UFO sightings analysis

Research tasks:

- Find patterns in distribution of UFO sightings in USA
- Find relations between UFO sightings and weather conditions

Used datasets:

- UFO sightings. Contains coordinates, timestamp and brief description
- US cities coordinates
- Weather archive. Contains worldwide daily measures with related weather station codes.
- Weather stations metadata. Contains station codes and coordinates.

In [ ]:
```
import pandas as pd
import json
from datetime import datetime

from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.tree.tree import DecisionTreeClassifier
from scipy import stats
from IPython.display import Image
import sklearn.tree
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import seaborn as sns
import math
import os.path
import sys
import folium
import folium.features

%matplotlib inline
sns.set_style("whitegrid")
sns.set_context("poster", font_scale=1.5, rc={"lines.linewidth": 2.5})
```

Find patterns in distribution of UFO sightings in USA

Step 1. Acquire data

In [ ]:
```
#Used UFO sightings dataset from https://www.kaggle.com/NUFORC/ufo-sightings
data = pd.read_csv("scrubbed.csv", low_memory=False)
data.head()
```

In [ ]:
```
#Used cities data from https://simplemaps.com/data/us-cities
cities_data = pd.read_csv("uscitiesv1.3.csv")

#selects cities with population over 50000
large_cities = cities_data[cities_data["population"]>50000]
large_cities.set_index("city", inplace=True)
large_cities.head()
```

Step2. Data preparation

In [ ]:
```
# UFO sightings dataset contains shape of object
print(data["shape"].unique())
```

In [ ]:
```
#We select knowingly non-technogenic objects, that not like aircrafts
selectedshapes = ["circle", "sphere", "flash", "light", "fireball", "oval", "formation", "o
```

In [ ]:
```
#Parse datetime and numeric attributes with mistakes
data["dt"] = pd.to_datetime(data["datetime"], format="%m/%d/%Y %H:%M", errors="coerce")
data["lat"] = pd.to_numeric(data["latitude"], errors="coerce")
data["long"] = pd.to_numeric(data["longitude "], errors="coerce")

#Select only US data for required shape and period
condition1 = data['country']=="us"
condition2 = data["shape"].isin(selectedshapes)
condition3 = data["dt"].dt.year>=2010

data.dropna(inplace=True, axis=0)
data = data[condition1 & condition2 & condition3]

#Select only required attributes
features = ["dt", "shape", "comments", "lat", "long"]
selected = data.loc[:,features]
```

In [35]:
```
selected.head()
```

Out[35]:

	dt	shape	comments	lat	long
212	2010-10-10 01:00:00	light	Xmas colored rotating lights. ((NUFORC Note: ...	42.767500	-78.744167
213	2010-10-10 02:30:00	circle	possible UFO sighting	40.273611	-76.884722
214	2010-10-10 03:00:00	circle	2 objects blinking red and white&#44 disappear...	41.593056	-81.526944
215	2010-10-10 08:30:00	formation	Strange orange lights in the night sky	34.376944	-82.695833
216	2010-10-10 12:00:00	light	"Star" like objects during clear day...	41.026389	-73.628889

In [36]:
```python
#Show part of dataset as markers on map with popups. We can't show all data because of Foli
#We can check that usage of cluster analysis is useful.
m = folium.Map(zoom_start=6,  tiles="OpenStreetMap", location=[36.174465, -86.767960])
sample = selected.sample(frac=0.1)
for i in range(0,len(sample), 5):
    row = sample.iloc[i]
    p = "{}; {}; {}".format(row["comments"], str(row["dt"]), row["shape"])
    folium.Marker(location=[row["lat"], row["long"]], popup=p).add_to(m)
m
```

Out[36]:

In [37]:
```python
#Get data for cluster analysis
clusteringfeatures=["lat", "long"]
clusteringdata=selected.loc[:,clusteringfeatures]
clusteringdata.head()
```

Out[37]:

	lat	long
212	42.767500	-78.744167
213	40.273611	-76.884722
214	41.593056	-81.526944
215	34.376944	-82.695833
216	41.026389	-73.628889

Step 3. Data analysis

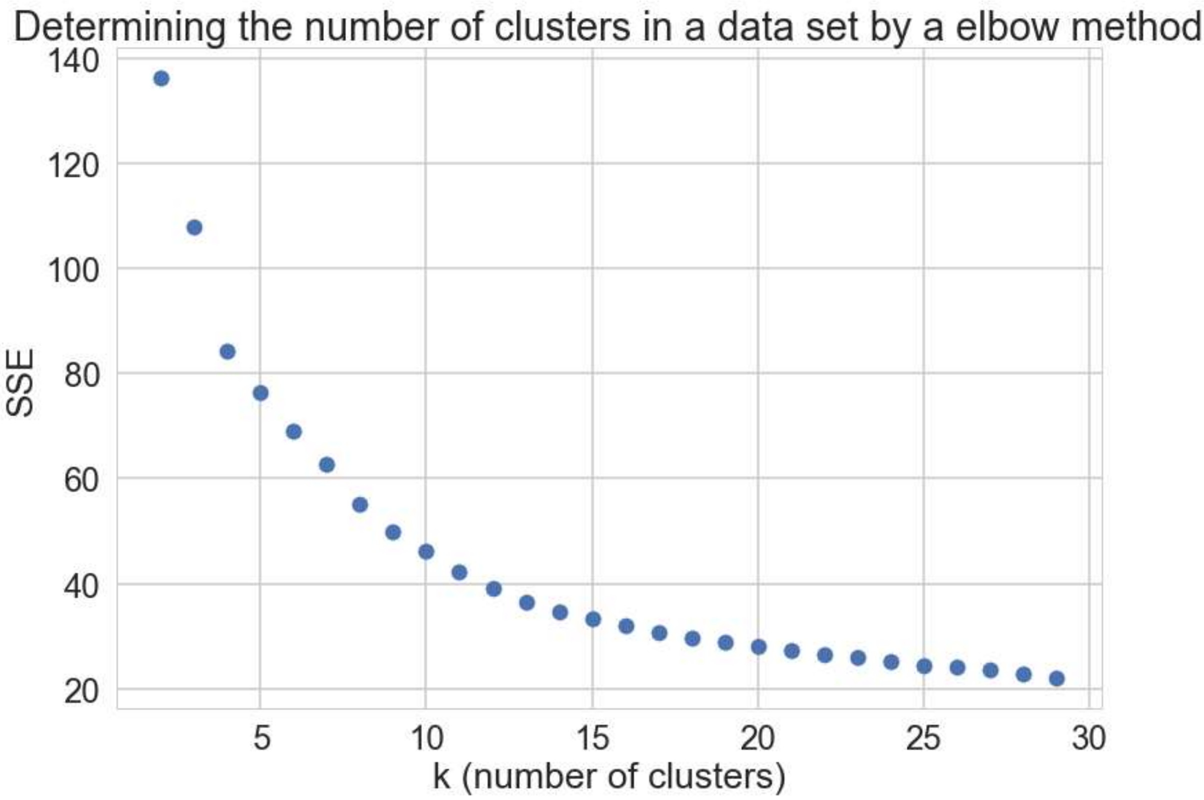
In [38]:
```python
# Normalize data
scaler = StandardScaler()
transformed_data = scaler.fit_transform(clusteringdata)
```

In [39]:

```
#Do clusterisation by K-mean for different k (2-30). Store for each k model and error.
clustering_models = dict()
clustering_errors = dict()
for k in range(2,30):
    kmeans = KMeans(n_clusters=k, random_state=0)
    model = kmeans.fit(transformed_data)
    clustering_models[k] = model
    clustering_errors[k] = math.sqrt(model.inertia_)
```

In [40]:

```
#Show error vs k and select best k.
plt.scatter(x=[x for x in clustering_errors], y=[clustering_errors[y] for y in clustering_e
plt.title("Determining the number of clusters in a data set by a elbow method")
plt.xlabel("k (number of clusters)")
plt.ylabel("SSE")
plt.show()
```



In [41]:

```
selected_k = 15
selected_model = clustering_models[selected_k]
```

In [42]:
```
#merge cluster centers and main dataset
cluster_centers = pd.DataFrame(scaler.inverse_transform(selected_model.cluster_centers_),
                               columns=["cluster_lat", "cluster_long"])
cluster_centers["cluster"] = range(0, len(cluster_centers))
selected["cluster"] = selected_model.labels_
selected = pd.merge(selected, cluster_centers, how="inner", on="cluster")
selected.head()
```

Out[42]:

	dt	shape	comments	lat	long	cluster	cluster_lat	cluster_long
0	2010-10-10 01:00:00	light	Xmas colored rotating lights. ((NUFORC Note: ...	42.767500	-78.744167	11	42.652549	-72.966838
1	2010-10-10 17:10:00	light	Saw a light in the sky fading in and out over ...	41.166944	-73.205278	11	42.652549	-72.966838
2	2010-10-10 20:20:00	fireball	Bus sized fireball object over 91 about 3-400 ...	41.852500	-72.644167	11	42.652549	-72.966838
3	2010-10-10 21:30:00	circle	Circle of light SUNY Albany.	42.652500	-73.756667	11	42.652549	-72.966838
4	2011-10-10 10:30:00	circle	Amber object in night sky during full moon&#44...	42.096389	-79.375833	11	42.652549	-72.966838

Step 4. Visualization

In [43]:
```
#Function for calculate distance on earth between two locations given by latitude and longi
def haversine(lat1, lon1, lat2, lon2):
    R = 6378.137 #Earth radius in km
    dLat = lat2 * math.pi / 180 - lat1 * math.pi / 180
    dLon = lon2 * math.pi / 180 - lon1 * math.pi / 180
    a = math.sin(dLat/2) * math.sin(dLat/2) + math.cos(lat1 * math.pi / 180) \
        * math.cos(lat2 * math.pi / 180) * math.sin(dLon/2) * math.sin(dLon/2)
    c = 2 * math.atan2(math.sqrt(a), math.sqrt(1-a))
    d = R * c
    return d * 1000
```

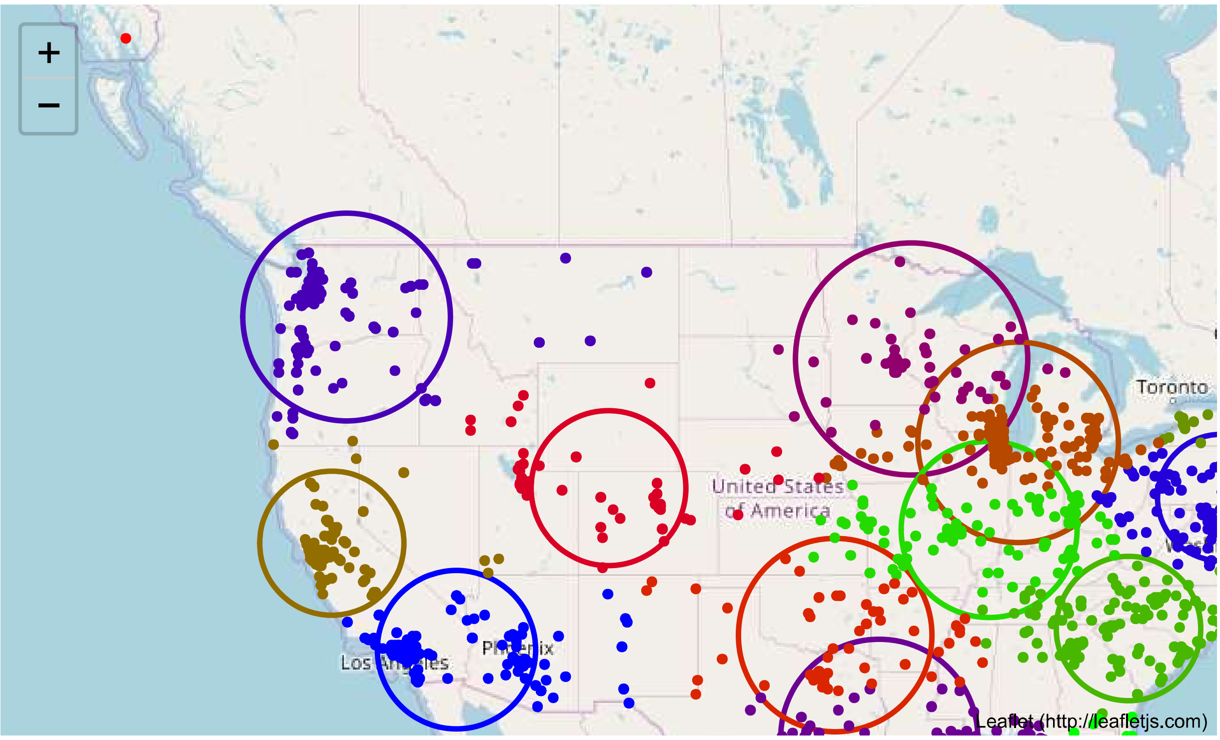
In [44]:
```
#Append to dataset distances between location of sighting and cluster center
selected["distance"] = selected.apply(lambda x: haversine(x["lat"], x["long"], x["cluster_l

#Calculate cluster confidence circle for cluster visualization on map
cluster_radius = pd.DataFrame(selected.groupby("cluster").std()["distance"] * 2.326)
cluster_radius['cluster'] = cluster_radius.index
cluster_centers = pd.merge(cluster_centers, cluster_radius, how="inner", on="cluster")
```

In [45]:
```
#Function to convert color from RGBA tuple to string format usable with HTML (like #345466)
def rgb_to_hex(color):
    return "#{0:02x}{1:02x}{2:02x}".format(int(color[0]*255), int(color[1]*255), int(color[
```

In [46]:
```
#Function for clusters visualization
def getclusteredmap():
    m = folium.Map(zoom_start=4,  tiles="OpenStreetMap", location=[39.007504, -94.529625])
    n = len(cluster_centers)
    maxcluster = cluster_centers["cluster"].max()

    #Visualize clusters as confidence circles
    for i in range(0,n):
        row= cluster_centers.iloc[i]
        c = rgb_to_hex(cm.brg(float(row["cluster"])/maxcluster))
        r = cluster_radius.loc[row["cluster"]]["distance"]
        folium.Circle(location=[row["cluster_lat"], row["cluster_long"]],  radius=r, color=

    #Visualize each 1 of 10 sighting for
    for i in range(0,len(selected), 10):
        row = selected.iloc[i]
        c = rgb_to_hex(cm.brg(float(row["cluster"])/maxcluster))
        folium.CircleMarker(location=[row["lat"], row["long"]], radius=1.5, color=c).add_to
    return m
```

In [47]:
```
getclusteredmap()
```

Out[47]:



In [48]:

```
# Function for selection of cities closest to cluster centers
def find_closest_city(lat, long):

    #Due to low calculation speed we narrow square of finding closest city. This gives obou
    c1 = large_cities["lat"]< (lat + 2)
    c2 = large_cities["lat"]> (lat - 2)
    c3 = large_cities["lng"]> (long - 2)
    c4 = large_cities["lng"]< (long + 2)
    partial = large_cities[c1 & c2 & c3 & c4]

    if len(partial)>0:
        return partial.apply(lambda x: (math.pow(lat - x["lat"], 2) + math.pow(long - x["ln
    else:
        return large_cities.apply(lambda x: (math.pow(lat - x["lat"], 2) + math.pow(long - 

cluster_centers["closest_city"]=cluster_centers.apply(lambda x: (find_closest_city( x["clus

# We got cities wich closest to cluster centers
cluster_centers.loc[:,["closest_city"]]
```

Out[48]:

	closest_city
0	Lake Havasu City
1	Lancaster
2	Yakima
3	Beaumont
4	Woodbury
5	Daly City
6	Grand Junction
7	Anchorage
8	McKinney
9	Gary
10	Lodi
11	Chicopee
12	Rock Hill
13	Decatur
14	Poinciana

In [49]:

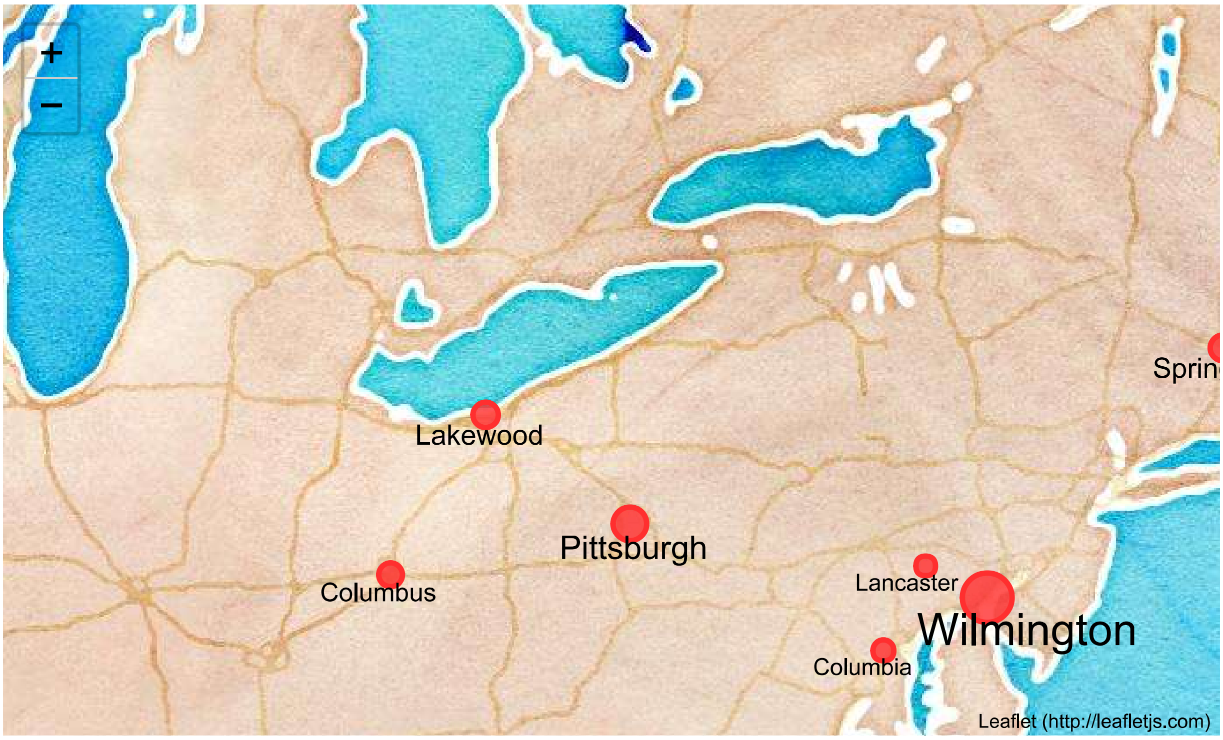
```
# Find city that closest to each UFO sighting
selected["closest_city"]=selected.apply(lambda x: (find_closest_city( x["lat"], x["long"]))

# Group data and find top 10 cities for number of sightings
cities = selected.groupby("closest_city").count().iloc[:,3].sort_values(ascending = False)[
cities
```

Out[49]:

```
closest_city
Wilmington     281
Portland       273
Pittsburgh     191
Springfield    147
Lakewood       144
Seattle        141
Columbus       135
Columbia       118
Lancaster      111
Saint Louis    110
Name: lat, dtype: int64
```

In [50]:
```python
# Function for visualization cities on map. Used map tiles without text. Radius of marker p
def getcirclemap():
    m = folium.Map(zoom_start=6,  tiles="stamenwatercolor", location=[40.440624, -76.995888

    for i in range(0,10):
        row= large_cities.loc[large_cities.index== cities.index[i]].iloc[0,:]
        r = int(cities[i])/20
        location=[row["lat"], row["lng"]]
        folium.CircleMarker(location,  radius=r, color='#ff2f2f', fill_color='#ff2f2f', fil
        folium.Marker(location=location, icon=folium.DivIcon(icon_size=(150,36), icon_ancho
    return m
getcirclemap()
```

Out[50]:



Find relations between UFO sightings and weather conditions

Steps 1 and 2. Acquire and prepare additional data (weather dataset)

In [ ]:

```
# Dataset from https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/by_year/
# Due to RAM limitations we use chunked csv reading

for year in range(2010:2015):
    #Filter by country
    weather_iterator = pd.read_csv("{0}.csv".format(year), iterator=True, chunksize=10000,
                                   names=['id','date','parameter','value', 'm', 'q', 's', '
    wd = pd.concat([chunk[chunk['id'].str.startswith("US")] for chunk in weather_iterator])
    wd.loc[:,"id":"value"].to_csv("us{0}.csv".format(year), index=False)

    #Select only stations with known temperature
    weather_iterator = pd.read_csv("us{0}.csv".format(year), iterator=True, chunksize=10000
    wd = pd.concat([chunk[chunk['parameter']=="TMAX"] for chunk in weather_iterator])
    pd.DataFrame(wd["id"].unique()).to_csv("stations_with_t{0}}.csv".format(year), index =

    #Clean sources for stations with t
    ids = pd.read_csv("stations_with_t{0}.csv".format(year))
    weather_iterator = pd.read_csv("us{0}.csv".format(year), iterator=True, chunksize=10000
    wd = pd.concat([chunk[chunk['id'].isin(ids["0"])] for chunk in weather_iterator])
    wd.to_csv("limited{0}.csv".format(year), index = False)

    #Pivot table. Source dataset on for of pairs (parameter:value). We need it in form of t
    wd = pd.read_csv("limited{0}.csv".format(year))
    wd["key"] = wd["id"] + wd["date"].apply(str)
    pivoted_wd = wd.pivot(columns="parameter", values="value", index="key")
    pivoted_wd.to_csv("wdp{0}.csv".format(year))
```

In [51]:

```
# Got list of stations with known temperatures
w  = [pd.read_csv("stations_with_t{0}.csv".format(year), ";") for year in range(2010,2015)]
s = pd.DataFrame(pd.concat(w)["0"].unique())
s.columns=["Id"]

# We got weather station coordinates and filter it to only required stations
ws = pd.read_csv("ws.csv", ";")
ws = ws.merge(s, how="inner", on="Id")
ws.set_index("Id", inplace=True)
ws.head(3)
```

Out[51]:

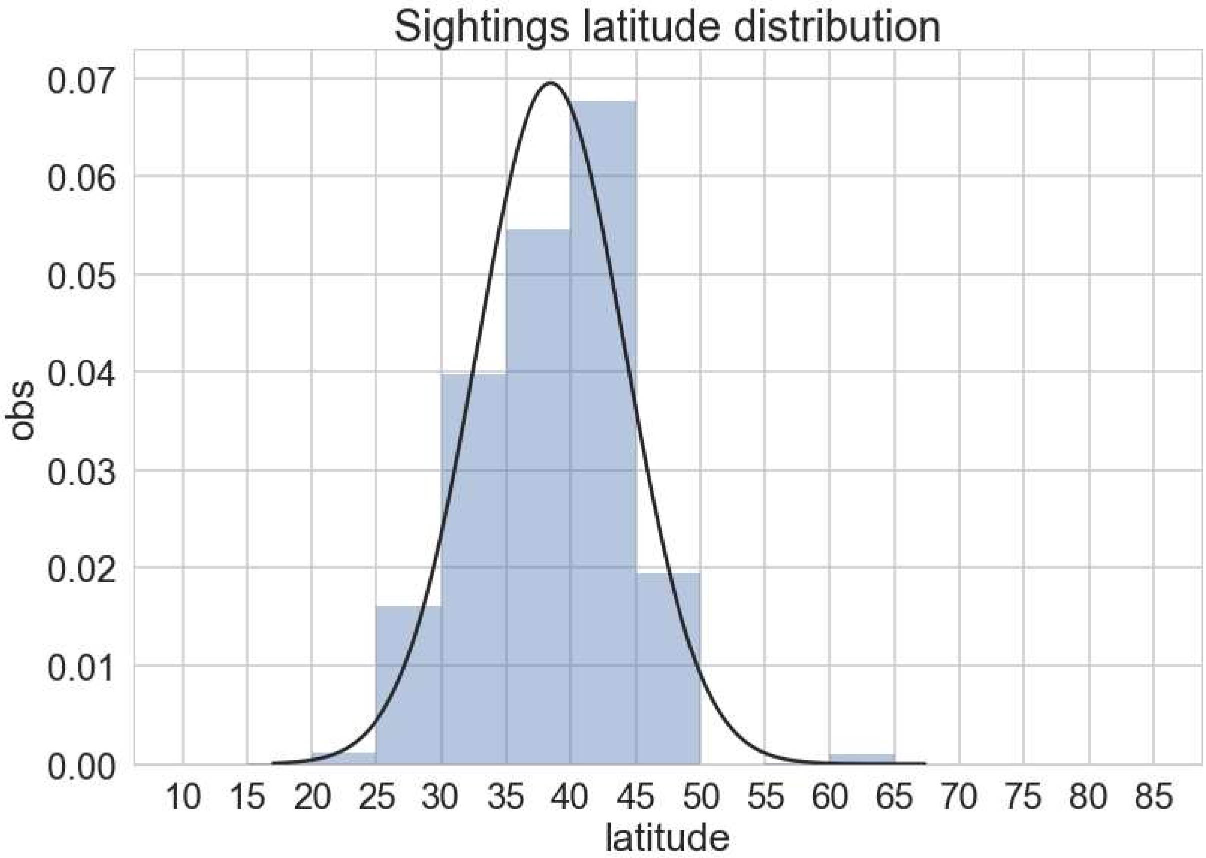
Id	Lat	Long
US009052008	43.7333	-96.6333
USC00010063	34.2553	-87.1814
USC00010160	32.9453	-85.9481

In [52]:

```
# prepare data of UFO sightings (DataFrame "selected") for weather analysis
#Look at latitude distribution
def showhist(par, feat, bins):
    sns.distplot(selected.loc[:][feat], bins=bins, fit=stats.norm, kde=False)
    plt.xlabel(par)
    plt.ylabel("obs")
    plt.xticks(bins)
    plt.title("Sightings latitude distribution")
    plt.show()
```

In [53]:
```
print("Before filtering")
showhist("latitude", "lat", range(10,90,5))
```

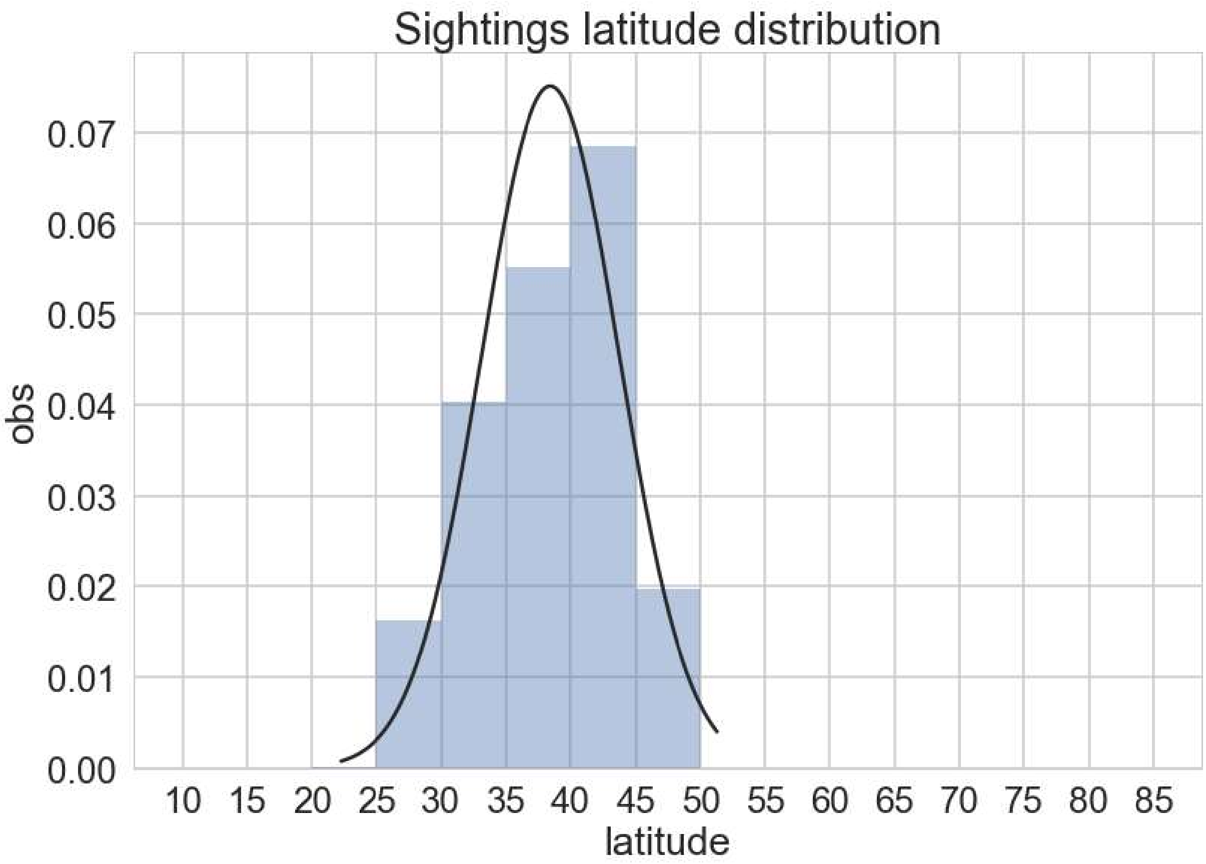
Before filtering



In [54]:
```
#We seen some outliers
#We must to narrow latitude band of observations due to different climate on outlier's terr

mean = cluster_centers["cluster_lat"].mean()
std = cluster_centers["cluster_lat"].std()
min_lat = mean - 1.65 * std
max_lat = mean + 1.65 * std
c1 = min_lat < selected["cluster_lat"]
c2 = max_lat > selected["cluster_lat"]
selected = selected[c1 & c2]
selected_clusters = pd.DataFrame(selected["cluster"].unique(), columns=["cluster"])
cluster_centers = pd.merge(cluster_centers, selected_clusters, how="inner", on="cluster")
```

In [55]:
```
print("After filtering")
showhist("latitude", "lat", range(10,90,5))
```

```
After filtering
```



In [56]:
```
# Now find closests weather station for each sighting

def find_closest_station(lat, long):

    #speedup optimization
    c1 = ws["Lat"] < (lat + 2)
    c2 = ws["Lat"] > (lat - 2)
    c3 = ws["Long"] > (long - 2)
    c4 = ws["Long"] < (long + 2)
    partial = ws[c1 & c2 & c3 & c4]
    if len(partial)>0:
        return partial.apply(lambda x: (math.pow(lat - x["Lat"], 2) + math.pow(long - x["Lo
    else:
        return ws.apply(lambda x: (math.pow(lat - x["Lat"], 2) + math.pow(long - x["Long"],

selected["closest_station"]=selected.apply(lambda x: (find_closest_station( x["lat"], x["lo
selected.head()
```

Out[56]:

	dt	shape	comments	lat	long	cluster	cluster_lat	cluster_long	distance	close
0	2010-10-10 01:00:00	light	Xmas colored rotating lights. ((NUFORC Note: ...	42.767500	-78.744167	11	42.652549	-72.966838	472649.610466	Cheek
1	2010-10-10 17:10:00	light	Saw a light in the sky fading in and out over ...	41.166944	-73.205278	11	42.652549	-72.966838	166552.028876	Bric
2	2010-10-10 20:20:00	fireball	Bus sized fireball object over 91 about 3-400 ...	41.852500	-72.644167	11	42.652549	-72.966838	92944.656239	East H
3	2010-10-10 21:30:00	circle	Circle of light SUNY Albany.	42.652500	-73.756667	11	42.652549	-72.966838	64665.292303	
4	2011-10-10 10:30:00	circle	Amber object in night sky during full moon&#44...	42.096389	-79.375833	11	42.652549	-72.966838	530554.932607	

In [57]:
```
true = pd.Series([True for x in range(0, selected.shape[0])], name="UFO")

#Key of UFO data is closest weather station and date of sighting

keys = pd.Series(selected["closest_station"]+selected["dt"].dt.strftime("%Y%m%d"), name="ke
ufo = pd.concat([keys, true], axis=1)
ufo.drop_duplicates()
ufo.head()
```

Out[57]:

	key	UFO
0	USC0030162520101010	True
1	USW0009470220101010	True
2	USW0001474020101010	True
3	USW0001473520101010	True
4	USC0036136220111010	True

In [58]:
```
#read and concatenate datasets for 5 years
wdp  = [(pd.read_csv("wdp201{0}.csv".format(n)).loc[:,["key", "TMIN", "TMAX", "PRCP", "SNOW
weather = pd.DataFrame(pd.concat(wdp, axis=0))

#Rename columns to readable
weather.columns=["key", "T day min", "T day max", "Precipitations", "Snowfall"]
weather["T range"] = weather["T day max"] - weather["T day min"]
weather.dropna(how="any", axis=0, inplace=True)

#Merge with UFO sightings data by key.
toclassify = pd.merge(weather, ufo, how="left", on="key")

#Fill empty UFO with False (no sighting) for days/stations with no sightings
toclassify["UFO"].fillna(axis=0, value=False, inplace=True)

#Balance selection. Reduce no-sightings data to size equal of sighting data
reduceData = toclassify[toclassify["UFO"]==False]
todelete = reduceData.sample(n=reduceData.shape[0]-ufo.shape[0])["key"]
toclassify = toclassify[~toclassify['key'].isin(todelete)]

#Now we have dataset with weather parameters. Half of dataset with UFO sighting and half -
```

In [59]:
```
toclassify.describe().T
```

Out[59]:

	count	mean	std	min	25%	50%	75%	max
T day min	22445.0	52.332591	111.091576	-528.0	-22.0	56.0	139.0	350.0
T day max	22445.0	180.212341	121.078756	-456.0	89.0	200.0	278.0	506.0
Precipitations	22445.0	21.402183	74.919613	0.0	0.0	0.0	3.0	2080.0
Snowfall	22445.0	2.549833	17.036548	0.0	0.0	0.0	0.0	559.0
T range	22445.0	127.879751	51.560586	-155.0	89.0	127.0	161.0	339.0

Step 3. Data analysis

In [60]:
```
#Select required variables
y = toclassify["UFO"].copy()
common_features = ["T day min", "T day max", "Precipitations", "Snowfall", "T range"]
x = toclassify[common_features].copy()

#Split data to train and test parts
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.5)
```

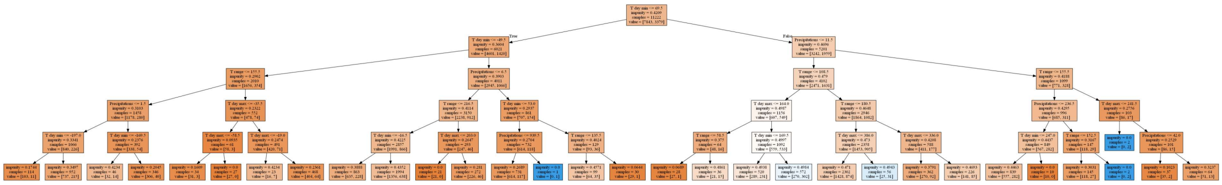
In [61]:
```
#Use decision tree classification to find difference between UFO-sighting and no-UFO-sighti
UFO_classifier = DecisionTreeClassifier(max_depth=5)
UFO_classifier.fit(x_train, y_train)

predictions = UFO_classifier.predict(x_test)
pred = pd.Series(predictions, name="prediction")


#calculate prediction rate of UFO==true cases
correct = 0
for a in range(0, len(predictions)):
    if (predictions[a] & y_test.values[a]):
        correct+=1

print ("Correct predictions of UFO sighting: "
       +str(round(correct / ufo.shape[0] * 100, 2)) +" %, tree depth="+str(UFO_classifier.t
```

```
Correct predictions of UFO sighting: 1.94 %, tree depth=5
```

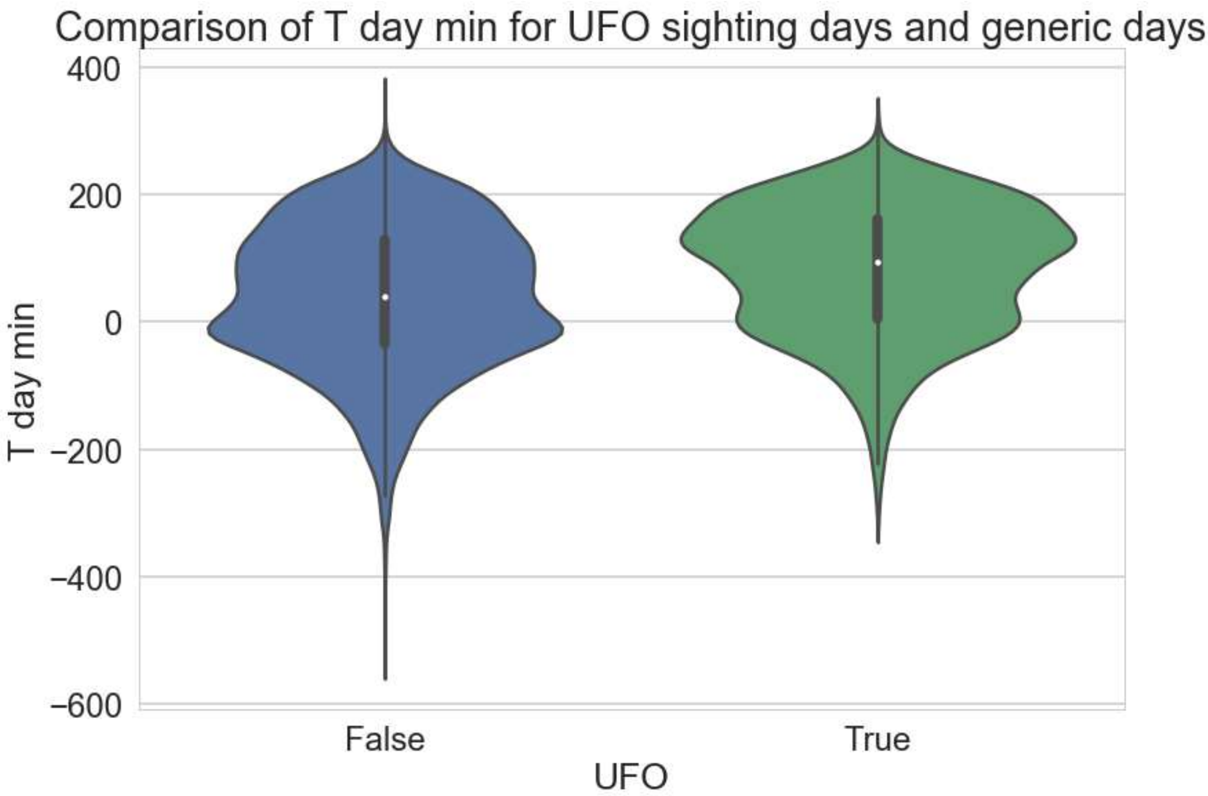
In [62]:

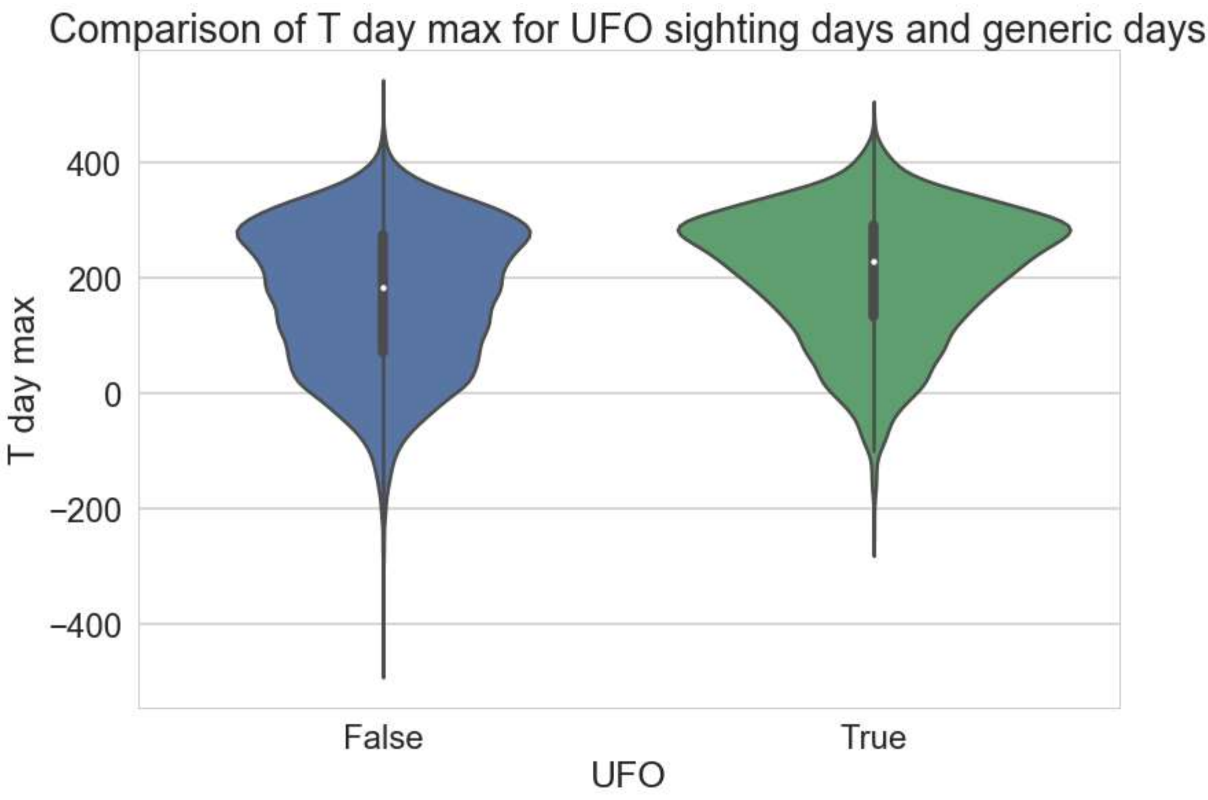
```
#Show tree with graphviz
sklearn.tree.export_graphviz(UFO_classifier.tree_, out_file='tree.dot', feature_names=x_tra
from subprocess import call
call(['dot', '-T', 'png', 'tree.dot', '-o', 'tree.png'])
Image("tree.png")
```

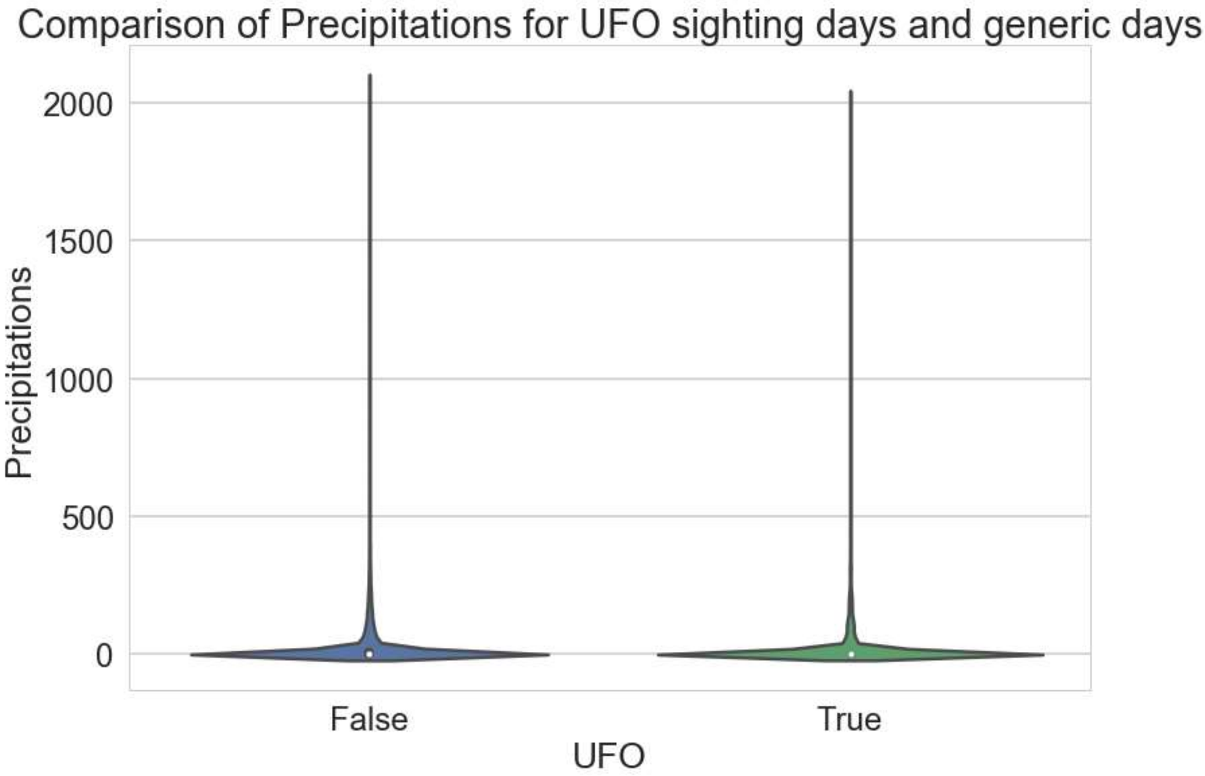
Out[62]:

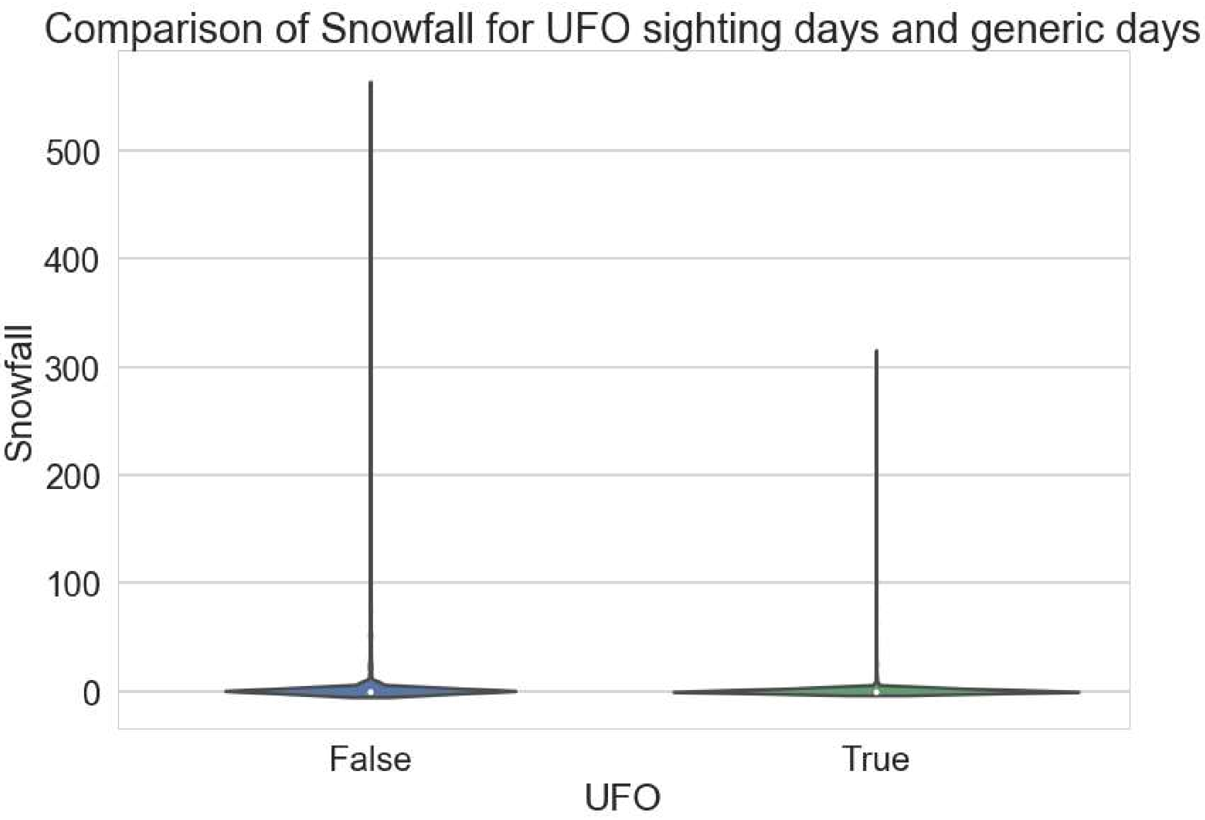


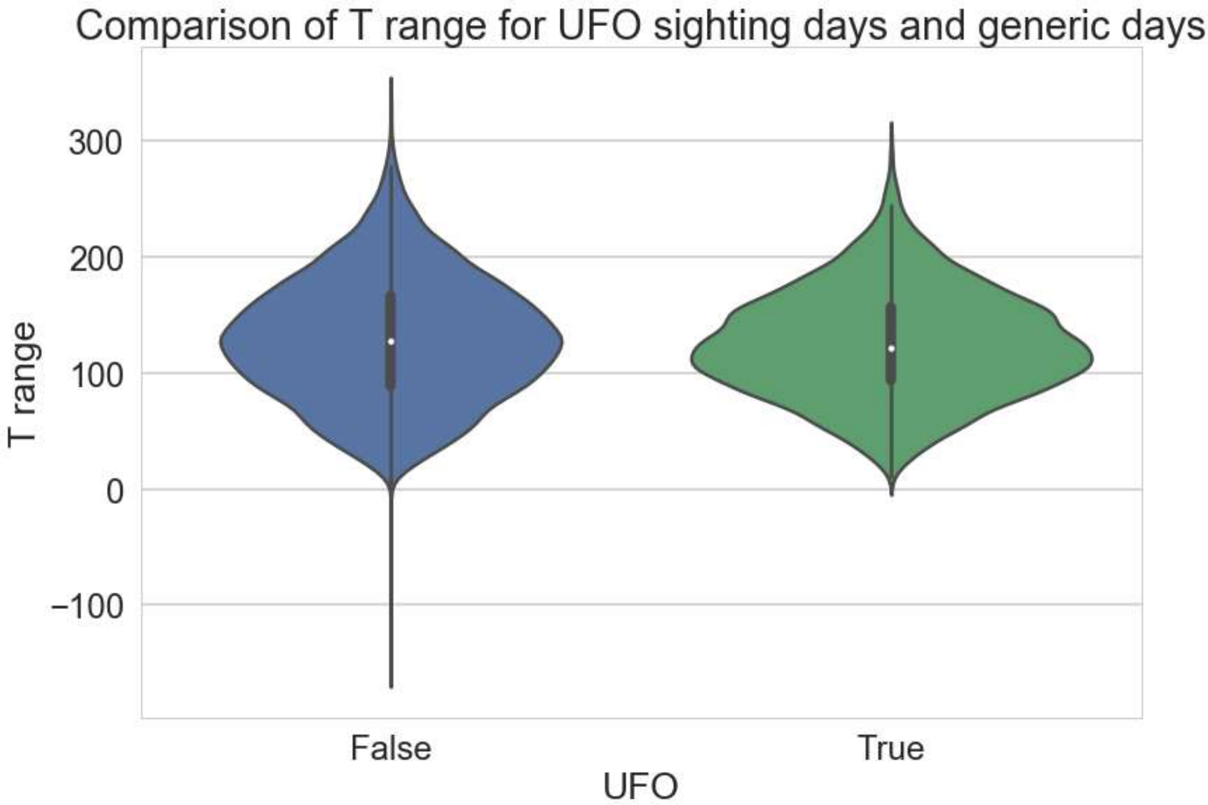
In [63]:
```python
#Now compare two groups (UFO-sighting and no-UFO-sighting) by each parameter
def showviolinplot(parameter):
    sns.violinplot(data=toclassify, x="UFO", y=parameter)
    plt.ylabel(parameter)
    plt.title("Comparison of "+parameter+" for UFO sighting days and generic days")
    plt.show()

[showviolinplot(c) for c in toclassify.columns[1:6]];
```






Comparison of Precipitations for UFO sighting days and generic days
Precipitations
2000
1500
1000
500
0
False
True
UFO


Comparison of Snowfall for UFO sighting days and generic days
Snowfall
500
400
300
200
100
0
False
True
UFO



In [ ]:
```
#We find that UFO=true group has higher temperatures
```

Conclusions

- UFO sightings can be clustered around 15 cities
- Found cities with very high sighting rate (about 1 per week)
- UFO sighting can not be predicted by generic weather parameters
- UFO sighting often occurs in warm days
- Deeper analysis requires more resources than available

In [ ]:
```
```