Setting up python environment

In [1]:

```
import numpy as np # pyton library for linear algebra
import pandas as pd # python library for data processing (data manipulation and a
nalysis)
import matplotlib.pyplot as plt
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/new-york-city-taxi-fare-prediction/GCP-Coupons-Instructions.rtf
/kaggle/input/new-york-city-taxi-fare-prediction/train.csv
/kaggle/input/new-york-city-taxi-fare-prediction/test.csv
/kaggle/input/new-york-city-taxi-fare-prediction/sample_submission.csv
```

Setting up training and testing data

As the training dataset is too large, we can not load whole dataset at the same time. So, we are skipping some part of the data.

In [2]:

```
train_df = pd.read_csv('/kaggle/input/new-york-city-taxi-fare-prediction/train.cs
v', nrows = 10_000_000)
```

In [3]:

```
test_df = pd.read_csv('/kaggle/input/new-york-city-taxi-fare-prediction/test.csv'
)
```

In [4]:

```
train_df.dtypes
```

Out[4]:

```
key                   object
fare_amount          float64
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
dtype: object
```

In [5]:

```
test_df.dtypes
```

Out[5]:

```
key                   object
pickup_datetime       object
pickup_longitude     float64
pickup_latitude      float64
dropoff_longitude    float64
dropoff_latitude     float64
passenger_count        int64
```

```
dtype: object
```

In [6]:

```
# dataset shape

print('train_df: ' + str(train_df.shape))
print('test_df: ' + str(test_df.shape))
```

```
train_df: (10000000, 8)
test_df: (9914, 7)
```

In [7]:

```
# looking some sample data

train_df.head(5)
```

Out[7]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_l
0	2009-06-15 17:26:21.0000001	4.5	2009-06-15 17:26:21 UTC	-73.844311	40.721319	-73.841610	40.
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16 UTC	-74.016048	40.711303	-73.979268	40.
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00 UTC	-73.982738	40.761270	-73.991242	40.
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42 UTC	-73.987130	40.733143	-73.991567	40.
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00 UTC	-73.968095	40.768008	-73.956655	40.

In [8]:

```
# describe training data

train_df.describe()
```

Out[8]:

	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count
count	1.000000e+07	1.000000e+07	1.000000e+07	9.999931e+06	9.999931e+06	1.000000e+07
mean	1.133854e+01	-7.250775e+01	3.991934e+01	-7.250897e+01	3.991913e+01	1.684793e+00
std	9.799930e+00	1.299421e+01	9.322539e+00	1.287532e+01	9.237280e+00	1.323423e+00
min	-1.077500e+02	-3.439245e+03	-3.492264e+03	-3.426601e+03	-3.488080e+03	0.000000e+00
25%	6.000000e+00	-7.399207e+01	4.073491e+01	-7.399139e+01	4.073403e+01	1.000000e+00
50%	8.500000e+00	-7.398181e+01	4.075263e+01	-7.398016e+01	4.075316e+01	1.000000e+00
75%	1.250000e+01	-7.396710e+01	4.076712e+01	-7.396367e+01	4.076810e+01	2.000000e+00
max	1.273310e+03	3.457626e+03	3.344459e+03	3.457622e+03	3.351403e+03	2.080000e+02

PART 1 -> DATA CLEANSING

Cleaning NaN / null values

In [9]:

```
# count and check how many null/missing values in training data

print(train_df.isnull().sum())
```

```
key                   0
fare_amount           0
pickup_datetime       0
pickup_longitude      0
pickup_latitude       0
dropoff_longitude    69
dropoff_latitude     69
passenger_count       0
dtype: int64
```

In [10]:

```
# remove all null valued fields from the training datset

print('Training data: Previous size: ' + str(len(train_df)))
train_df = train_df.dropna(how = 'any', axis = 'rows')
print('Training data: Updated size: ' + str(len(train_df)))
```

```
Training data: Previous size: 10000000
Training data: Updated size: 9999931
```

Remove negative fare amount

Fare amount can not be zero or negative. So, we can remove these fields.

In [11]:

```
# check the target column first
train_df['fare_amount'].describe()
```

Out[11]:

```
count    9.999931e+06
mean     1.133849e+01
std      9.799845e+00
min     -1.077500e+02
25%      6.000000e+00
50%      8.500000e+00
75%      1.250000e+01
max      1.273310e+03
Name: fare_amount, dtype: float64
```

yes, negative values exist

count how many negative and Zero values are here

from collections import Counter Counter(train_df['fare_amount'] < 0) and fare can't be zero!

In [12]:

```
from collections import Counter
Counter(train_df['fare_amount'] <= 0)
```

Out[12]:

```
Counter({False: 9999242, True: 689})
```

In [13]:

```
# remove these fields from dataset
```

```
# remove these fields from dataset
print('before: ' + str(train_df.shape))
train_df = train_df.drop(train_df[train_df['fare_amount'] <= 0].index, axis = 0)
print('after: ' + str(train_df.shape))
```

```
before: (9999931, 8)
after: (9999242, 8)
```

In [14]:

```
# now check again

train_df['fare_amount'].describe()
```

Out[14]:

```
count    9.999242e+06
mean     1.133966e+01
std      9.798609e+00
min      1.000000e-02
25%      6.000000e+00
50%      8.500000e+00
75%      1.250000e+01
max      1.273310e+03
Name: fare_amount, dtype: float64
```

no more invalied fare value, yahoooo!

Check passenger_count variable

In [15]:

```
train_df['passenger_count'].describe()
```

Out[15]:

```
count    9.999242e+06
mean     1.684807e+00
std      1.323424e+00
min      0.000000e+00
25%      1.000000e+00
50%      1.000000e+00
75%      2.000000e+00
max      2.080000e+02
Name: passenger_count, dtype: float64
```

In [16]:

```
train_df['passenger_count'].sort_values(ascending=False)
```

Out[16]:

```
2154045    208
2910347    208
4103745    208
3107489    208
7001143    208
          ...
2550560      0
9688764      0
189239       0
6344835      0
7974314      0
Name: passenger_count, Length: 9999242, dtype: int64
```

The number of passenger must be at least one. On the other hand, a stranded size taxi can't have passengers more than 6. That is we're only keeping the rows, those have passengers [1, 6]

passengers more than 6. That is we're only keeping the rows, those have passengers [1, 6]

In [17]:

```
# remove these fields from dataset
print('before: ' + str(train_df.shape))
train_df = train_df.drop(train_df[train_df['passenger_count'] <= 0].index, axis = 0) # remove numbers less or equal 0
train_df = train_df.drop(train_df[train_df['passenger_count'] > 6].index, axis = 0) # remove numbers greater or equal 0
print('after: ' + str(train_df.shape))
```

```
before: (9999242, 8)
after: (9963965, 8)
```

In [18]:

```
train_df['passenger_count'].describe()
```

Out[18]:

```
count    9.963965e+06
mean     1.690557e+00
std      1.306525e+00
min      1.000000e+00
25%      1.000000e+00
50%      1.000000e+00
75%      2.000000e+00
max      6.000000e+00
Name: passenger_count, dtype: float64
```

Feature Engineering

In [19]:

```
# calculate logtitude and latitude dif and add as feature

def add_distance_dif_features(df):
    df['longitude_distance'] = abs(df['pickup_longitude'] - df['dropoff_longitude'])
    df['latitude_distance'] = abs(df['pickup_latitude'] - df['dropoff_latitude'])
    return df

train_df = add_distance_dif_features(train_df)
```

In [20]:

```
# calculate straight distance and add as feature

def calculate_add_distance_feature(df):
    df['distance'] = (df['longitude_distance'] ** 2 + df['latitude_distance'] ** 2) ** .5
    return df

train_df = calculate_add_distance_feature(train_df)
```

In [21]:

```
# remove unlealistic distance valued fields from dataset
# we assume unrealistic distnace which are less than 0.1 miles

def drop_unrealistic_distance(df):
    print('before: ' + str(df.shape))
    df = df.drop(df[train_df['distance'] < 0.01].index, axis = 0)
    print('after: ' + str(df.shape))
    return df
```

```
train_df = drop_unrealistic_distance(train_df)
```

```
before: (9963965, 11)
after: (8224381, 11)
```

In [22]:

```
train_df.groupby('passenger_count')['distance','fare_amount'].mean()
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:1: FutureWarning: Ind
exing with multiple keys (implicitly converted to a tuple of keys) will be depreca
ted, use a list instead.
  """Entry point for launching an IPython kernel.
```

Out[22]:

	distance	fare_amount
passenger_count		
1	0.325402	12.198541
2	0.263791	12.840180
3	0.260806	12.545002
4	0.307009	12.743767
5	0.227303	12.284363
6	0.390197	13.371031

In [23]:

```
print(f'average_fare: {train_df.fare_amount.sum()/train_df.distance.sum()}')
```

```
average_fare: 40.19018345014175
```

Time Range of train and test dataset

In [24]:

```
def print_time_range(df1, df2):
    train_df_time_start = df1.pickup_datetime.min()
    train_df_time_end = df1.pickup_datetime.max()
    print("Train Datqaset Time Starts: {}, Ends {}".format(train_df_time_start, t
rain_df_time_end))

    test_df_time_start = df2.pickup_datetime.min()
    test_df_time_end = df2.pickup_datetime.max()
    print("Test Dataset Time Starts: {}, Ends {}".format(test_df_time_start, test
_df_time_end))

print_time_range(train_df, test_df)
```

```
Train Datqaset Time Starts: 2009-01-01 00:00:46 UTC, Ends 2015-06-30 23:59:54 UTC
Test Dataset Time Starts: 2009-01-01 11:04:24 UTC, Ends 2015-06-30 20:03:50 UTC
```

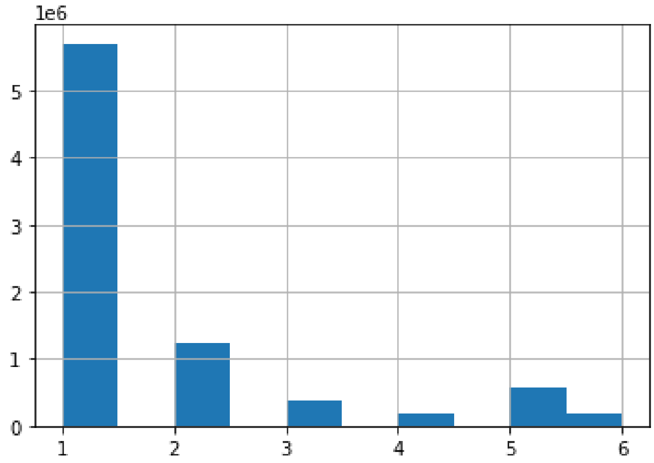
Plots and Diagrams

In [25]:

```
train_df.passenger_count.hist()
```

Out[25]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff748370b50>
```

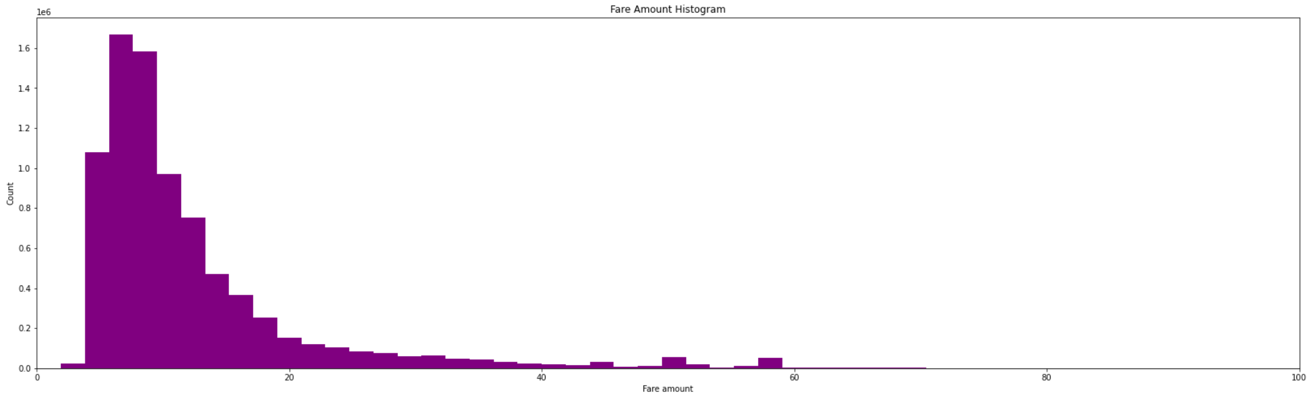


In [26]:

```
plt.figure(figsize=(28,8))
plt.hist(train_df["fare_amount"], 500, facecolor="purple")
plt.xlabel("Fare amount")
plt.ylabel("Count")
plt.title("Fare Amount Histogram")
plt.xlim(0,100)
```

Out[26]:

```
(0.0, 100.0)
```

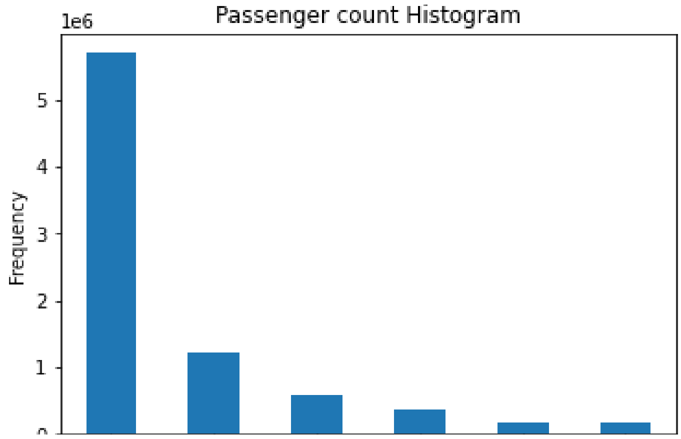


In [27]:

```
train_df["passenger_count"].value_counts().plot.bar()
plt.title("Passenger count Histogram")
plt.xlabel("Passenger Count")
plt.ylabel("Frequency")
```

Out[27]:

```
Text(0, 0.5, 'Frequency')
```



In [28]:

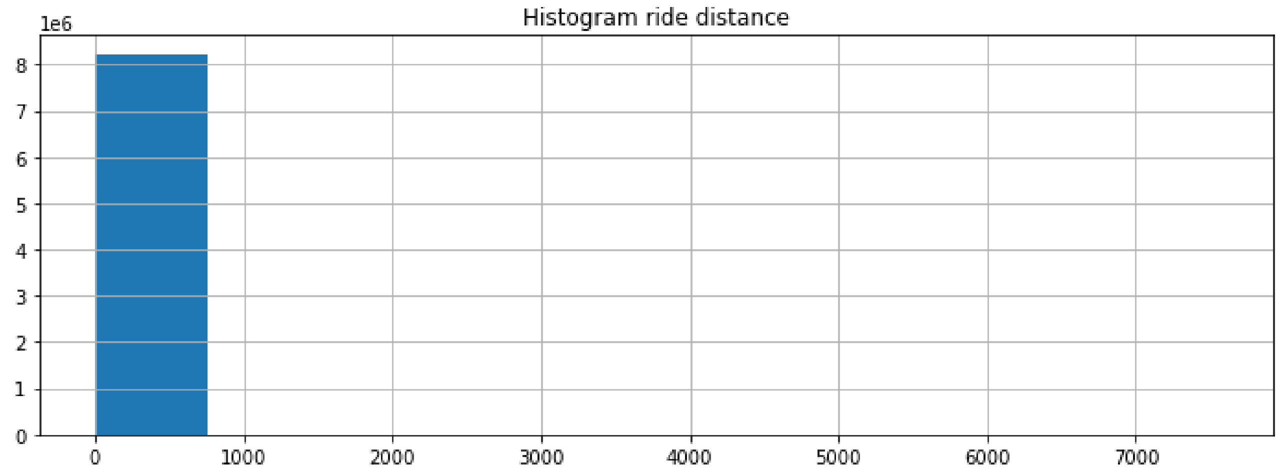
```
train_df.distance.describe()
```

Out[28]:

```
count    8.224381e+06
mean     3.073621e-01
std      1.539901e+01
min      1.000000e-02
25%      1.675648e-02
50%      2.570094e-02
75%      4.397095e-02
max      7.548848e+03
Name: distance, dtype: float64
```

In [29]:

```
train_df["distance"].hist(figsize=(12,4))
plt.title("Histogram ride distance");
```



In [30]:

```
train_df["fare_per_distance"] = train_df["fare_amount"] / train_df["distance"]
train_df["fare_per_distance"].describe()
```

Out[30]:

```
count    8.224381e+06
mean     3.745553e+02
std      1.526987e+02
min      1.183805e-04
25%      2.830627e+02
50%      3.509738e+02
75%      4.348068e+02
max      1.891399e+04
Name: fare_per_distance, dtype: float64
```

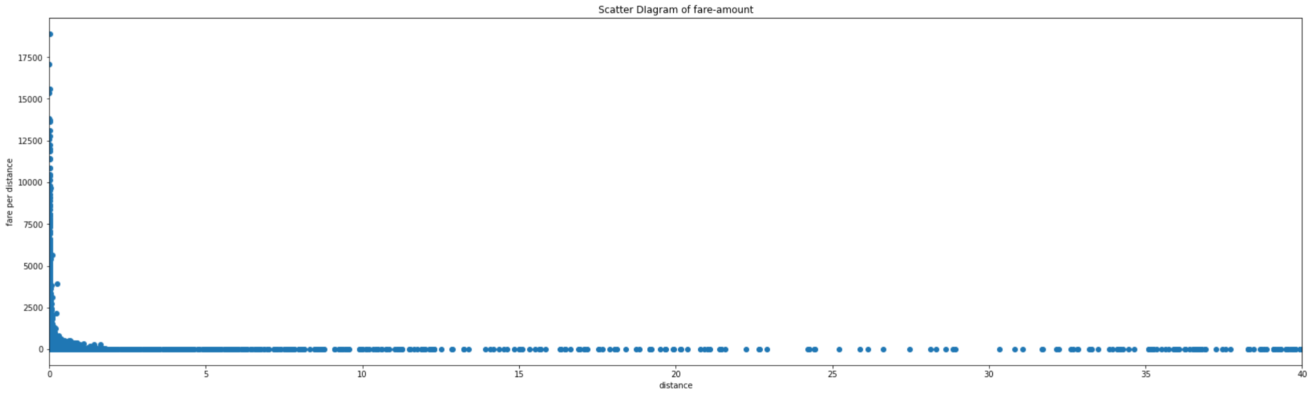
In [31]:

```
plt.figure(figsize=(28,8))
plt.scatter(train_df["distance"], train_df["fare_per_distance"])
plt.xlabel("distance")
plt.ylabel("fare per distance")
plt.xlim(0,40)
plt.title("Scatter DIagram of fare-amount")
```

Out[31]:

```
Text(0.5, 1.0, 'Scatter DIagram of fare-amount')
```

Text(0.5, 1.0, 'Scatter Diagram of fare-amount')



In [32]:

```
def add_time_features(df):
    df['pickup_datetime'] = df['pickup_datetime'].str.replace(" UTC", "")
    df['pickup_datetime'] = pd.to_datetime(df['pickup_datetime'], format='%Y-%m-%
d %H:%M:%S')
    df['hour'] = df.pickup_datetime.dt.hour
    #df['week'] = df.pickup_datetime.dt.week
    df['weekday'] = df.pickup_datetime.dt.weekday
    df['month'] = df.pickup_datetime.dt.month
    df['year'] = df.pickup_datetime.dt.year

    return df

train_df = add_time_features(train_df)
```

In [33]:

```
train_df.head()
```

Out[33]:

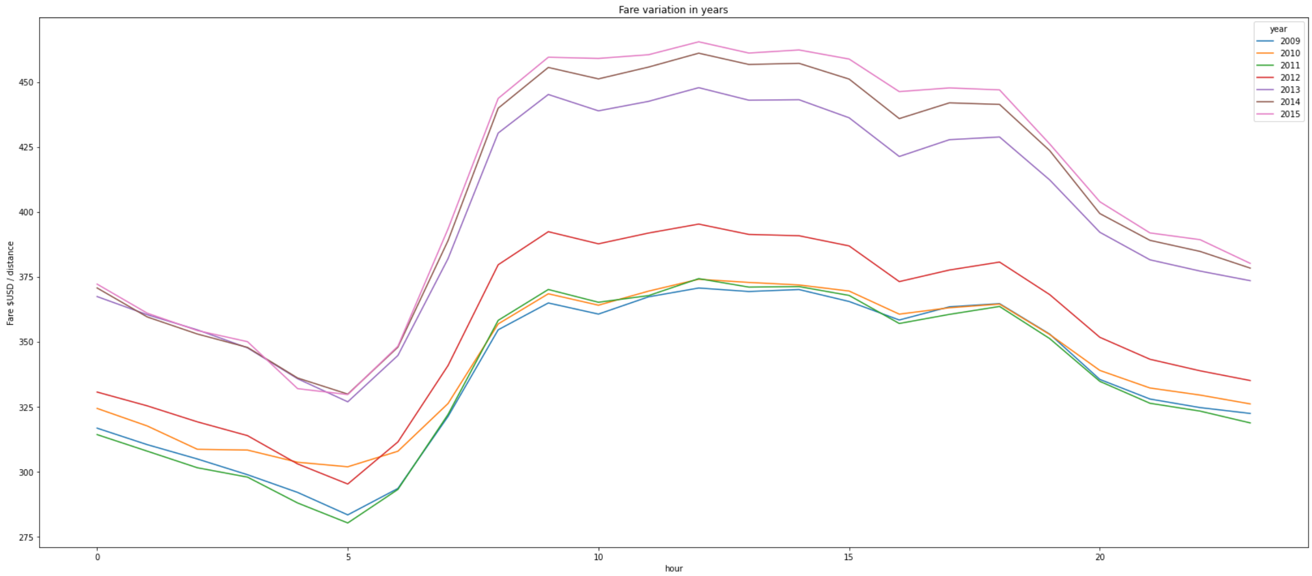
	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_l
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16	-74.016048	40.711303	-73.979268	40.
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00	-73.982738	40.761270	-73.991242	40.
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42	-73.987130	40.733143	-73.991567	40.
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00	-73.968095	40.768008	-73.956655	40.
5	2011-01-06 09:50:45.0000002	12.1	2011-01-06 09:50:45	-74.000964	40.731630	-73.972892	40.

In [34]:

```
#train_df['hour'] = train_df["pickup_datetime"].apply(lambda t: pd.to_datetime(t)
.hour)
#train_df['year'] = train_df["pickup_datetime"].apply(lambda t: pd.to_datetime(t)
.year)
#train_df['weekday'] = train_df["pickup_datetime"].apply(lambda t: pd.to_datetime
(t).weekday())
train_df.pivot_table("fare_per_distance", index="hour", columns="year").plot(figs
ize=(28,12))
plt.ylabel("Fare $USD / distance");
plt.title("Fare variation in years")
```

Out[34]:

```
Text(0.5, 1.0, 'Fare variation in years')
```



In [35]:

```
train_df.describe()
```

Out[35]:

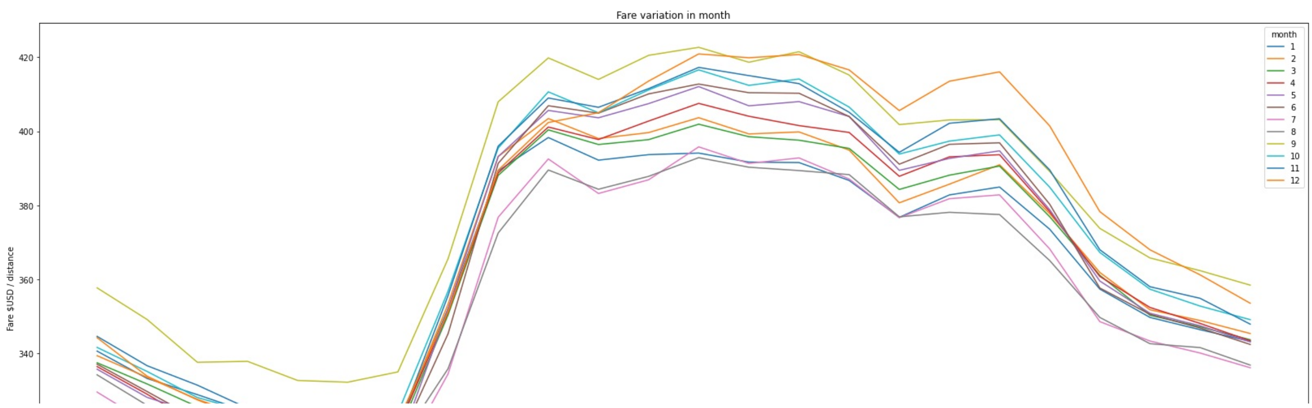
	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	longitu
count	8.224381e+06	8.224381e+06	8.224381e+06	8.224381e+06	8.224381e+06	8.224381e+06	8
mean	1.235294e+01	-7.383737e+01	4.065059e+01	-7.383914e+01	4.065062e+01	1.692171e+00	2
std	9.813382e+00	8.501846e+00	7.732585e+00	8.247128e+00	7.606393e+00	1.305173e+00	1
min	1.000000e-02	-3.439245e+03	-3.492264e+03	-3.426601e+03	-3.461541e+03	1.000000e+00	0
25%	6.900000e+00	-7.399247e+01	4.073564e+01	-7.399165e+01	4.073452e+01	1.000000e+00	8
50%	9.300000e+00	-7.398215e+01	4.075286e+01	-7.398037e+01	4.075347e+01	1.000000e+00	1
75%	1.370000e+01	-7.396829e+01	4.076747e+01	-7.396455e+01	4.076847e+01	2.000000e+00	2
max	9.520000e+02	3.457626e+03	3.344459e+03	3.457622e+03	3.351403e+03	6.000000e+00	6

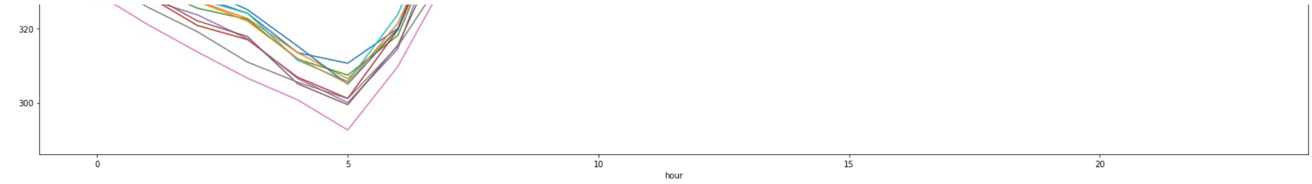
In [36]:

```
train_df.pivot_table("fare_per_distance", index="hour", columns="month").plot(fig
size=(28,12))
plt.ylabel("Fare $USD / distance");
plt.title("Fare variation in month")
```

Out[36]:

```
Text(0.5, 1.0, 'Fare variation in month')
```



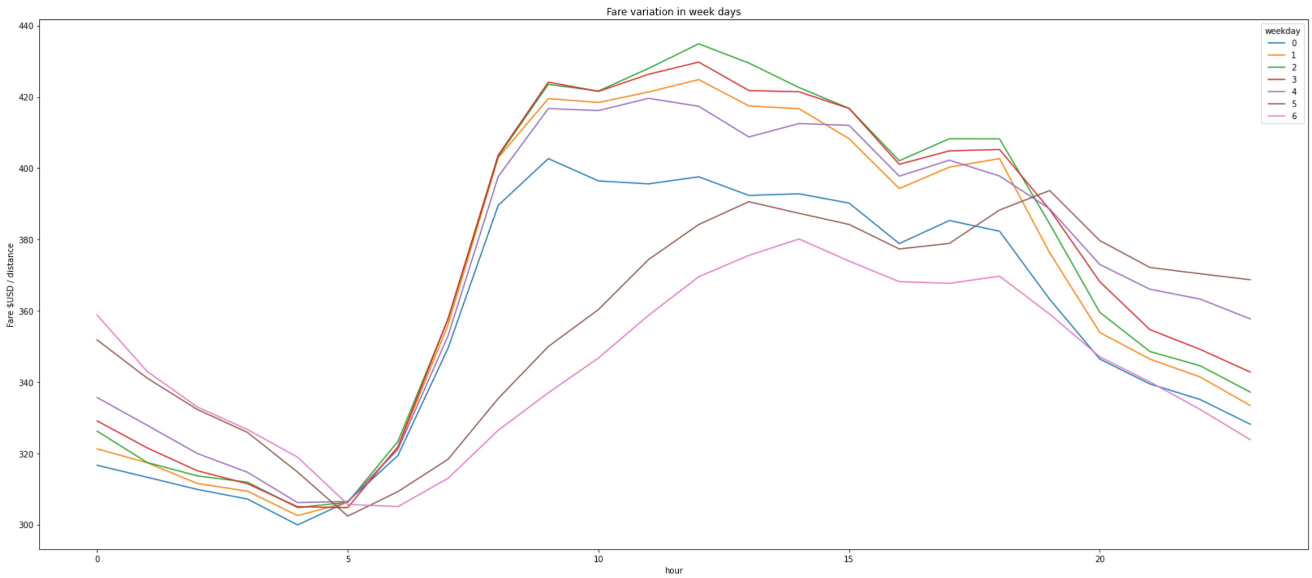


In [37]:

```
train_df.pivot_table("fare_per_distance", index="hour", columns="weekday").plot(f
igsize=(28,12))
plt.ylabel("Fare $USD / distance");
plt.title("Fare variation in week days")
```

Out[37]:

```
Text(0.5, 1.0, 'Fare variation in week days')
```

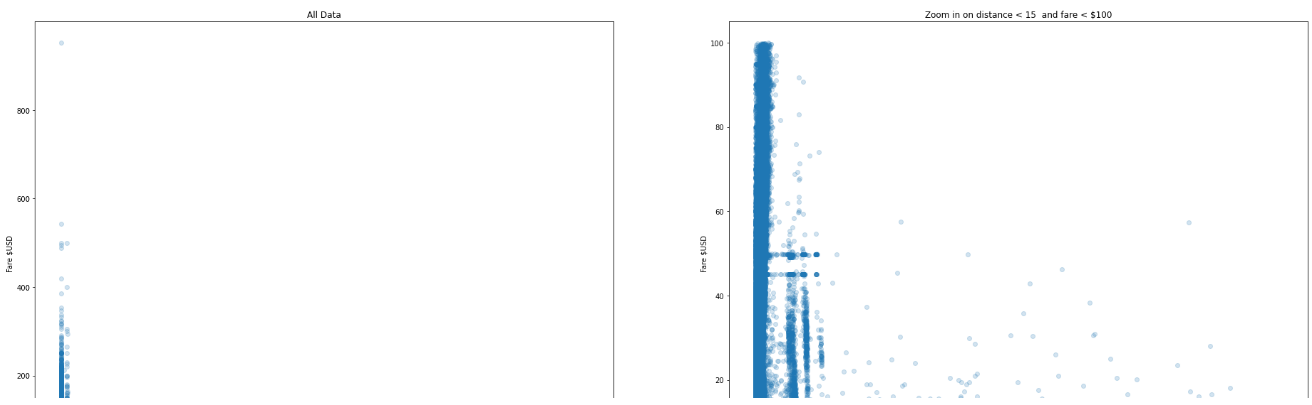


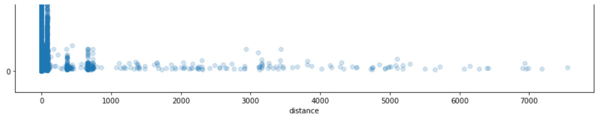
In [38]:

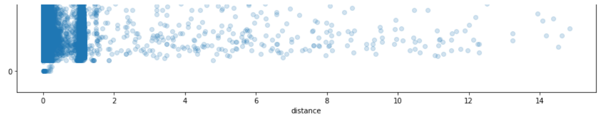
```
fig, axs = plt.subplots(1, 2, figsize=(32,12))
axs[0].scatter(train_df["distance"], train_df["fare_amount"], alpha=0.2)
axs[0].set_xlabel("distance")
axs[0].set_ylabel("Fare $USD")
axs[0].set_title("All Data")

idx = ((train_df['distance'] < 15) & (train_df["fare_amount"] < 100))
axs[1].scatter(train_df[idx]["distance"], train_df[idx]["fare_amount"], alpha=0.2
)
axs[1].set_xlabel("distance")
axs[1].set_ylabel("Fare $USD")
axs[1].set_title("Zoom in on distance < 15  and fare < $100")
```

Out[38]:

```
Text(0.5, 1.0, 'Zoom in on distance < 15  and fare < $100')
```







Train our model

In [39]:

```
train_df.dtypes
```

Out[39]:

```
key                           object
fare_amount                  float64
pickup_datetime       datetime64[ns]
pickup_longitude             float64
pickup_latitude              float64
dropoff_longitude            float64
dropoff_latitude             float64
passenger_count                int64
longitude_distance           float64
latitude_distance            float64
distance                     float64
fare_per_distance            float64
hour                           int64
weekday                        int64
month                          int64
year                           int64
dtype: object
```

In [40]:

```
train_df.shape
```

Out[40]:

```
(8224381, 16)
```

In [41]:

```
train_df.head()
```

Out[41]:

	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_l
1	2010-01-05 16:52:16.0000002	16.9	2010-01-05 16:52:16	-74.016048	40.711303	-73.979268	40.
2	2011-08-18 00:35:00.00000049	5.7	2011-08-18 00:35:00	-73.982738	40.761270	-73.991242	40.
3	2012-04-21 04:30:42.0000001	7.7	2012-04-21 04:30:42	-73.987130	40.733143	-73.991567	40.
4	2010-03-09 07:51:00.000000135	5.3	2010-03-09 07:51:00	-73.968095	40.768008	-73.956655	40.
5	2011-01-06 09:50:45.0000002	12.1	2011-01-06 09:50:45	-74.000964	40.731630	-73.972892	40.

Our model will take the form X·w=y where X is a matrix of input features, and y is a column of the target variable, fare_amount, for each row. The weight column w is what we will "learn".

First let's setup our input matrix X and target column y from our training set. The matrix X should consist of the two GPS coordinate differences, plus a third term of 1 to allow the model to learn a

constant bias term. The column y should consist of the target fare_amount values.

In [42]:

```
# Construct and return an Nx3 input matrix for our linear model
# using the travel vector, plus a 1.0 for a constant bias term.
def get_input_matrix(df):
    return np.column_stack((df.passenger_count, df.longitude_distance, df.latitud
e_distance, df.distance, df.hour, df.weekday, df.month, df.year, np.ones(len(df))
))

train_X = get_input_matrix(train_df)
train_y = np.array(train_df['fare_amount'])

print(train_X.shape)
print(train_y.shape)
```

```
(8224381, 9)
(8224381,)
```

In [43]:

```
(w, _, _, _) = np.linalg.lstsq(train_X, train_y, rcond = None)
print(w)
```

```
[ 1.17226317e-01  1.56755040e-02  1.22347660e-02 -1.44528738e-02
 -3.02436198e-02 -2.22568186e-02  1.13357319e-01  7.17530547e-01
 -1.43157532e+03]
```

In [44]:

```
w_OLS = np.matmul(np.matmul(np.linalg.inv(np.matmul(train_X.T, train_X)), train_X
.T), train_y)
print(w_OLS)
```

```
[ 1.17226318e-01  1.56755040e-02  1.22347660e-02 -1.44528738e-02
 -3.02436198e-02 -2.22568186e-02  1.13357319e-01  7.17530547e-01
 -1.43157532e+03]
```

In [45]:

```
test_df = add_distance_dif_features(test_df)
test_df = calculate_add_distance_feature(test_df)
test_df = add_time_features(test_df)
test_df.head()
```

Out[45]:

	key	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passeng
0	2015-01-27 13:08:24.0000002	2015-01-27 13:08:24	-73.973320	40.763805	-73.981430	40.743835	
1	2015-01-27 13:08:24.0000003	2015-01-27 13:08:24	-73.986862	40.719383	-73.998886	40.739201	
2	2011-10-08 11:53:44.0000002	2011-10-08 11:53:44	-73.982524	40.751260	-73.979654	40.746139	
3	2012-12-01 21:12:12.0000002	2012-12-01 21:12:12	-73.981160	40.767807	-73.990448	40.751635	
4	2012-12-01 21:12:12.0000003	2012-12-01 21:12:12	-73.966046	40.789775	-73.988565	40.744427	

In [46]:

```
test_X = get_input_matrix(test_df)
```

```
print(test_X.shape)
```

```
(9914, 9)
```

In [47]:

```
test_y_predictions = np.matmul(test_X, w).round(decimals = 2)
```

In [48]:

```
submission = pd.DataFrame(
    {'key': test_df.key, 'fare_amount': test_y_predictions},
    columns = ['key', 'fare_amount'])
submission.to_csv('submission1.csv', index = False)

print(os.listdir('.'))
```

```
['__notebook__.ipynb', 'submission1.csv']
```