Last-Question

September 15, 2020

1 Optional Question

Focus on the trip data during 2019-01 and 2019-12 only. Now, the client of MSBA & Company wants to understand the key factors that explains the difference in the (average daily) ridership between different pairs of origin and destination. Please explore auxiliary data sets and discuss your findings. [3pts]

As for this problem, there are several categories of factors that will affect the daily average number of riders for a specific routine(Origin-destination pair). - Information only related to start/end location - Geographic information - Latitude - Longitude - District - Infrastructure information - Total docks - Traffic information - Rider gender distribution - Direction distribution(Identify most riderships are ride in or ride out?) - Peak hour(Identify the busiest time of the place) - Standard deviation of daily number(Identify the location's service is rigid demand or elastic demand.) - Features related to both locations - Geographic distance - Distance between two stations - Whether the two sites are cross-regional - Positioning distance - Gender distribution distance - Direction distribution distance - Peak hour distance - Standard deviation distance - Dock number gap

[1]:
```
import sys
import matplotlib
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

[2]:
```
sys.path.append(
    r'D:\OneDrive\Programming\documents_python\NUS␣
↪Courses\DBA5106\Course-DBA5106\assignment\IndividualAssignment2')
```

[3]:
```
from utils.logger import logger
from utils.config import PROCESSED_DATA_DIR
from utils.data_porter import read_from_csv
```

1.1 Data Cleaning

[4]:
```
# Set hyper parameter
START_DATE = '2019-01-01'
END_DATE = '2019-12-31'
```

[5]:
```
# Prepare the trip data
tripdata_df = read_from_csv('tripdata.csv', PROCESSED_DATA_DIR,
                            parse_dates=['starttime', 'stoptime'])
tripdata_df['datetime'] = tripdata_df['starttime'].dt.strftime("%Y-%m-%d")
tripdata_used = tripdata_df.loc[(tripdata_df['datetime'] >= START_DATE) &
                                (tripdata_df['datetime'] <= END_DATE)]
```

[6]:
```
# Prepare the station info
station_info = read_from_csv('Stations.csv', PROCESSED_DATA_DIR)
station_info['District'].value_counts()

# create usertype map(remain usertype id in the main file)
district_dict = {'Boston': 1, 'Cambridge': 2,'Somerville': 3,
                 'Brookline': 4, 'Everett': 5}
station_info['district_id'] = station_info['District'].map(district_dict)

# Drop unrelated columns
drop_lst = ['Name', 'District', 'Public']
station_info.drop(drop_lst, axis=1, inplace=True)

print(station_info.head())
```

	Station Id	Latitude	Longitude	Total docks	district_id
0	149	42.363796	-71.129164	18	1
1	378	42.380323	-71.108786	19	3
2	330	42.381001	-71.104025	15	3
3	116	42.370803	-71.104412	23	2
4	333	42.375002	-71.148716	25	2

[7]:
```
# Ignore the trips that station id is not in the station information file
station_lst = station_info['Station Id'].tolist()
tripdata_cleaned = tripdata_used.loc[(tripdata_used['start station id'].
 ↪isin(station_lst)) &
                                     (tripdata_used['end station id'].
 ↪isin(station_lst))]
tripdata_cleaned.dtypes
```

[7]:
```
tripduration               int64
starttime          datetime64[ns]
stoptime           datetime64[ns]
start station id             int64
end station id               int64
bikeid                       int64
birth year                   int64
gender                     float64
usertype_id                  int64
datetime                    object
```

```
dtype: object
```

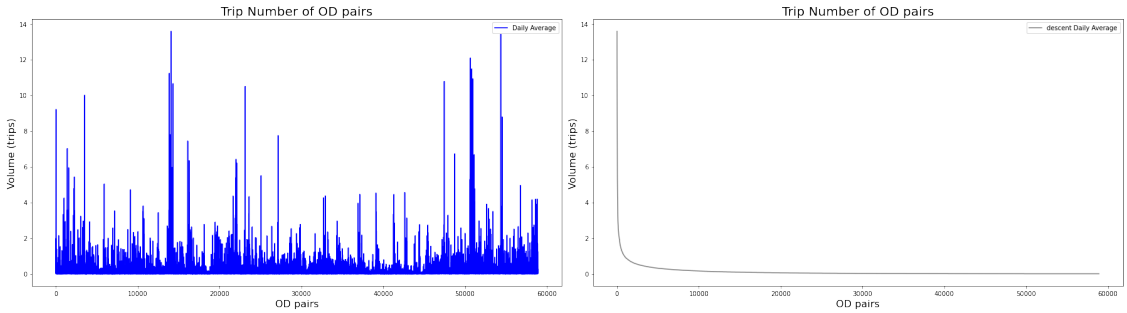
[8]:
```
# To silence the Warning
pd.set_option('mode.chained_assignment', None)

# Creat unique id for a origin-destiney pair
tripdata_cleaned['od_pair'] = tripdata_cleaned.apply(
    lambda x: str(x['start station id']) + '_' + str(x['end station id']),␣
 ↪axis=1)
```

[9]:
```
tripdata_cleaned.head(2)
```

[9]:
```
         tripduration               starttime                stoptime  \
5212224           371 2019-01-01 00:09:13.798 2019-01-01 00:15:25.336
5212225           264 2019-01-01 00:33:56.182 2019-01-01 00:38:20.880

         start station id  end station id  bikeid  birth year  gender  \
5212224                80             179    3689        1987     1.0
5212225               117             189    4142        1990     1.0

         usertype_id    datetime  od_pair
5212224            1  2019-01-01   80_179
5212225            1  2019-01-01  117_189
```

[10]:
```
od_pair = tripdata_cleaned['od_pair'].value_counts().sort_index()/365
```

[11]:
```
fig = plt.figure(figsize=(25, 7))
ax1 = plt.subplot(121)
ax1.plot(od_pair.tolist(), color='blue', label='Daily Average')
ax1.set_xlabel('OD pairs', fontsize=16)
ax1.set_ylabel('Volume (trips)', fontsize=16)
ax1.set_title(f'Trip Number of OD pairs', fontsize=20)
ax1.legend(loc='upper right')

ax2 = plt.subplot(122)
ax2.plot(od_pair.sort_values(ascending=False).tolist(),color='Grey',␣
 ↪label='descent Daily Average')
ax2.set_xlabel('OD pairs', fontsize=16)
ax2.set_ylabel('Volume (trips)', fontsize=16)
ax2.set_title(f'Trip Number of OD pairs', fontsize=20)
ax2.legend(loc='upper right')

plt.tight_layout()
plt.show()
```



1.2 Feature Engineering

1.2.1 Feature Engineering – Traffic information

- Information only related to start/end location
  - Traffic information
    - Daily Average Trips
    - Daily Average Ride In Trips
    - Daily Average Ride Out Trips
    - Rider gender distribution
    - Direction distribution(Identify most riderships are ride in or ride out?)
    - Peak hour(Identify the busiest time of the place)
    - Standard deviation of daily number(Identify the location's service is rigid demand or elastic demand.)

[12]:
```
def calcu_stat(station_id, stat):
    """calculate the station statistic information"""
    data_selected = tripdata_cleaned.loc[(tripdata_cleaned['start station id']␣
↪== station_id) |
                                         (tripdata_cleaned['end station id'] ==␣
↪station_id)]
    if stat == 'trip_num':
        return(len(data_selected))
    elif stat == 'ride_in_num':
        return(len(data_selected.loc[(tripdata_cleaned['end station id'] ==␣
↪station_id)]))
    elif stat == 'ride_out_num':
        return(len(data_selected.loc[(tripdata_cleaned['start station id'] ==␣
↪station_id)]))
    elif stat == 'ride_in_ratio':
        trip_num = len(data_selected)
        ride_in_num = len(
            data_selected.loc[(tripdata_cleaned['end station id'] ==␣
↪station_id)])
        return(ride_in_num/trip_num)
    elif stat == 'gender_ratio':
```

```
        gender_ratio = len(
            data_selected.loc[(tripdata_cleaned['gender'] == 1)])/len(
            data_selected.loc[(tripdata_cleaned['gender'] == 0)])
        return(gender_ratio)
    elif stat == 'sd':
        return(data_selected['datetime'].value_counts().std())
    elif stat == 'ring_route_ratio':
        trip_num = len(data_selected)
        ring_route_num = len(
            tripdata_cleaned.loc[(tripdata_cleaned['start station id'] ==␣
↪station_id) &
                                 (tripdata_cleaned['end station id'] ==␣
↪station_id)])
        return(ring_route_num/trip_num)
    else:
        raise Exception
```

[13]:
```
station_info.head(2)
```

[13]:

	Station Id	Latitude	Longitude	Total docks	district_id
0	149	42.363796	-71.129164	18	1
1	378	42.380323	-71.108786	19	3

[14]:
```
station_info['trip_num'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='trip_num'))
station_info['ride_in_num'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='ride_in_num'))
station_info['ride_out_num'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='ride_out_num'))
station_info['ride_in_ratio'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='ride_in_ratio'))
station_info['gender_ratio'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='gender_ratio'))
station_info['sd'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='sd'))
station_info['ring_route_ratio'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='ring_route_ratio'))
station_info['ring_route_ratio'] = station_info['Station Id'].apply(
    lambda x: calcu_stat(x, stat='ring_route_ratio'))
print('The statistical characteristics of the station are processed')
```

```
The statistical characteristics of the station are processed
```

[15]:
```
station_info.head(2)
```

[15]:

	Station Id	Latitude	Longitude	Total docks	district_id	trip_num	\
0	149	42.363796	-71.129164	18	1	22081	

```
1          378  42.380323 -71.108786           19            3     10880

   ride_in_num  ride_out_num  ride_in_ratio  gender_ratio         sd  \
0        11429         11144       0.517594      4.736295  36.722545
1         5364          5605       0.493015      7.928894  14.747012

   ring_route_ratio
0          0.022282
1          0.008180
```

1.2.2 Feature Engineering – Others related to start/end location

[16]:
```
dataset = pd.DataFrame(od_pair)
dataset.reset_index(inplace=True)
dataset.columns = ['od_pair', 'y_true']
```

[17]:
```
dataset['original_id'] = dataset['od_pair'].apply(lambda x: int(x.
 ↪split("_")[0]))
dataset['destination_id'] = dataset['od_pair'].apply(lambda x: int(x.
 ↪split("_")[1]))
dataset.head(2)
```

[17]:
```
    od_pair    y_true  original_id  destination_id
0   100_10   0.112329          100              10
1  100_100   1.986301          100             100
```

[18]:
```
dataset = pd.merge(left=dataset, right=station_info,
                   how='left', left_on='original_id', right_on='Station Id')
dataset = pd.merge(left=dataset, right=station_info,
                   how='left', left_on='destination_id', right_on='Station Id',␣
 ↪suffixes=['_o', '_d'])
```

1.2.3 Feature Engineering – Others related to both

- Features related to both locations
  - Geographic distance
    - Distance between two stations
    - Whether the two sites are cross-regional
  - Positioning distance
    - Gender distribution distance
    - Direction distribution distance
    - Peak hour distance
    - Standard deviation distance
    - Dock number gap

[19]:
```
dataset.head(2)
```

[19]:
```
   od_pair    y_true  original_id  destination_id  Station Id_o  Latitude_o  \
0   100_10  0.112329          100              10           100   42.396969
1  100_100  1.986301          100             100           100   42.396969

   Longitude_o  Total docks_o  district_id_o  trip_num_o  …  Longitude_d  \
0   -71.123024             25              3       30597  …   -71.108279
1   -71.123024             25              3       30597  …   -71.123024

   Total docks_d  district_id_d  trip_num_d  ride_in_num_d  ride_out_num_d  \
0             11              1       33897          17316           17181
1             25              3       30597          16707           14615

   ride_in_ratio_d  gender_ratio_d       sd_d  ring_route_ratio_d
0         0.510842        6.754360  55.949996            0.017701
1         0.546034        5.358989  40.135713            0.023695

[2 rows x 28 columns]
```

[20]:
```
from math import radians, cos, sin, asin, sqrt

def haversine(lon1, lat1, lon2, lat2): # Longitude 1, Latitude 1, Longitude 2,␣
 ↪Latitude 2 (decimal number)
    """
    Calculate the great circle distance between two points
    on the earth (specified in decimal degrees)
    """
    # Convert the decimal number into radians
    lon1, lat1, lon2, lat2 = map(radians, [lon1, lat1, lon2, lat2])

    # haversine
    dlon = lon2 - lon1
    dlat = lat2 - lat1
    a = sin(dlat/2)**2 + cos(lat1) * cos(lat2) * sin(dlon/2)**2
    c = 2 * asin(sqrt(a))
    r = 6371 # The average radius of the earth (kilometers)
    return c * r * 1000
```

[21]:
```
dataset['geographic_distance'] = dataset.apply(
    lambda x: haversine(x['Longitude_o'], x['Latitude_o'],
                        x['Longitude_d'], x['Latitude_d']), axis=1)
```

[22]:
```
# Whether the two sites are cross-regional
dataset['cross_regional'] = dataset.apply(
    lambda x: 0 if x['district_id_o'] == x['district_id_d'] else 1, axis=1)
```

[23]:
```
# Direction distribution distance
dataset['direction_distribution_distance'] = dataset.apply(
```

```
    lambda x: abs(x['ride_in_ratio_o'] - x['ride_in_ratio_d']), axis=1)
```

[24]:
```
# Standard deviation distance
dataset['sd_distance'] = dataset.apply(
    lambda x: abs(x['sd_o'] - x['sd_d']), axis=1)

# Mean value of the Standard deviation of two stations
dataset['sd_mean'] = dataset.apply(
    lambda x: (x['sd_o'] + x['sd_d'])/2, axis=1)
```

[25]:
```
# Dock number gap
dataset['dock_num_gap'] = dataset.apply(
    lambda x: abs(x['Total docks_o'] - x['Total docks_d']), axis=1)

# Mean value of the number of Dock number at two stations
dataset['dock_num_mean'] = dataset.apply(
    lambda x: (x['Total docks_o'] + x['Total docks_d'])/2, axis=1)
```

[26]:
```
# Mean value of the daily average trip number of two stations
dataset['trip_num_mean'] = dataset.apply(
    lambda x: (x['trip_num_o'] + x['trip_num_d'])/2, axis=1)
```

[27]:
```
dataset.head(2)
```

[27]:
```
    od_pair    y_true  original_id  destination_id  Station Id_o  Latitude_o  \
0   100_10   0.112329          100              10           100   42.396969
1  100_100   1.986301          100             100           100   42.396969

   Longitude_o  Total docks_o  district_id_o  trip_num_o  …       sd_d  \
0   -71.123024             25              3       30597  …  55.949996
1   -71.123024             25              3       30597  …  40.135713

   ring_route_ratio_d  geographic_distance  cross_regional  \
0            0.017701          5317.364565               1
1            0.023695             0.000000               0

   direction_distribution_distance  sd_distance    sd_mean  dock_num_gap  \
0                         0.035192    15.814283  48.042854            14
1                         0.000000     0.000000  40.135713             0

   dock_num_mean  trip_num_mean
0           18.0        32247.0
1           25.0        30597.0

[2 rows x 36 columns]
```

1.3 Multiple Linear Regression

[28]:
```
# Delete irrelevant items
drop_lst = ['od_pair', 'original_id', 'destination_id', 'Station Id_o',␣
 ↪'Station Id_d']
dataset = dataset.drop(drop_lst, axis=1)

# Data description
dataset.describe().head(2)
```

[28]:
```
             y_true    Latitude_o   Longitude_o  Total docks_o  district_id_o  \
count  58895.000000  58895.000000  58895.000000   58895.000000   58895.000000
mean       0.114028     42.354334    -71.089136      18.192139       1.571594

         trip_num_o  ride_in_num_o  ride_out_num_o  ride_in_ratio_o  \
count  58895.000000   58895.000000    58895.000000     58895.000000
mean   19647.679073    9995.761474     9980.825011         0.510624

       gender_ratio_o  …          sd_d  ring_route_ratio_d  \
count    58895.000000  …  58895.000000         58895.00000
mean         6.789064  …     31.791055             0.02626

       geographic_distance  cross_regional  direction_distribution_distance  \
count         58895.000000    58895.000000                     58895.000000
mean           3814.449189        0.487614                         0.032378

        sd_distance       sd_mean  dock_num_gap  dock_num_mean  trip_num_mean
count  58895.000000  58895.000000  58895.000000   58895.000000   58895.000000
mean      27.219594     32.035115      4.231921      18.182197   19494.550276

[2 rows x 31 columns]
```

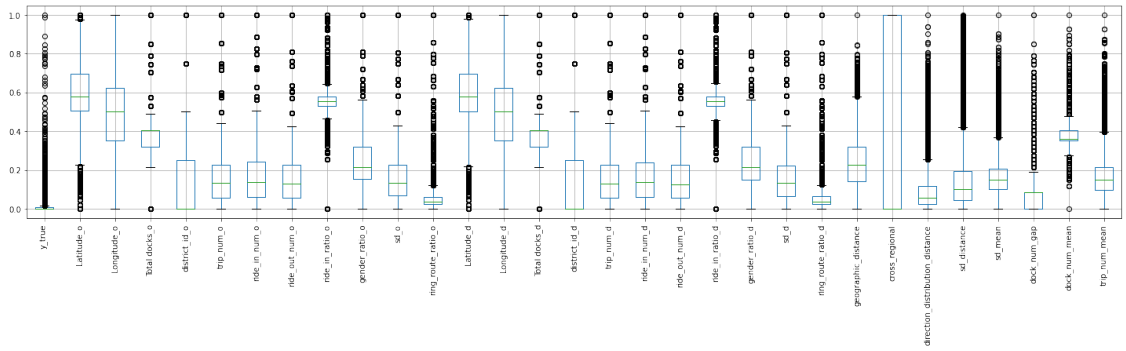
[29]:
```
# Missing value test
dataset[dataset.isnull()==True].count()
```

[29]:
```
y_true                          0
Latitude_o                      0
Longitude_o                     0
Total docks_o                   0
district_id_o                   0
trip_num_o                      0
ride_in_num_o                   0
ride_out_num_o                  0
ride_in_ratio_o                 0
gender_ratio_o                  0
sd_o                            0
ring_route_ratio_o              0
```

```
Latitude_d                          0
Longitude_d                         0
Total docks_d                       0
district_id_d                       0
trip_num_d                          0
ride_in_num_d                       0
ride_out_num_d                      0
ride_in_ratio_d                     0
gender_ratio_d                      0
sd_d                                0
ring_route_ratio_d                  0
geographic_distance                 0
cross_regional                      0
direction_distribution_distance     0
sd_distance                         0
sd_mean                             0
dock_num_gap                        0
dock_num_mean                       0
trip_num_mean                       0
dtype: int64
```

[30]:
```
# Normalized
from sklearn import preprocessing
scaler = preprocessing.MinMaxScaler()
dataset_scale = scaler.fit_transform(dataset)
dataset_scale = pd.DataFrame(dataset_scale)
dataset_scale.columns = dataset.columns
```

[31]:
```
dataset_scale.boxplot(figsize=(25, 5))
plt.xticks(rotation=90)
plt.show()
```

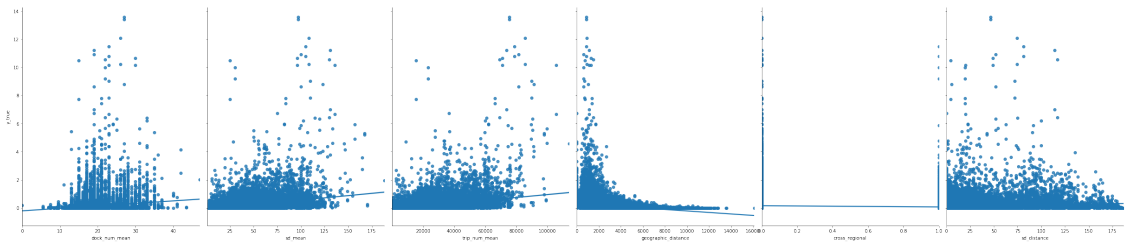


[32]:
```
# Correlation coefficient r(correlation coefficient) = cov(x,y) / x * y
# 0 ~ 0.3 weak correlation
```

```
# 0.3 ~ 0.6 moderate correlation
# 0.6 ~ 1 strong correlation
dataset_scale.corr()['y_true']
```

[32]:
```
y_true                              1.000000
Latitude_o                          0.042615
Longitude_o                         0.016018
Total docks_o                       0.118151
district_id_o                      -0.014742
trip_num_o                          0.258691
ride_in_num_o                       0.256800
ride_out_num_o                      0.259586
ride_in_ratio_o                    -0.021724
gender_ratio_o                      0.098052
sd_o                                0.243486
ring_route_ratio_o                 -0.069837
Latitude_d                          0.044523
Longitude_d                         0.020615
Total docks_d                       0.119359
district_id_d                      -0.019031
trip_num_d                          0.265761
ride_in_num_d                       0.266196
ride_out_num_d                      0.264367
ride_in_ratio_d                    -0.011715
gender_ratio_d                      0.096069
sd_d                                0.255302
ring_route_ratio_d                 -0.073733
geographic_distance                -0.306196
cross_regional                     -0.125794
direction_distribution_distance    -0.075724
sd_distance                         0.106085
sd_mean                             0.359147
dock_num_gap                        0.076230
dock_num_mean                       0.168310
trip_num_mean                       0.378669
Name: y_true, dtype: float64
```

[33]:
```
# By adding a parameter kind='reg', seaborn can add a best-fitting line and a␣
 ↪95% confidence band.
import seaborn as sns

sns.pairplot(dataset, x_vars=['dock_num_mean', 'sd_mean', 'trip_num_mean',␣
 ↪'geographic_distance', 'cross_regional', 'sd_distance'],
             y_vars='y_true', height=7, aspect=0.8, kind='reg')
plt.savefig("pairplot.jpg")
plt.show()
```



[34]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

variable_list = dataset_scale.columns
variable_list = variable_list.drop('y_true')

X_train,X_test,Y_train,Y_test =␣
 ↪train_test_split(dataset_scale[variable_list],dataset['y_true'],train_size=.
 ↪80)

LR_model = LinearRegression()

LR_model.fit(X_train,Y_train)

a  = LR_model.intercept_ # intercept

b = LR_model.coef_ # Regression coefficients

print('Intercept: ', a)
print('Regression coefficients: ', b)
```

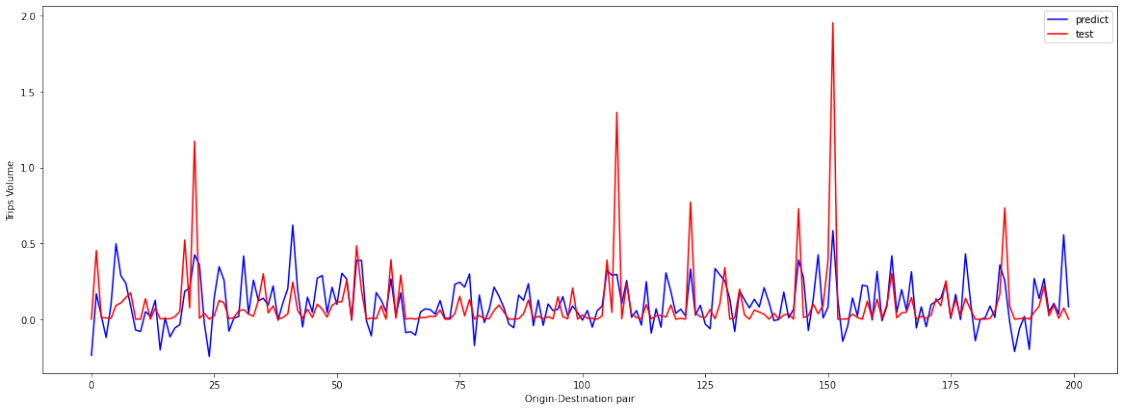
```
Intercept:  0.11918771603885987
Regression coefficients:  [-0.00612002 -0.079795    0.05314028  0.12323747
4.09131361 -2.74717387
 -2.74046716 -0.09322651 -0.02084284  0.31001354  0.26779192 -0.02077072
 -0.07973744  0.04479086  0.12594168  3.67567938 -2.02063789 -3.07531934
 -0.05118046 -0.01967976  0.30604996  0.26008544 -0.50784653 -0.13626559
  0.03787919 -0.67083899  0.30803175 -0.05096877  0.04896557  3.88349649]
```

[35]:
```
score = LR_model.score(X_train, Y_train)
print(score)
```

```
0.25955021485518937
```

[36]:
```
Y_pred = LR_model.predict(X_test)
plt.figure(figsize=(20,7))
plt.plot(range(len(Y_pred[:200])),Y_pred[:200],'b',label="predict")
plt.plot(range(len(Y_pred[:200])),Y_test[:200],'r',label="test")
```

```
plt.legend(loc="upper right")
plt.xlabel("Origin-Destination pair")
plt.ylabel('Trips Volume')
plt.show()
```



- The final R-square of the model is 0.26.
- In real life, this model can only explain a part of the trip number of a Origin-Destiny pair.
- It also means that there are many variables that we have not taked into consideration.
- Varibles that contribute to the model:
  - 'dock_num_mean': Mean value of the dock number of the od pair
  - 'sd_mean': Mean value of the Demand Elasticity(Standard Deviation) of the od pair
  - 'trip_num_mean': Mean value of the daily average trip number of the od pair
  - 'geographic_distance': Geographical distance between two stations
  - 'cross_regional': Whether the two stations are cross-regional
  - 'sd_distance': The difference in demand elasticity between the two stations
- For improvement(neglected features):
  - Date information of sports games held in Boston(such as Boston Celtics Basketball Team)
  - Calendar of Boston Schools(Stanford/MIT)