
```python
#After outliers
plt.boxplot(df["fare_amount"])
plt.show()
```

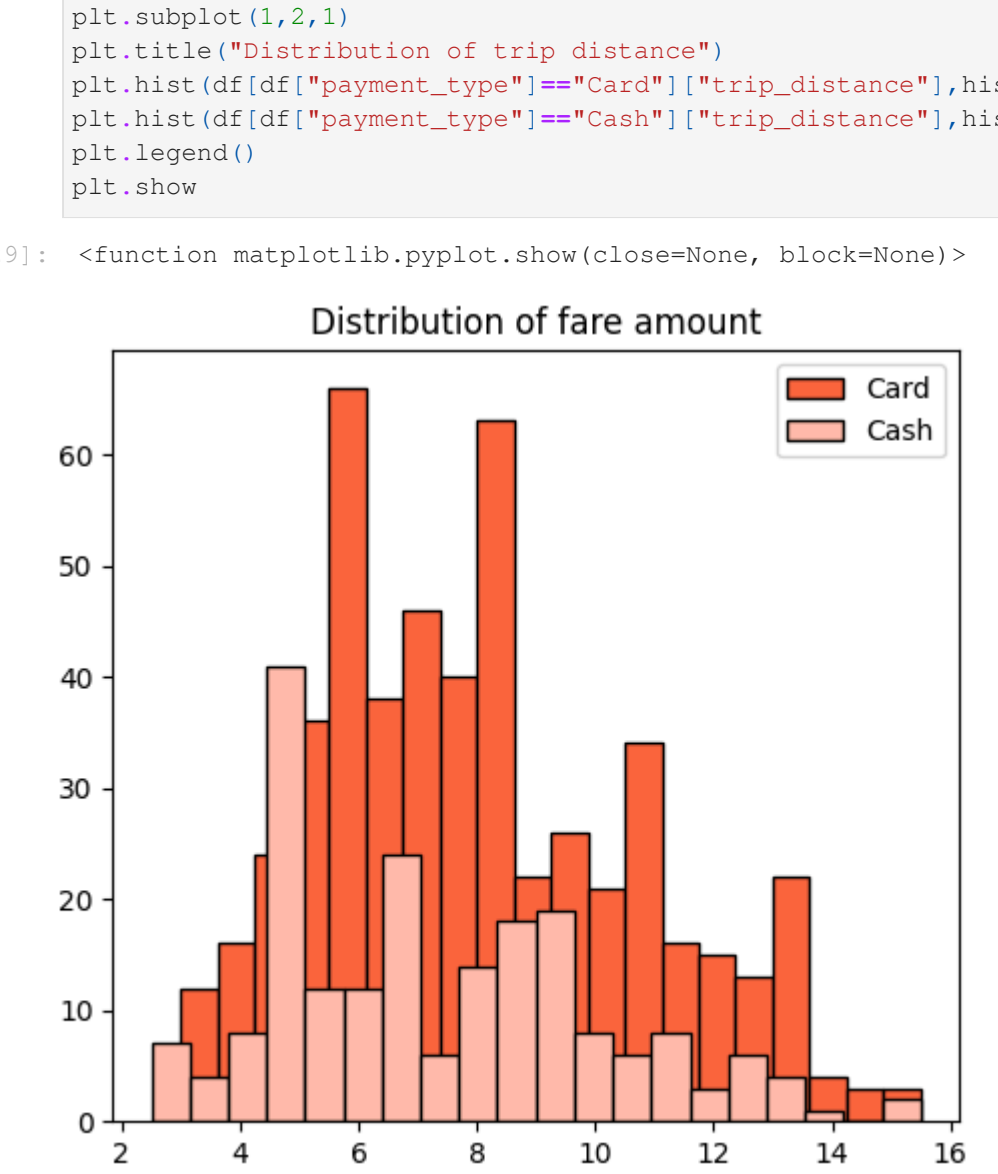


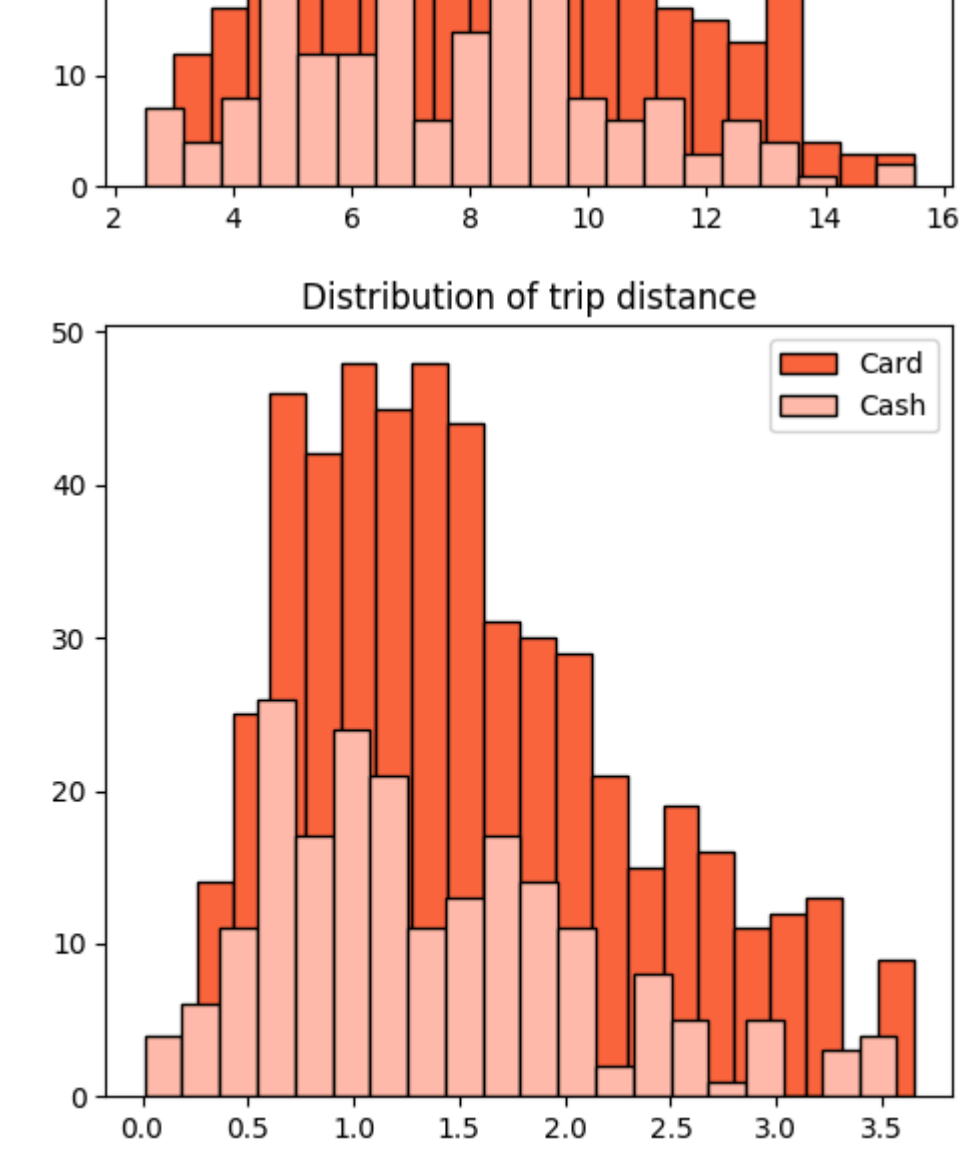
4.Journey Insights:

- Customers paying with cards tend to have a slightly higher average trip distance and fare amount compared to those paying with cash.
- Indicates that customers prefers to pay more with cards when they have high fare amount and long trip distance.

In [29]:
```python
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.title("Distribution of fare amount")
plt.hist(df[df["payment_type"]=="Card"]["fare_amount"],histtype="barstacked",bins=20,edgecolor="k",color="#FA643F",label="Card")
plt.hist(df[df["payment_type"]=="Cash"]["fare_amount"],histtype="barstacked",bins=20,edgecolor="k",color="#FFBCAB",label="Cash")
plt.legend()
plt.show
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.title("Distribution of trip distance")
plt.hist(df[df["payment_type"]=="Card"]["trip_distance"],histtype="barstacked",bins=20,edgecolor="k",color="#FA643F",label="Card")
plt.hist(df[df["payment_type"]=="Cash"]["trip_distance"],histtype="barstacked",bins=20,edgecolor="k",color="#FFBCAB",label="Cash")
plt.legend()
plt.show
```

Out[29]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```





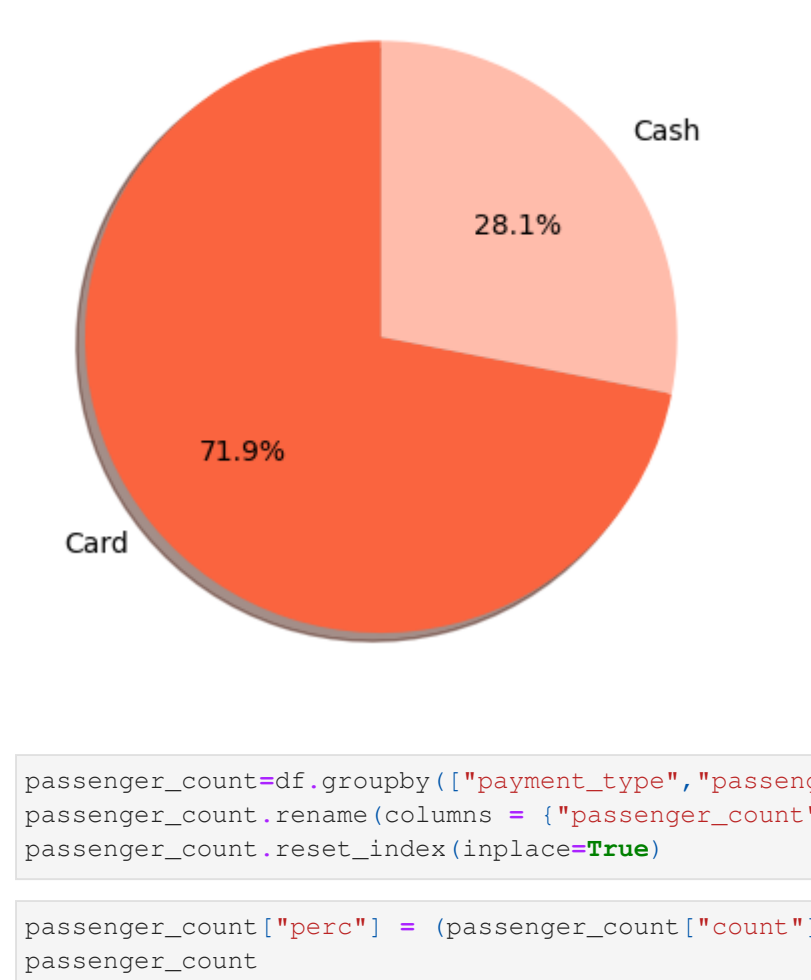
In [ ]:
```python
#using groupby
df.groupby("payment_type").agg({"fare_amount":["mean","std"],"trip_distance":["mean","std"]})
```

5.Preference of Payment Types:

- The proportion of customers paying with cards is significantly higher than those paying with cash, with card payments accounting for 67.5% of all transactions compared to cash payments at 32.5%.
- This indicates a strong preference among customers for using card payments over cash, potentially due to convenience, security, or incentives offered for card transactions.

In [ ]:

In [31]:
```python
plt.title("Preference of payment Type")
plt.pie(df["payment_type"].value_counts(normalize=True),labels = df["payment_type"].value_counts().index,
       startangle=90,shadow=True,autopct="%1.1f%%",colors=["#FA643F","#FFBCAB"])
plt.show()
```



In [32]:
```python
passenger_count=df.groupby(["payment_type","passenger_count"])[["passenger_count"]].count()
passenger_count.rename(columns = {"passenger_count":"count"},inplace=True)
passenger_count.reset_index(inplace=True)
```

In [34]:
```python
passenger_count["perc"] = (passenger_count["count"]/passenger_count["count"].sum())*100
passenger_count
```

Out[34]:

	payment_type	passenger_count	count	perc
0	Card	1	399	55.186722
1	Card	2	78	10.788382
2	Card	3	20	2.766252
3	Card	4	10	1.383126
4	Card	5	13	1.798064
5	Cash	1	160	22.130014
6	Cash	2	28	3.872752
7	Cash	3	6	0.829876
8	Cash	4	5	0.691563
9	Cash	5	4	0.553250

In [36]:
```python
df=pd.DataFrame(columns=["payment_type",1,2,3,4,5])
df["payment_type"]=["Card","Cash"]
df.iloc[0,1:]=passenger_count.iloc[0:5,-1]
df.iloc[1,1:]=passenger_count.iloc[5,-1]
df
```

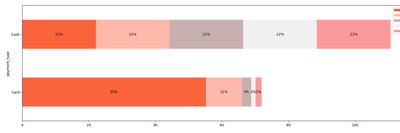
Out[36]:

	payment_type	1	2	3	4	5
0	Card	55.186722	10.788382	2.766252	1.383126	1.798064
1	Cash	22.130014	22.130014	22.130014	22.130014	22.130014

6.Passenger Count Analysis

- Among card payments, rides with a single passenger (passenger_count = 1) comprise the largest proportion, constituting 40.08% of all card transactions.
- Similarly, cash payments are predominantly associated with single-passenger rides, making up 20.04% of all cash transactions.
- There is a noticeable decrease in the percentage of transactions as the passenger count increases, suggesting that larger groups are less likely to use taxis or may opt for alternative payment methods.
- These insights emphasize the importance of considering both payment method and passenger count when analyzing transaction data, as they provide valuable insights into customer behavior and preferences.

In [52]:
```python
fig,ax = plt.subplots(figsize=(20,6))
df.plot(x="payment_type",kind="barh",stacked = True,ax=ax,color= ["#FA643F" ,"#FFBCAB","#CBB2B2","#F1F1F1","#FD9F9F"])
#Add percentage text
for p in ax.patches:
    width = p.get_width()
    height=p.get_height()
    x,y=p.get_xy()
    ax.text(x+width/2,
           y+ height/2,
           "{:.0f}%".format(width),
            horizontalalignment="center",
            verticalalignment="center")
```


1
2
3
4
5
payment_type
Cash
Card
22%
22%
22%
22%
22%
55%
11%
3%
1%
1%
0
20
40
60
80
100