Results:

1. Price & Time

Based on the ticket_data.csv file, the first objective is to find the lowest, average, and highest prices, as well as the lowest, highest, and average travel time for each trip.

My understanding is that the objective is to group the data by the departure city (o_city) and arrival city (d_city), as the trip is defined as the journey from one city to another. The final results will be presented accordingly.

1.1 Price

```
prix_result = ticket.groupby(['o_city', 'd_city'])['price_in_cents'] .agg(['min','mean','max'])
prix_result
```

o_city	d_city	min	mean	max
5	23	18600	20320.000000	22000
6	227	9860	11755.000000	13650
	504	2000	4042.666667	8920
	628	2600	2797.500000	3190
	845	700	864.626866	2420
...	...	...	...	...
11938	126	3000	4204.861111	5350
12124	1064	6000	6950.000000	7900
12166	857	5300	5300.000000	5300
12190	639	600	688.888889	850
	8937	9800	9800.000000	9800

1437 rows × 3 columns

1.2 Time

o_city	d_city	min	mean	max
5	23	0 days 08:53:00	0 days 10:18:48	0 days 15:54:00
6	227	0 days 12:24:00	0 days 13:42:30	0 days 15:01:00
	504	0 days 05:36:00	0 days 08:17:24	0 days 12:20:00
	628	0 days 09:40:00	0 days 12:10:00	0 days 14:30:00
	845	0 days 01:00:00	0 days 01:19:54.626865671	0 days 04:11:00
...	...	...	...	...
11938	126	0 days 05:30:00	0 days 07:25:16.666666666	1 days 11:20:00
12124	1064	0 days 11:10:00	0 days 17:10:00	0 days 23:10:00
12166	857	0 days 21:55:00	0 days 21:55:00	0 days 21:55:00
12190	639	0 days 01:10:00	0 days 01:28:53.333333333	0 days 02:40:00
	8937	0 days 09:10:00	0 days 09:10:00	0 days 09:10:00

1437 rows × 3 columns

Time in hours:

:

o_city	d_city	min	mean	max
5	23	8.883333	10.313333	15.900000
6	227	12.400000	13.708333	15.016667
	504	5.600000	8.290000	12.333333
	628	9.666667	12.166667	14.500000
	845	1.000000	1.331841	4.183333
...	...	...	...	...
11938	126	5.500000	7.421296	35.333333
12124	1064	11.166667	17.166667	23.166667
12166	857	21.916667	21.916667	21.916667
12190	639	1.166667	1.481481	2.666667
	8937	9.166667	9.166667	9.166667

1437 rows × 3 columns

2. The difference in price and time is derived from different distances and different modes of travel.

2.1 Straight line distance

First, we will calculate the straight-line distance between two cities based on the departure city (o_city) and arrival city (d_city) from the ticket_data.csv file, as well as the latitude and longitude information from the cities.csv file.

Since the distances in the table are all within 2000 km, we will divide the data into three groups: 0-200 km, 201-800 km, and 800-2000 km.

```
ticket_draft_0_200 = ticket_draft[ticket_draft['distance']<= 200]
ticket_draft_0_200.distance.agg(['min','max'])
```

```
min     18.962318
max    199.085694
Name: distance, dtype: float64
```

```
ticket_draft_201_800 = ticket_draft[(ticket_draft['distance']<= 800) & (ticket_draft['distance']> 200
ticket_draft_201_800.distance.agg(['min','max'])
```

```
min    200.566830
max    798.544558
Name: distance, dtype: float64
```

```
ticket_draft_801_2000 = ticket_draft[(ticket_draft['distance']<= 2000) & (ticket_draft['distance']> 8
ticket_draft_801_2000.distance.agg(['min','max'])
```

```
min     803.402293
max    1875.174971
Name: distance, dtype: float64
```

2.2 Defining functions

Define two functions (priceAVG) and (timeAVG) to derive the average of price and time for different categories based on different distances

```python
def priceAVG_timeAVG (df):
    priceAVG = df.groupby('transport_type').price_in_cents.agg('mean').apply(lambda x: np.round(x, 2)
    timeAVG = df.groupby('transport_type').apply(lambda x: (x['arrival_ts'] - x['departure_ts']).agg(

    return priceAVG , timeAVG
```

```python
priceAVG200 , timeAVG200 = priceAVG_timeAVG(ticket_draft_0_200)
```

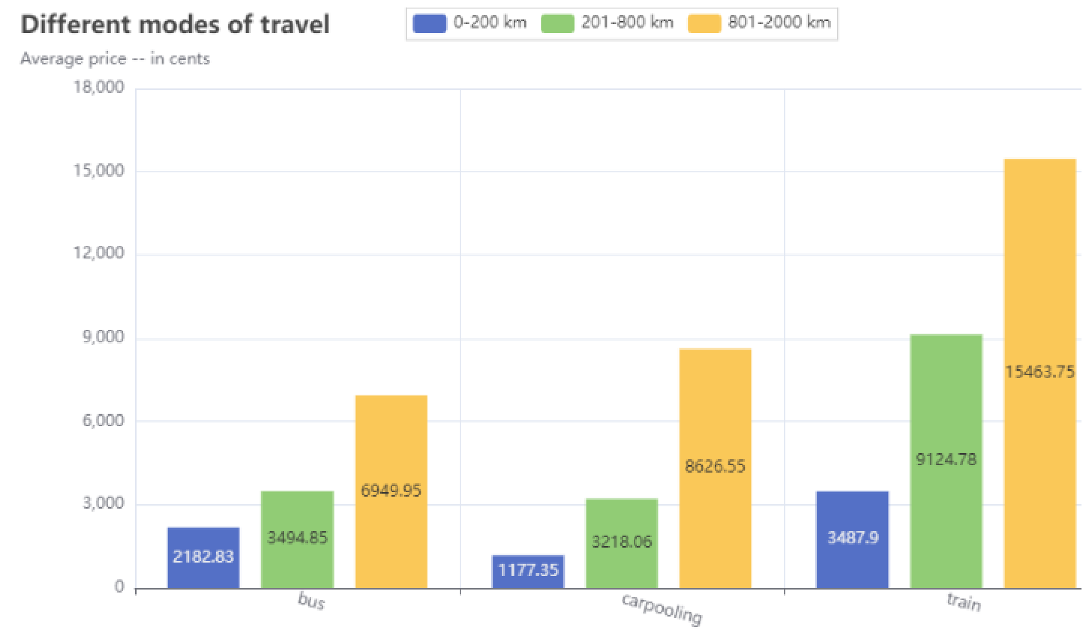
```python
priceAVG800 , timeAVG800 = priceAVG_timeAVG(ticket_draft_201_800)
```

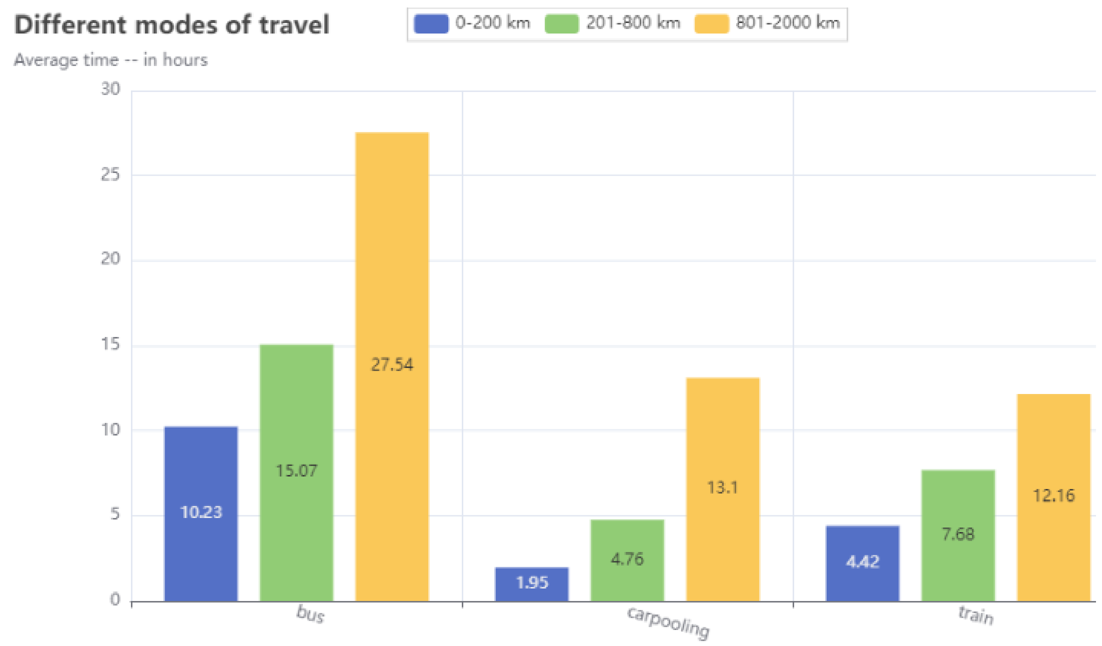
```python
priceAVG2000 , timeAVG2000 = priceAVG_timeAVG(ticket_draft_801_2000)
```

```python
print(priceAVG200 , timeAVG200 ,priceAVG800 , timeAVG800,priceAVG2000 , timeAVG2000)
```

```
transport_type
bus           2182.83
carpooling    1177.35
train         3487.90
Name: price_in_cents, dtype: float64 transport_type
bus           10.23
carpooling     1.95
train          4.42
dtype: float64 transport_type
bus           3494.85
carpooling    3218.06
train         9124.78
Name: price_in_cents, dtype: float64 transport_type
bus           15.07
carpooling     4.76
train          7.68
dtype: float64 transport_type
bus            6949.95
carpooling     8626.55
train         15463.75
Name: price_in_cents, dtype: float64 transport_type
bus           27.54
carpooling    13.10
train         12.16
dtype: float64
```

3. Introducing 'pyecharts' for data visualisation





4. Making price forecasts

4.1 Using dummie

First, we will use "dummy" variables to categorize the transport_type. This is necessary for predicting prices in the future. Although there are only three types of data in this case, replacing them would be possible, but using "dummy" variables would be more appropriate in case there are multiple types of data in the future.

4.2 First a simple prediction

Changing 'new_distance' or 'new_time' will give different results.

```
import pandas as pd
from sklearn.linear_model import LinearRegression

# Créer un modèle de régression linéaire
regressor = LinearRegression()


X.columns = ['Feature 1', 'Feature 2', 'Feature 3', 'Feature 4', 'Feature 5']
X = dummied_df[['distance', 'time','bus','carpooling','train']]


y = dummied_df['price_in_cents']

# Entraîner le modèle de régression linéaire
regressor.fit(X, y)


new_distance = 500
new_time = 4


new_price = regressor.predict([[new_distance, new_time,0,0,1]])


new_price
```

```
D:\Anaconda\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
```

```
array([9429.78429718])
```

4.3 Linear regression

Next, a simple machine learning model is used, the model is trained and the results are obtained

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression


Forecast_prices = dummied_df


X_train, X_test, y_train, y_test = train_test_split(
    Forecast_prices[['distance', 'time','bus','carpooling','train']], Forecast_prices['price_in_cents'


model = LogisticRegression()
model.fit(X_train, y_train)


score = model.score(X_test, y_test)
print('Accuracy: {:.2f}%'.format(score * 100))
```

```
D:\Anaconda\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs faile
d to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
Accuracy: 3.93%
```

4.4 Deep Learning--MLP

I chose to use deep learning as the results from the machine learning model were not as good as I would have liked. However, due to the sheer volume of data, my computer never ran the results, but I am sure there is nothing wrong with my ideas and code, so please try to come up with results if you can.

```
from  sklearn.neural_network  import  MLPClassifier
mlp = MLPClassifier(hidden_layer_sizes =(30 ,30 ,30),max_iter=300)

X_train, X_test, y_train, y_test = train_test_split(
    Forecast_prices[['distance', 'time','bus','carpooling','train']], Forecast_prices['price_in_cents'
history = mlp.fit(X_train, y_train)
```

```
score = model.score(X_test, y_test)
print('Accuracy: {:.2f}%'.format(score * 100))
```

```
y_pred = mlp.predict(X_test)

from  sklearn.metrics import  precision_score,recall_score,f1_score
print(classification_report(y_test,y_pred))
# OU SI VOUS PREFEREZ
print("precision = ",precision_score(y_test ,  y_pred))
print("rappel = ",recall_score(y_test ,  y_pred))
print("f1 = ",f1_score(y_test ,  y_pred))
```

Questions:

1. I was going to use databricks for price prediction, but for some reason the site keeps getting buggy, hopefully I can try it in the future.
2. The 'id' column in the providers.csv table is equal to the 'company' column in ticket_data.csv, so what does the What does 'company_id' mean?