In [34]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [35]:
```
df = pd.read_csv("uber.csv")
```

In [36]:
```
df.head()
```

Out[36]:

	Unnamed: 0	key	fare_amount	pickup_datetime	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude
0	24238194	2015-05-07 19:52:06.0000003	7.5	2015-05-07 19:52:06 UTC	-73.999817	40.738354	-73.999512	40.723217
1	27835199	2009-07-17 20:04:56.0000002	7.7	2009-07-17 20:04:56 UTC	-73.994355	40.728225	-73.994710	40.750325
2	44984355	2009-08-24 21:45:00.00000061	12.9	2009-08-24 21:45:00 UTC	-74.005043	40.740770	-73.962565	40.772647
3	25894730	2009-06-26 08:22:21.0000001	5.3	2009-06-26 08:22:21 UTC	-73.976124	40.790844	-73.965316	40.803349
4	17610152	2014-08-28 17:47:00.000000188	16.0	2014-08-28 17:47:00 UTC	-73.925023	40.744085	-73.973082	40.761247

In [37]:
```
df = df.drop(['Unnamed: 0', 'key'], axis = 1)
```

In [38]:
```
df.isnull().sum()
```

Out[38]:
```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

In [39]:
```
df['dropoff_longitude'].fillna(value = df['dropoff_longitude'].mean(),inplace=True)
df['dropoff_latitude'].fillna(value = df['dropoff_latitude'].mean(),inplace=True)
```

In [40]:
```
df.isnull().sum()
```

Out[40]:
```
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64
```

In [41]:
```
df.pickup_datetime = pd.to_datetime(df.pickup_datetime)
```

In [42]:
```
df = df.assign(hour = df.pickup_datetime.dt.hour,
               day = df.pickup_datetime.dt.day,
                month = df.pickup_datetime.dt.month,
               year = df.pickup_datetime.dt.year,
               dayofweek = df.pickup_datetime.dt.dayofweek)
```

In [43]:
```
df = df.drop(['pickup_datetime'], axis = 1)
```

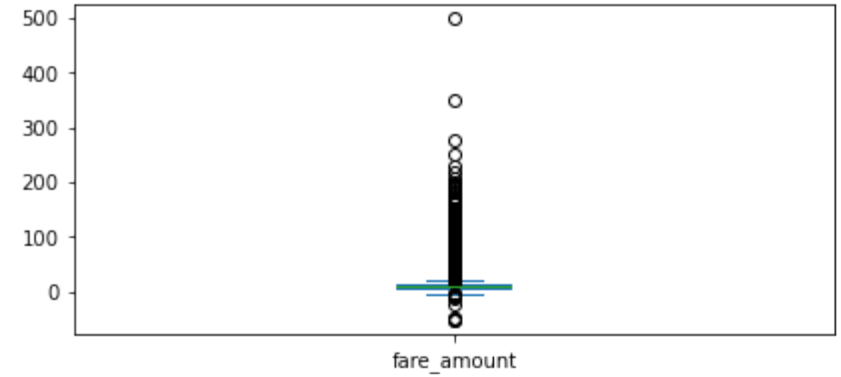
In [44]:
```
df.head()
```

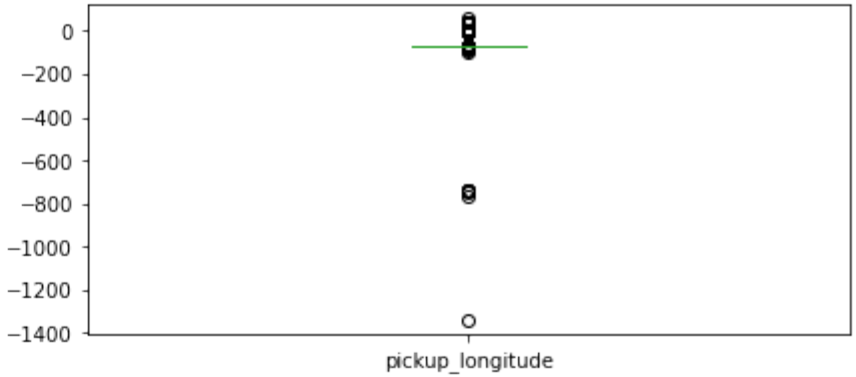
Out[44]:

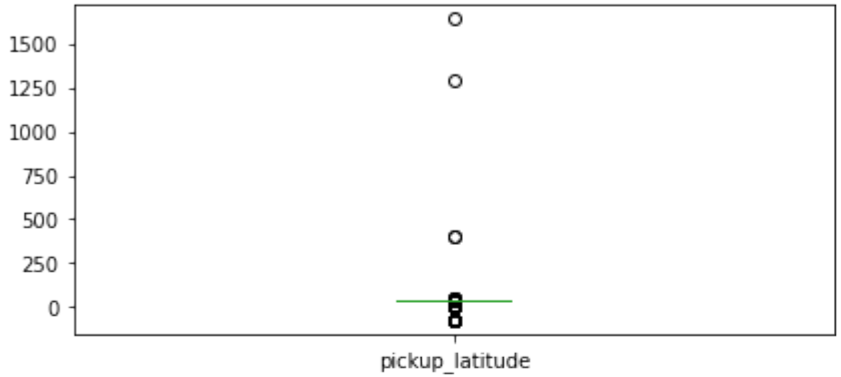
	fare_amount	pickup_longitude	pickup_latitude	dropoff_longitude	dropoff_latitude	passenger_count	hour	day	month	year	day
0	7.5	-73.999817	40.738354	-73.999512	40.723217	1	19	7	5	2015	
1	7.7	-73.994355	40.728225	-73.994710	40.750325	1	20	17	7	2009	
2	12.9	-74.005043	40.740770	-73.962565	40.772647	1	21	24	8	2009	
3	5.3	-73.976124	40.790844	-73.965316	40.803349	3	8	26	6	2009	
4	16.0	-73.925023	40.744085	-73.973082	40.761247	5	17	28	8	2014	

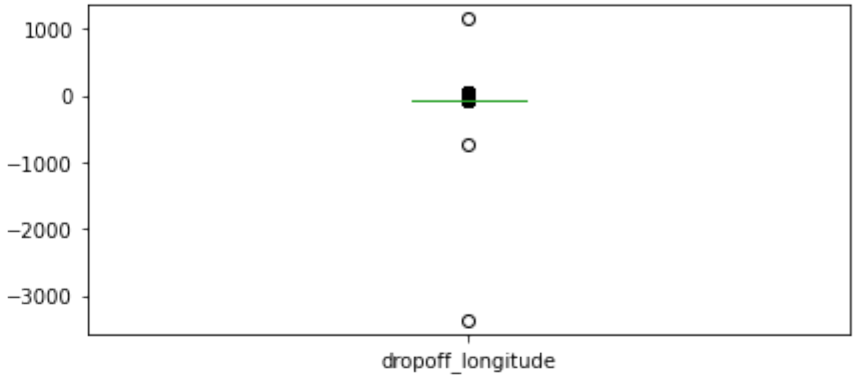
In [45]:
```
df.plot(kind='box', subplots=True, figsize=(15,25), layout=(7,2))
```

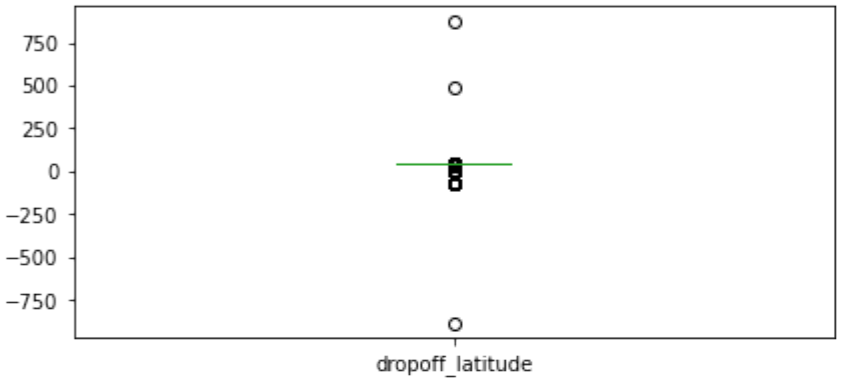
Out[45]:
```
fare_amount            AxesSubplot(0.125,0.787927;0.352273x0.0920732)
pickup_longitude     AxesSubplot(0.547727,0.787927;0.352273x0.0920732)
pickup_latitude        AxesSubplot(0.125,0.677439;0.352273x0.0920732)
dropoff_longitude    AxesSubplot(0.547727,0.677439;0.352273x0.0920732)
dropoff_latitude       AxesSubplot(0.125,0.566951;0.352273x0.0920732)
passenger_count      AxesSubplot(0.547727,0.566951;0.352273x0.0920732)
hour                   AxesSubplot(0.125,0.456463;0.352273x0.0920732)
day                  AxesSubplot(0.547727,0.456463;0.352273x0.0920732)
month                  AxesSubplot(0.125,0.345976;0.352273x0.0920732)
year                 AxesSubplot(0.547727,0.345976;0.352273x0.0920732)
dayofweek              AxesSubplot(0.125,0.235488;0.352273x0.0920732)
dtype: object
```

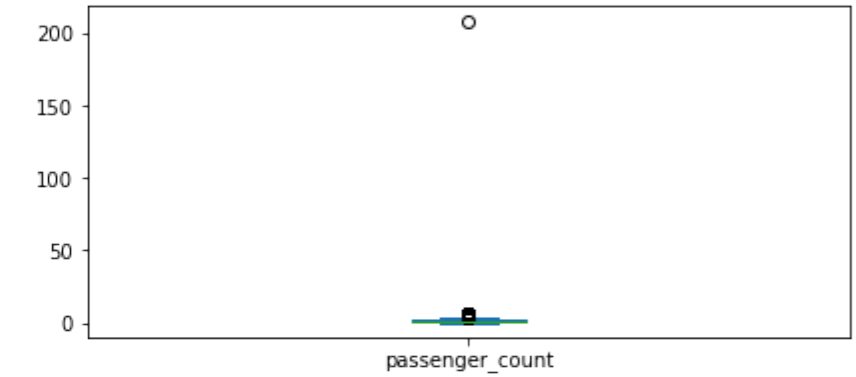

500
400
300
200
100
0
fare_amount

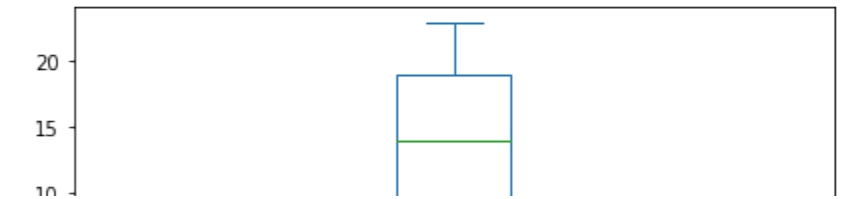

0
−200
−400
−600
−800
−1000
−1200
−1400
pickup_longitude

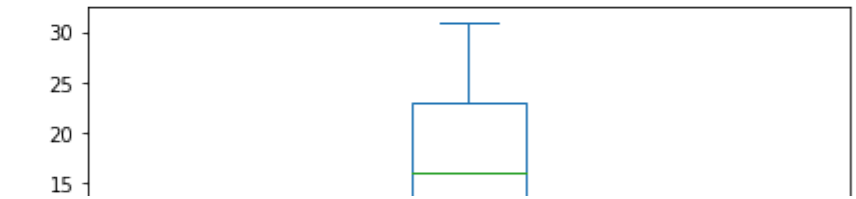

1500
1250
1000
750
500
250
0
pickup_latitude

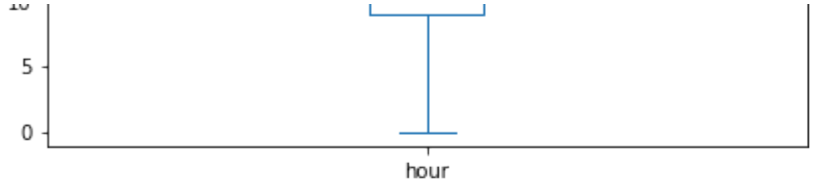

1000
0
−1000
−2000
−3000
dropoff_longitude

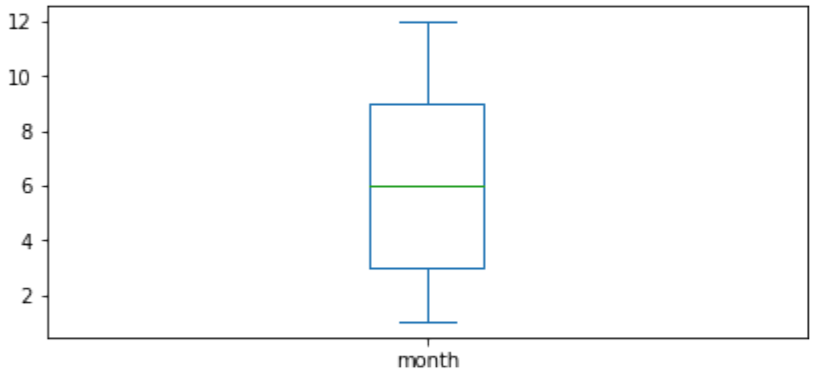

750
500
250
0
−250
−500
−750
dropoff_latitude

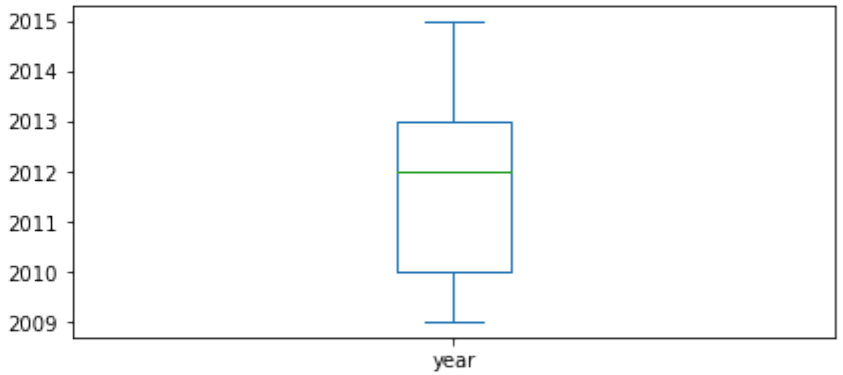

200
150
100
50
0
passenger_count

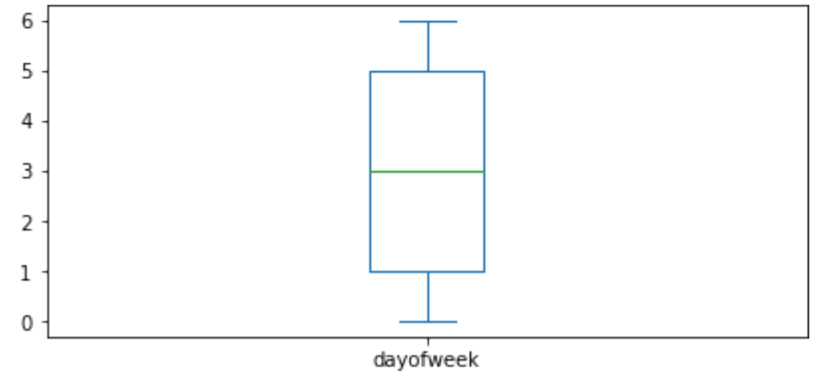

20
15


30
25
20
15









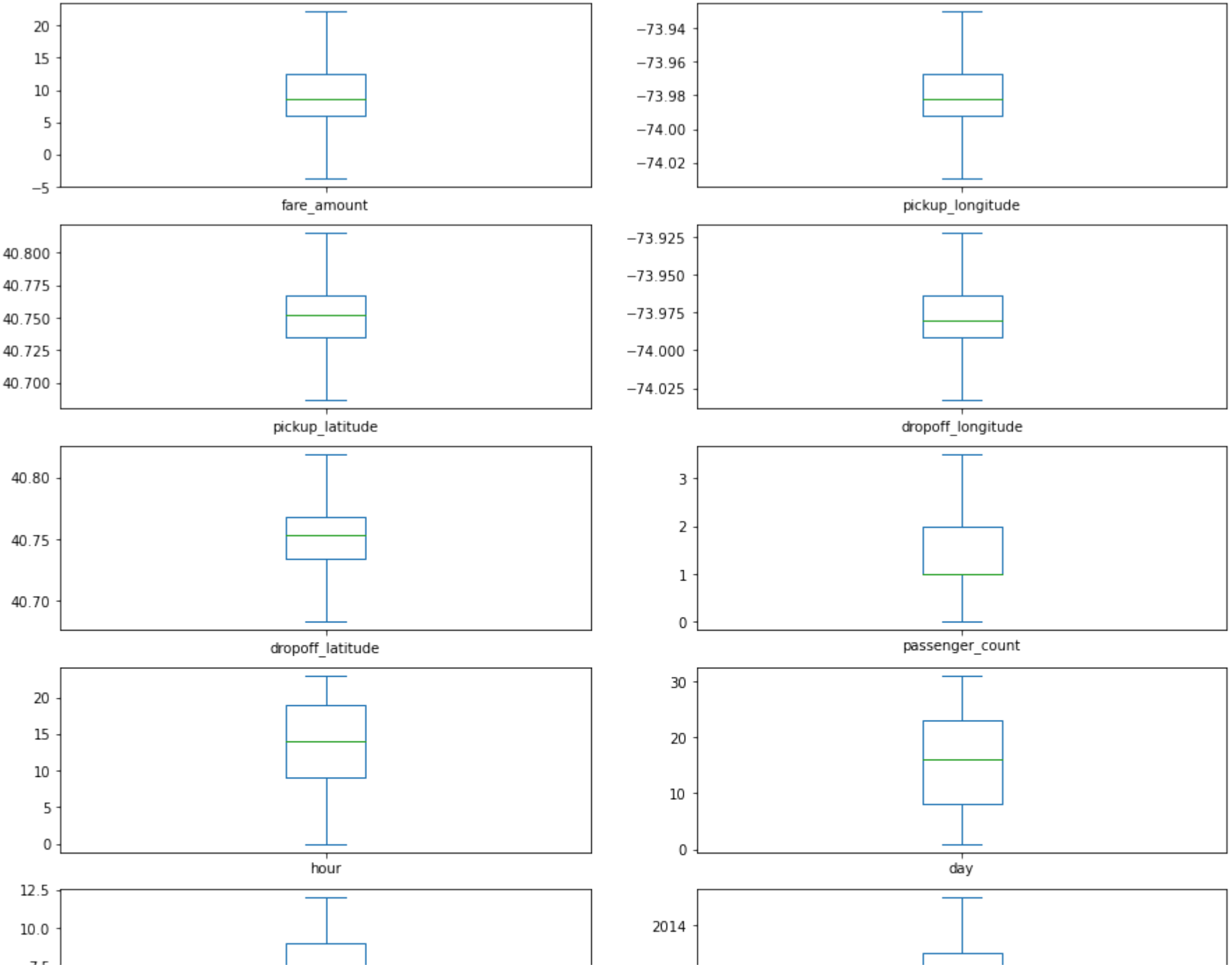
In [46]:
```
def remove_outliers(df1, col):
    Q1 = df1[col].quantile(0.25)
    Q3 = df1[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_whisker = Q1 - 1.5 * IQR
    higher_whisker = Q3 + 1.5 * IQR
    df[col] = np.clip(df1[col],lower_whisker,higher_whisker)
    return df1
def treat_outliers(df, cols_list):
    for c in cols_list:
```

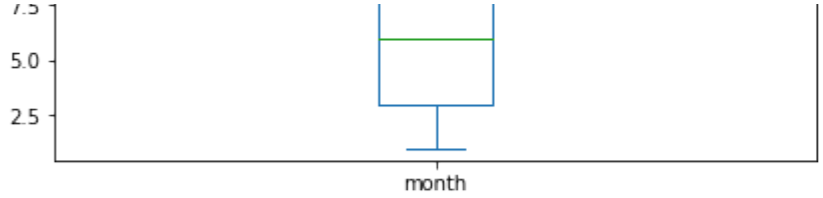
```
        df1 = remove_outliers(df,c)
    return df1
```

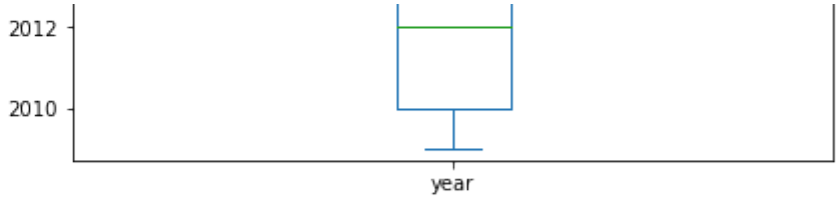
In [47]:
```
df = treat_outliers(df , df.iloc[: , 0::])
```

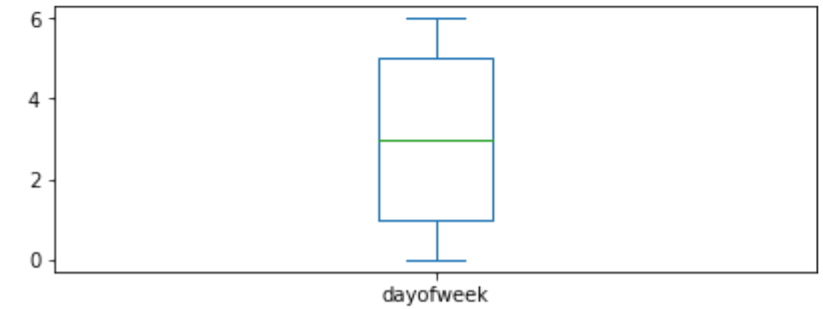
In [48]:
```
df.plot(kind='box', subplots = True, figsize = (15,20), layout = (7,2))
```

Out[48]:
```
fare_amount            AxesSubplot(0.125,0.787927;0.352273x0.0920732)
pickup_longitude     AxesSubplot(0.547727,0.787927;0.352273x0.0920732)
pickup_latitude        AxesSubplot(0.125,0.677439;0.352273x0.0920732)
dropoff_longitude    AxesSubplot(0.547727,0.677439;0.352273x0.0920732)
dropoff_latitude       AxesSubplot(0.125,0.566951;0.352273x0.0920732)
passenger_count      AxesSubplot(0.547727,0.566951;0.352273x0.0920732)
hour                   AxesSubplot(0.125,0.456463;0.352273x0.0920732)
day                  AxesSubplot(0.547727,0.456463;0.352273x0.0920732)
month                  AxesSubplot(0.125,0.345976;0.352273x0.0920732)
year                 AxesSubplot(0.547727,0.345976;0.352273x0.0920732)
dayofweek              AxesSubplot(0.125,0.235488;0.352273x0.0920732)
dtype: object
```


fare_amount
pickup_longitude
pickup_latitude
dropoff_longitude
dropoff_latitude
passenger_count
hour
day







In [49]:
```
pip install haversine
```

```
Defaulting to user installation because normal site-packages is not writeable
Collecting haversine
  Downloading haversine-2.8.1-py2.py3-none-any.whl (7.7 kB)
Installing collected packages: haversine
Successfully installed haversine-2.8.1
Note: you may need to restart the kernel to use updated packages.
```

In [51]:
```
pip install geopy
```

```
Defaulting to user installation because normal site-packages is not writeable
Collecting geopy
  Downloading geopy-2.4.1-py3-none-any.whl (125 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 125.4/125.4 KB 1.3 MB/s eta 0:00:00[36m0:00:01
Collecting geographiclib<3,>=1.52
  Downloading geographiclib-2.0-py3-none-any.whl (40 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 40.3/40.3 KB 503.1 kB/s eta 0:00:00 MB/s eta 0:00:01
Installing collected packages: geographiclib, geopy
Successfully installed geographiclib-2.0 geopy-2.4.1
Note: you may need to restart the kernel to use updated packages.
```

In [66]:
```
from geopy.distance import geodesic

# Step 1: Calculate Distance between Pickup and Dropoff Points
```

```
def haversine(lat1,long1, lat2,long2):
    return geodesic((lat1,long1), (lat2,long2)).km
```

In [67]:
```
# Apply the haversine function to create a new 'distance' column
df['distance'] = df.apply(lambda row: haversine(row['pickup_latitude'], row['pickup_longitude'],
                                                row['dropoff_latitude'], row['dropoff_longitude']), axis=1)
```

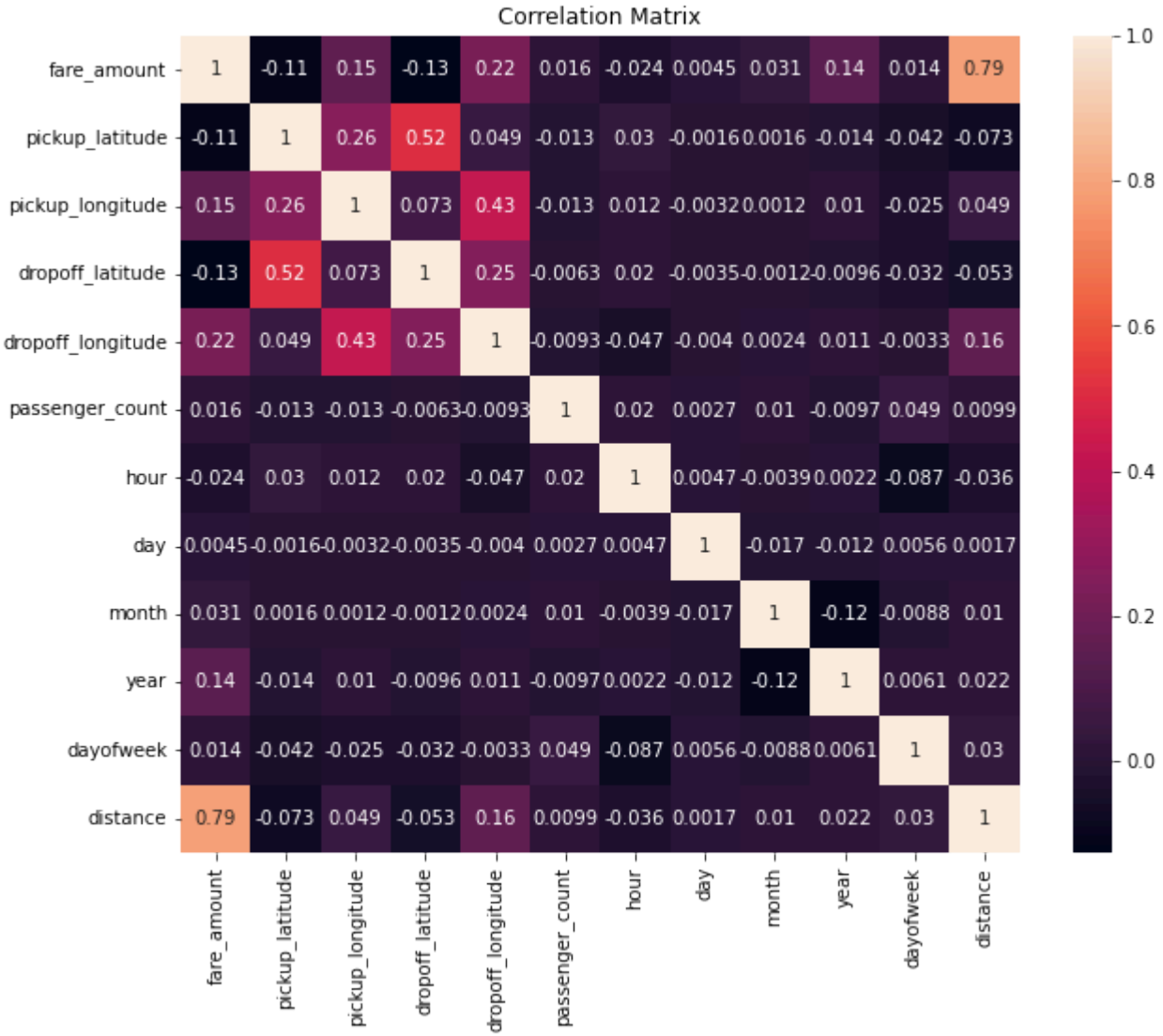
In [68]:
```
# Check the first few rows to ensure the distance column is created correctly
df[['pickup_latitude', 'pickup_longitude', 'dropoff_latitude', 'dropoff_longitude', 'distance']].head()
```

Out[68]:

	pickup_latitude	pickup_longitude	dropoff_latitude	dropoff_longitude	distance
0	40.738354	-73.999817	40.723217	-73.999512	1.681111
1	40.728225	-73.994355	40.750325	-73.994710	2.454363
2	40.740770	-74.005043	40.772647	-73.962565	5.039603
3	40.790844	-73.976124	40.803349	-73.965316	1.661442
4	40.744085	-73.929786	40.761247	-73.973082	4.123172

In [69]:
```
# Step 2: Correlation Analysis
# Let's calculate and visualize the correlation matrix
corr_matrix = df[['fare_amount', 'pickup_latitude', 'pickup_longitude', 'dropoff_latitude',
                  'dropoff_longitude', 'passenger_count', 'hour', 'day', 'month', 'year',
                  'dayofweek', 'distance']].corr()
```

In [70]:
```
# Visualize the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True)
plt.title('Correlation Matrix')
plt.show()
```



In [71]:
```
pip install scikit-learn
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: scikit-learn in /home/sahil/.local/lib/python3.10/site-packages (1.2.2)
Requirement already satisfied: numpy>=1.17.3 in /home/sahil/.local/lib/python3.10/site-packages (from scikit-learn)
(1.26.2)
Requirement already satisfied: joblib>=1.1.1 in /home/sahil/.local/lib/python3.10/site-packages (from scikit-learn)
(1.3.2)
Requirement already satisfied: scipy>=1.3.2 in /home/sahil/.local/lib/python3.10/site-packages (from scikit-learn)
(1.11.4)
Requirement already satisfied: threadpoolctl>=2.0.0 in /home/sahil/.local/lib/python3.10/site-packages (from scikit-
learn) (3.2.0)
Note: you may need to restart the kernel to use updated packages.
```

In [72]:
```
# Step 3: Train-Test Split
from sklearn.model_selection import train_test_split
# Define features and target variable
X = df[['pickup_latitude', 'pickup_longitude', 'dropoff_latitude', 'dropoff_longitude',
        'passenger_count', 'hour', 'day', 'month', 'year', 'dayofweek', 'distance']]
y = df['fare_amount']
```

In [73]:
```
# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [74]:
```
# Step 4: Model Building
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
```

In [75]:
```
# Linear Regression Model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
```

Out[75]:
```
▾ LinearRegression

LinearRegression()
```

In [76]:
```
# Random Forest Regressor Model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

Out[76]:
```
RandomForestRegressor
RandomForestRegressor(random_state=42)
```

In [77]:
```
# Step 5: Model Evaluation
from sklearn.metrics import mean_squared_error, r2_score

# Predict using Linear Regression
y_pred_lr = lr_model.predict(X_test)
r2_lr = r2_score(y_test, y_pred_lr)
rmse_lr = np.sqrt(mean_squared_error(y_test, y_pred_lr))
```

In [78]:
```
# Predict using Random Forest
y_pred_rf = rf_model.predict(X_test)
r2_rf = r2_score(y_test, y_pred_rf)
rmse_rf = np.sqrt(mean_squared_error(y_test, y_pred_rf))
```

In [79]:
```
# Display the evaluation results
print(f"Linear Regression - R²: {r2_lr:.4f}, RMSE: {rmse_lr:.4f}")
print(f"Random Forest - R²: {r2_rf:.4f}, RMSE: {rmse_rf:.4f}")
```

```
Linear Regression - R²: 0.6593, RMSE: 3.1838
Random Forest - R²: 0.7945, RMSE: 2.4729
```

Linear Regression - R^2: 0.6593: The linear regression model explains 65.93% of the variance in the fare_amount. This means that the model is able to capture a significant portion of the relationship between the features and the fare, but there's still about 34.07% of the variance that the model is unable to explain. Random Forest - R^2: 0.7945: The random forest model explains 79.45% of the variance in the fare_amount. This is a better fit compared to linear regression, meaning that the random forest model captures more of the underlying patterns in the data.

In [81]:
```
# Step 6: Prediction Example
# Let's make predictions for a new sample ride
new_ride = pd.DataFrame({
    'pickup_latitude': [-73.97337],
    'pickup_longitude': [40.755193],
    'dropoff_latitude': [-73.978265],
    'dropoff_longitude': [40.766375],
    'passenger_count': [1],
    'hour': [14],
    'day': [15],
    'month': [11],
```

```
    'year': [2024],
    'dayofweek': [2],  # Monday
    'distance': [1.5]  # Example distance in km
})

# Predict fare for the new ride using both models
pred_lr = lr_model.predict(new_ride)
pred_rf = rf_model.predict(new_ride)

print(f"Predicted Fare (Random Forest): ${pred_rf[0]:.2f}")
```

```
Predicted Fare (Random Forest): $17.84
```