Predikcija guzve u metrou na osnovu vremeskih prilika

Projekat iz nadgledanog ucenja

Biblioteke

In [ ]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from google.colab import files
import io
import seaborn as sns
import pydotplus
import math
from xgboost import XGBRegressor
from scipy.stats.mstats import winsorize
from datetime import datetime
from sklearn.preprocessing import LabelBinarizer
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score,GridSearchCV,StratifiedKFold
from sklearn.linear_model import LinearRegression,Lasso,Ridge
from sklearn.tree import DecisionTreeRegressor
from IPython.display import Image
from sklearn import tree
from sklearn.ensemble import RandomForestRegressor,VotingRegressor
from sklearn.feature_selection import SelectFromModel
from sklearn.decomposition import PCA
from sklearn.svm import SVR
from sklearn.metrics import *
import warnings
warnings.filterwarnings('ignore')
```

Ucitavanje

In [ ]:
```
url = 'https://raw.githubusercontent.com/aleksicmilica/ml-projekat1/main/dataset.csv'
dataset = pd.read_csv(url)
```

In [ ]:
```
dataset.head()
```

Out[ ]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	date_time	traffi
0	None	288.28	0.0	0.0	40	Clouds	scattered clouds	2012-10-02 09:00:00	
1	None	289.36	0.0	0.0	75	Clouds	broken clouds	2012-10-02 10:00:00	
2	None	289.58	0.0	0.0	90	Clouds	overcast clouds	2012-10-02 11:00:00	
3	None	290.13	0.0	0.0	90	Clouds	overcast clouds	2012-10-02 12:00:00	
4	None	291.14	0.0	0.0	75	Clouds	broken clouds	2012-10-02 13:00:00	

In [ ]:

```
dataset.columns
```

Out[ ]:

```
Index(['holiday', 'temp', 'rain_1h', 'snow_1h', 'clouds_all', 'weather_main',
       'weather_description', 'date_time', 'traffic_volume'],
      dtype='object')
```

Predobrada

Provera prisustva missing values

In [ ]:

```
total_missing = dataset.isnull().sum()
print(total_missing)
if (total_missing == 0).all():
  print("Sve vrednosti su prisutne u dataset-u")
```

```
holiday                0
temp                   0
rain_1h                0
snow_1h                0
clouds_all             0
weather_main           0
weather_description    0
date_time              0
traffic_volume         0
dtype: int64
Sve vrednosti su prisutne u dataset-u
```

Za svaku kolone je vrsena provera da li postoje missing values, i utvrdjeno je da ni u jednoj koloni ne postoje.

Provera da li su svi podaci odgovarajuceg tipa

In [ ]:
```
irregular_values = ((dataset.clouds_all < 0) | (dataset.clouds_all > 100)).sum() + (da
print(irregular_values)
```

```
0
```

In [ ]:
```
numerical_type = pd.api.types.is_numeric_dtype(dataset["temp"].dtype) and pd.api.types
print(numerical_type)
```

```
True
```

In [ ]:
```
string_type = dataset['holiday'].apply(lambda x: x.replace(" ", "").isalpha() or x.iss
print(string_type)
```

```
True
```

In [ ]:
```
if irregular_values == 0 and numerical_type and string_type:
  print("Svi podaci su odgovarajuceg tipa")
```

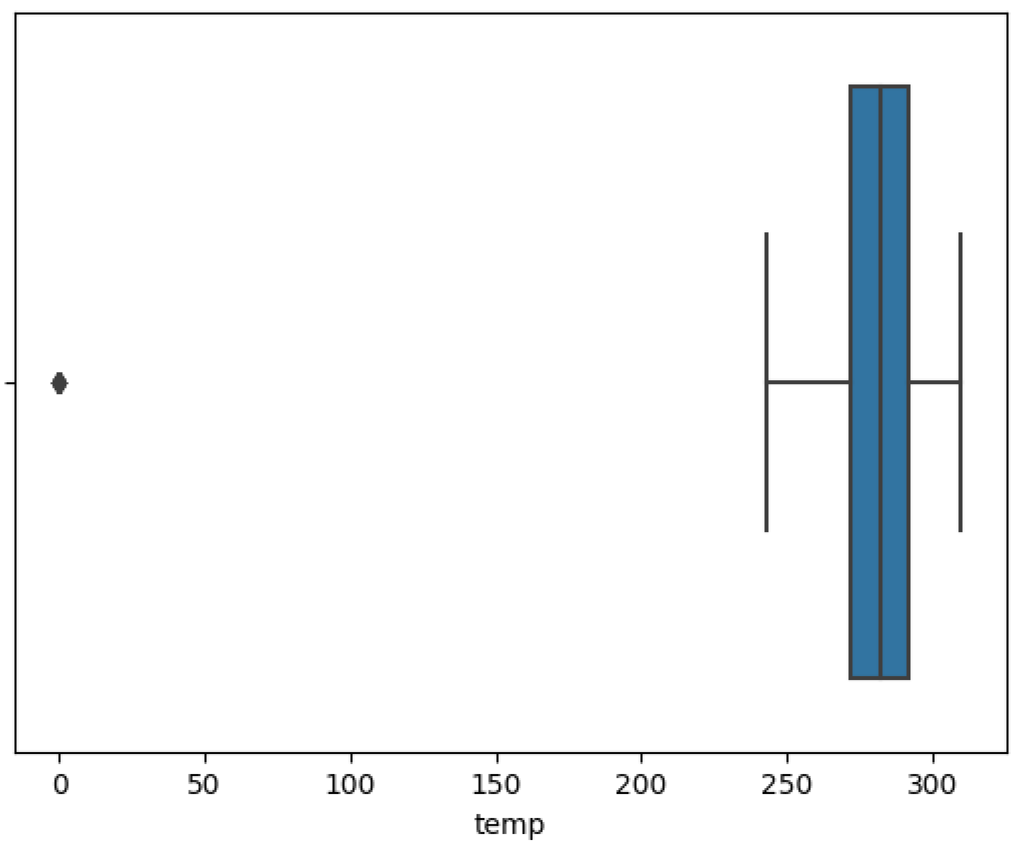
```
Svi podaci su odgovarajuceg tipa
```

Izvrsena je provera da li su podaci u kolonama odgovarajuceg tipa i za numericke atribute poput **rain_1h**, **snow_1h**, **traffic_volume**, da li su nenegativni i za atribut **clouds_all**, kako predstavlja procente, da li je u opsegu [0,100].

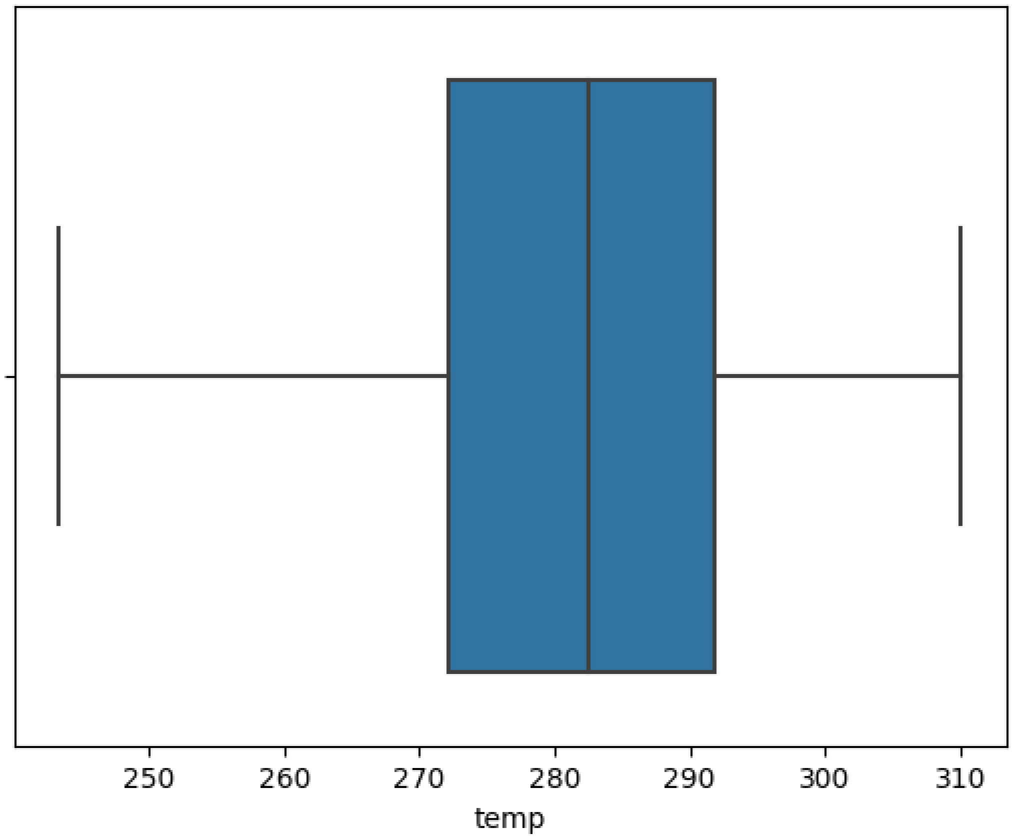
Detekcija i otklanjanje outlier-a, normalizacija podataka

Prvi atribut koji se obradjuje je temperatura

In [ ]:
```
sns.boxplot(x = dataset['temp'])
plt.show()
```

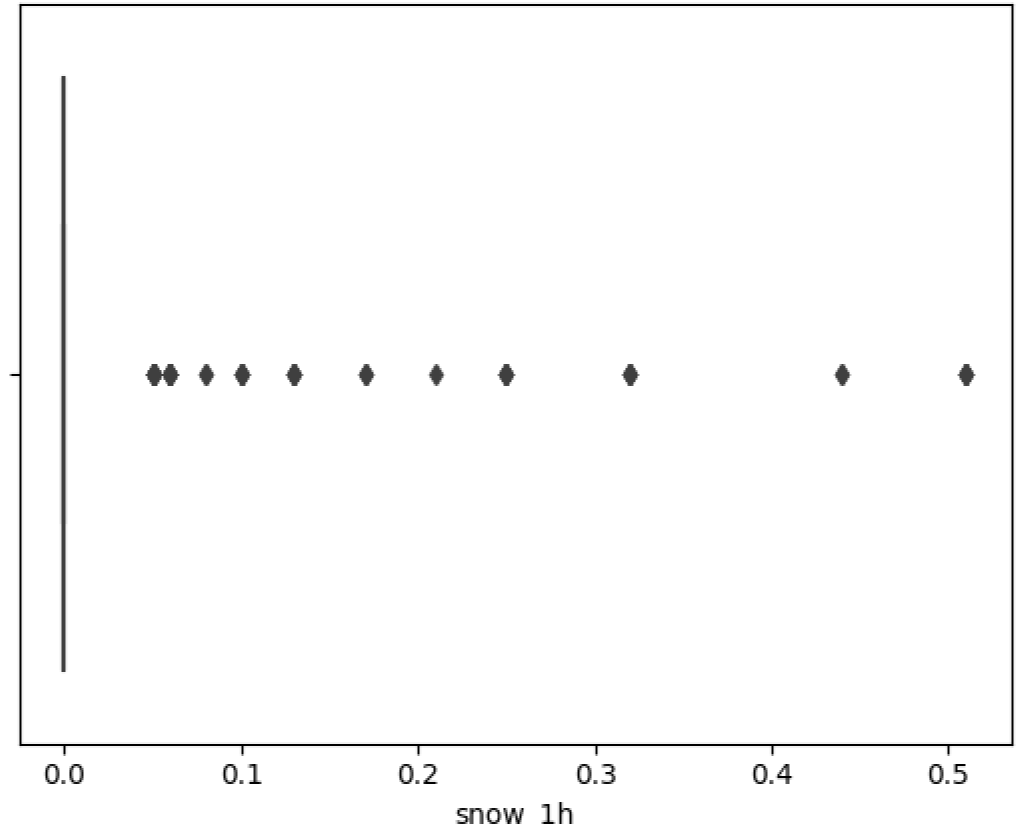


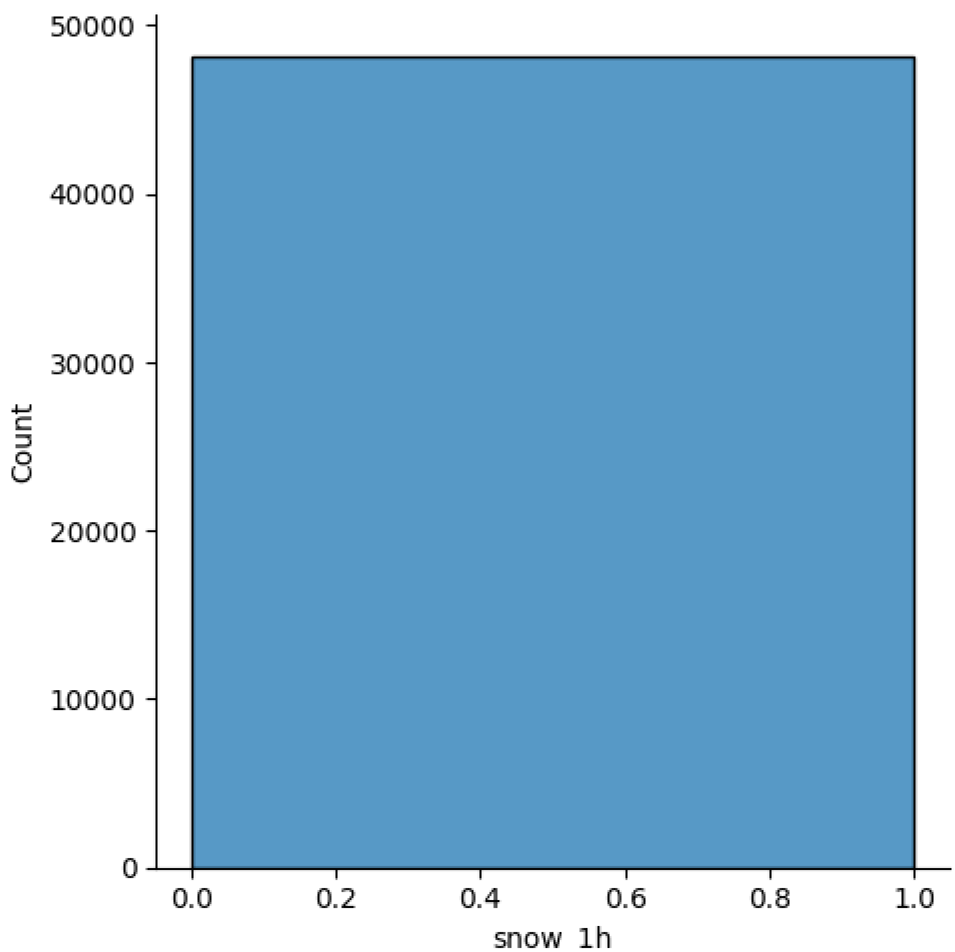
In [ ]:
```
Q1 = dataset['temp'].quantile(0.25)
Q3 = dataset['temp'].quantile(0.75)
IQR = Q3 - Q1
lower_lim = Q1 - 1.5 * IQR
upper_lim = Q3 + 1.5 * IQR
outliers_15_low = (dataset['temp']<lower_lim)
outliers_15_up = (dataset['temp']> upper_lim)
dataset = dataset[~(outliers_15_low | outliers_15_up)]
sns.boxplot(x = dataset['temp'])
plt.show()
```



Primenom IQR moze se primetiti prisustvu outlier-a koji se otklanjaju, nakon cega grafikon raspodele ima bolju formu

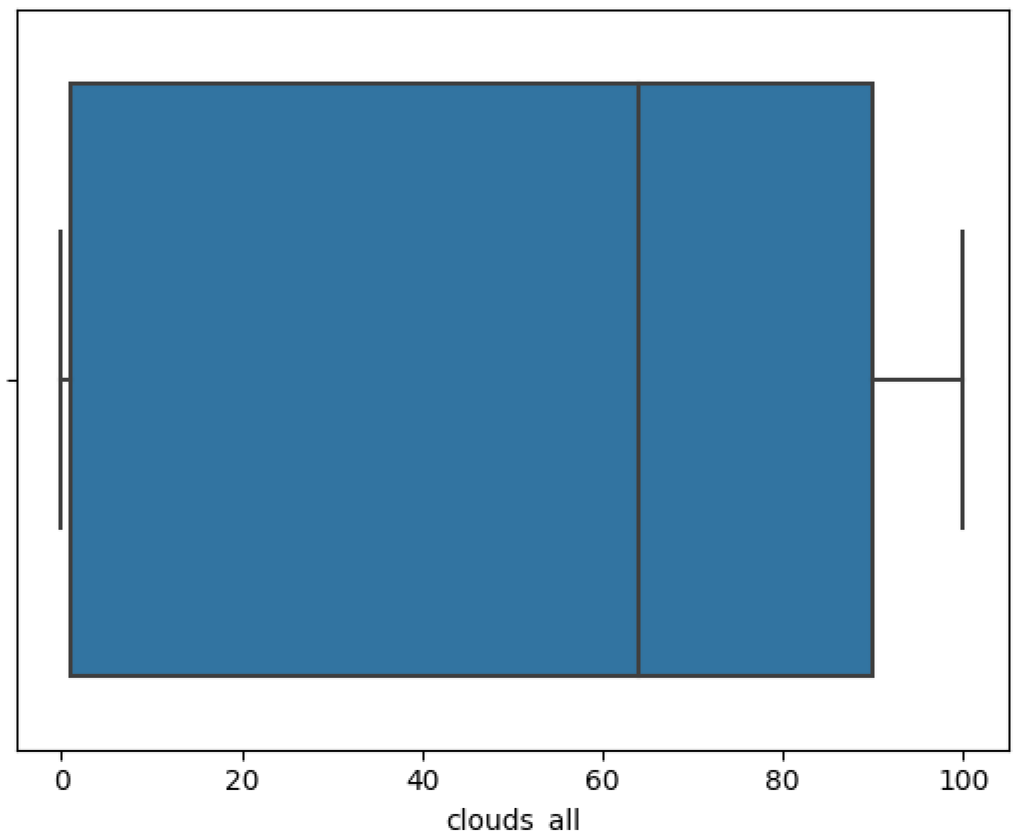
In [ ]:
```
sns.boxplot(x = dataset['snow_1h'])
sns.displot(dataset, x = dataset['snow_1h'],binwidth=1)
plt.show()
```

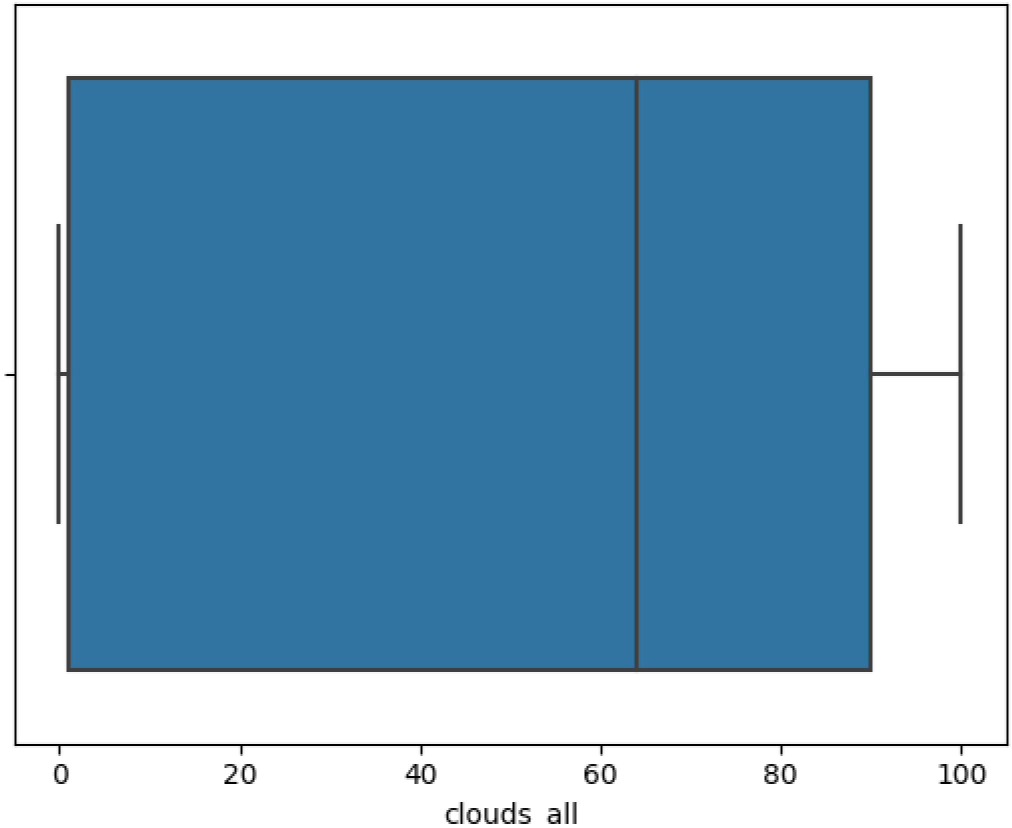

0.0
0.1
0.2
0.3
0.4
0.5
snow_1h


50000
40000
30000
20000
10000
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
snow_1h

Naredni atribut koji se obradjuje je **snow_1h**, za koji se dobija da se sve vrednosti krecu u opsegu od 0 do 1, pa nije izvrsena pretraga outliera, jer vrednost 0 znacajno vise zastupljena u odnosu na ostale, pa bi sve ostale vrednosti proglasile za outlier-e, nakon cega bi bilo moguce izbaciti atribut, a atribut logicki smatrano ima udela na izlaznu vrednost, pa se ne vrsi izbacivanje outliera

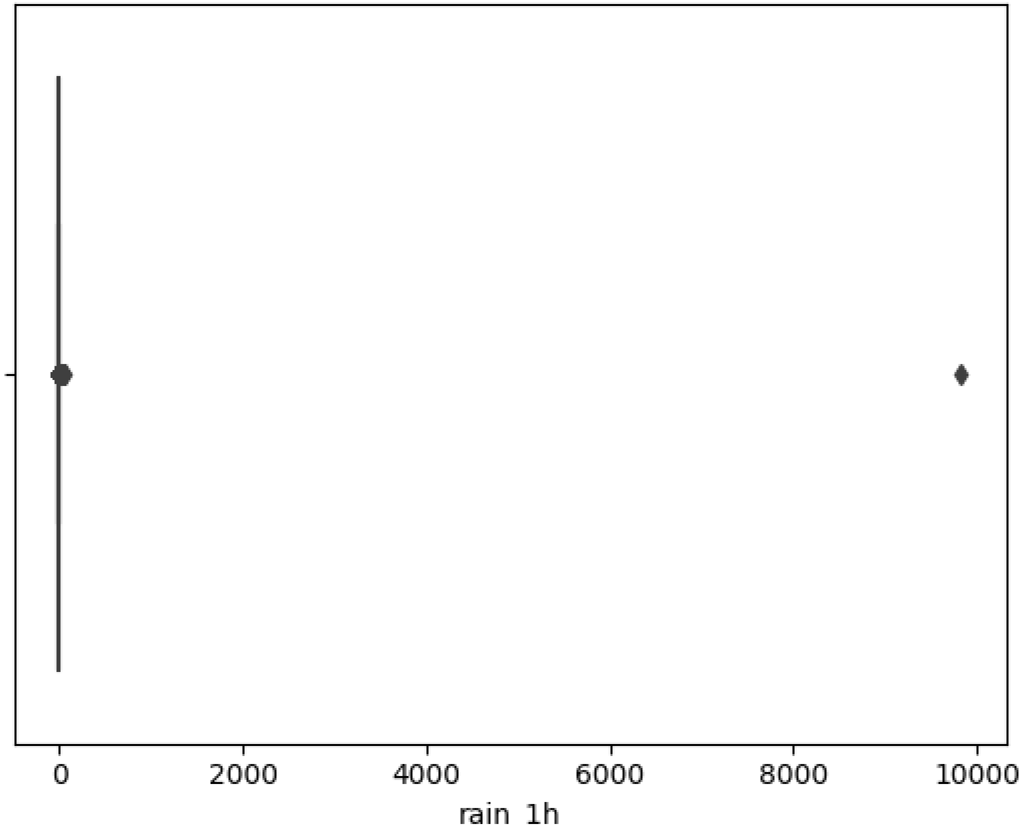
In [ ]:
```
sns.boxplot(x = dataset['clouds_all'])
plt.show()
Q1 = dataset['clouds_all'].quantile(0.25)
Q3 = dataset['clouds_all'].quantile(0.75)
IQR = Q3 - Q1
lower_lim = Q1 - 1.5 * IQR
upper_lim = Q3 + 1.5 * IQR
outliers_15_low = (dataset['clouds_all']<lower_lim)
outliers_15_up = (dataset['clouds_all']> upper_lim)
dataset = dataset[~(outliers_15_low | outliers_15_up)]
sns.boxplot(x = dataset['clouds_all'])
plt.show()
```



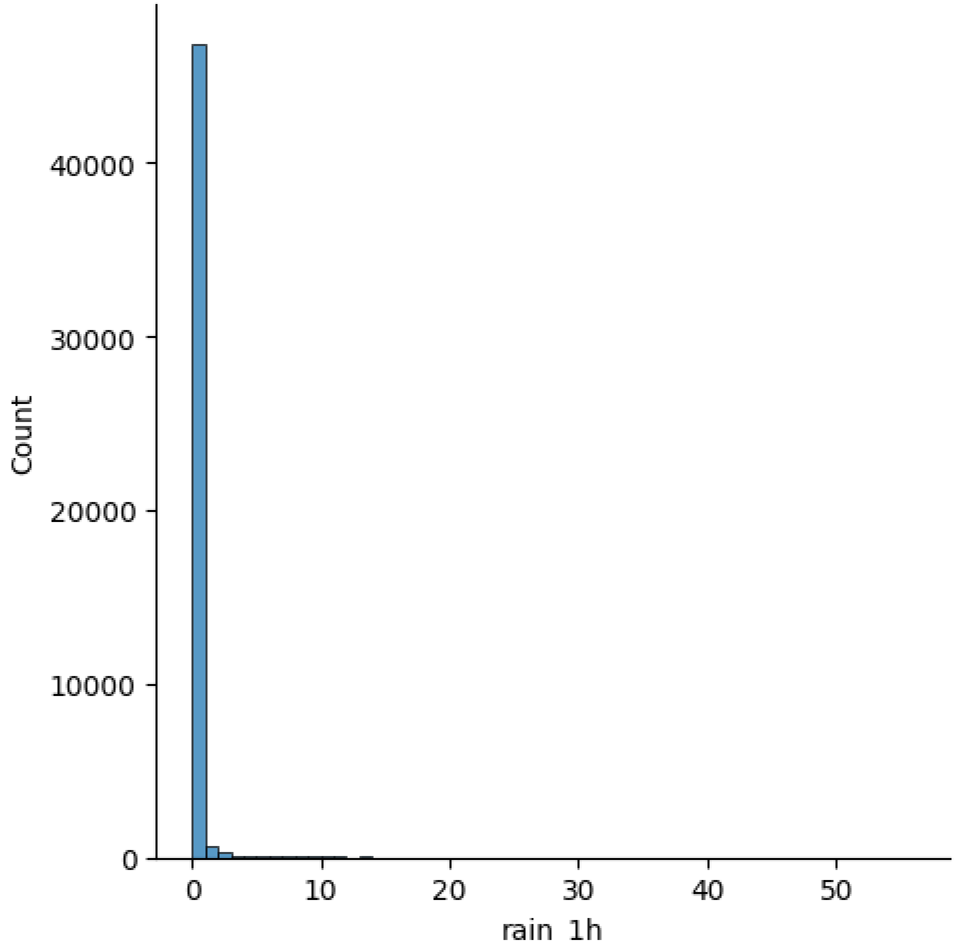


Nakon plotovanja distribucije atributa **clouds_all** vizuelno se moze utvrditi da ne postoje outlier-i, ali je ipak primenjen IQR algoritam za otklanjanje radi sigurnosti.

In [ ]:
```
sns.boxplot(x = dataset['rain_1h'])
plt.show()
```



In [ ]:
```
dataset = dataset[dataset['rain_1h']<2000]
sns.displot(dataset, x = dataset['rain_1h'],binwidth=1)
plt.show()
```



Za atribut **rain_1h** nakon plotovanja distribucije, utvrdjuje se postojanje jedno vrednosti, znatno vece od ostalih, te se ona proglasa za outliera i izbacuje iz dataseta.

In [ ]:
```
for index,i in  enumerate(['temp', 'rain_1h', 'snow_1h', 'clouds_all']):

  min_vr = dataset[i].min()
  dataset[i] = dataset[i] - min_vr
  max_vr = dataset[i].max()
  dataset[i] = dataset[i] / max_vr
dataset
```

Out[ ]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	date_time
0	None	0.673215	0.0	0.0	0.40	Clouds	scattered clouds	2012-10-02 09:00:00
1	None	0.689412	0.0	0.0	0.75	Clouds	broken clouds	2012-10-02 10:00:00
2	None	0.692711	0.0	0.0	0.90	Clouds	overcast clouds	2012-10-02 11:00:00
3	None	0.700960	0.0	0.0	0.90	Clouds	overcast clouds	2012-10-02 12:00:00
4	None	0.716107	0.0	0.0	0.75	Clouds	broken clouds	2012-10-02 13:00:00
...	...	...	...	...	...	...	...	...
48199	None	0.600780	0.0	0.0	0.75	Clouds	broken clouds	2018-09-30 19:00:00
48200	None	0.590432	0.0	0.0	0.90	Clouds	overcast clouds	2018-09-30 20:00:00
48201	None	0.589982	0.0	0.0	0.90	Thunderstorm	proximity thunderstorm	2018-09-30 21:00:00
48202	None	0.580384	0.0	0.0	0.90	Clouds	overcast clouds	2018-09-30 22:00:00
48203	None	0.580834	0.0	0.0	0.90	Clouds	overcast clouds	2018-09-30 23:00:00

48193 rows × 9 columns

Izvrsena je normalizacija numerckih atributa na opseg [0,1]

Kodiranje katerogickih vrednosti

In [ ]:

```
dataset['weather_description'] = dataset['weather_description'].str.lower()
dataset['weather_main'] = dataset['weather_main'].str.lower()
dataset['holiday'] = dataset['holiday'].str.lower()
```

In [ ]:

```
dataset['weather_main'].value_counts()
```

Out[ ]:
```
clouds          15164
clear           13381
mist             5950
rain             5671
snow             2876
drizzle          1821
haze             1360
thunderstorm     1034
fog               912
smoke              20
squall              4
Name: weather_main, dtype: int64
```

In [ ]:
```
dataset[dataset['weather_main'] == 'snow']['weather_description'].value_counts()
```

Out[ ]:
```
light snow              1946
heavy snow               616
snow                     293
light shower snow         11
light rain and snow        6
sleet                      3
shower snow                1
Name: weather_description, dtype: int64
```

In [ ]:
```
dataset[dataset['weather_main'] == 'rain']['weather_description'].value_counts()
```

Out[ ]:
```
light rain                      3372
moderate rain                   1664
heavy intensity rain             467
proximity shower rain            136
very heavy rain                   17
light intensity shower rain       13
freezing rain                      2
Name: weather_description, dtype: int64
```

In [ ]:
```
dataset[dataset['weather_main'] == 'fog']['weather_description'].value_counts()
```

Out[ ]:
```
fog    912
Name: weather_description, dtype: int64
```

Ideja je da se atributi **weather_main** i **weather_description** kodiraju jednom decimalnom vrednoscu, tako da se izmedju 0 i 1 nalaze sve vrednosti **weather_description** koje se nalaze uz jednu vrednost atributa **weather_main**-a, pa od 1 do 2 sve vrednosti **weather_description** koje se nalaze uz drugu vrednost atributa **weather_main**-a itd.

In [ ]:
```
r_dict = {}
for index,i in  enumerate(dataset['weather_main'].unique()):
  deo = dataset[dataset['weather_main']==i]['weather_description'].unique()
  br = len(deo)
  r_dict[i]={}
  for index2, i2 in enumerate(deo):
    r_dict[i][i2] = index+index2/br
r_dict
```

Out[ ]:
```
{'clouds': {'scattered clouds': 0.0,
  'broken clouds': 0.25,
  'overcast clouds': 0.5,
  'few clouds': 0.75},
 'clear': {'sky is clear': 1.0},
 'rain': {'light rain': 2.0,
  'proximity shower rain': 2.142857142857143,
  'moderate rain': 2.2857142857142856,
  'heavy intensity rain': 2.4285714285714284,
  'freezing rain': 2.571428571428571,
  'light intensity shower rain': 2.7142857142857144,
  'very heavy rain': 2.857142857142857},
 'drizzle': {'light intensity drizzle': 3.0,
  'drizzle': 3.25,
  'heavy intensity drizzle': 3.5,
  'shower drizzle': 3.75},
 'mist': {'mist': 4.0},
 'haze': {'haze': 5.0},
 'fog': {'fog': 6.0},
 'thunderstorm': {'proximity thunderstorm': 7.0,
  'thunderstorm with light rain': 7.111111111111111,
  'proximity thunderstorm with rain': 7.222222222222222,
  'thunderstorm with heavy rain': 7.333333333333333,
  'thunderstorm with rain': 7.444444444444445,
  'proximity thunderstorm with drizzle': 7.555555555555555,
  'thunderstorm': 7.666666666666667,
  'thunderstorm with light drizzle': 7.777777777777778,
  'thunderstorm with drizzle': 7.888888888888889},
 'snow': {'heavy snow': 8.0,
  'snow': 8.142857142857142,
  'shower snow': 8.285714285714286,
  'light rain and snow': 8.428571428571429,
  'light snow': 8.571428571428571,
  'light shower snow': 8.714285714285714,
  'sleet': 8.857142857142858},
 'squall': {'squalls': 9.0},
 'smoke': {'smoke': 10.0}}
```

In [ ]:
```python
for i in  dataset.index:
  dataset['weather'] = 0
for i in  dataset.index:
  dataset['weather'][i] = r_dict[dataset['weather_main'][i]][dataset['weather_descript
```

In [ ]:
```python
dataset
```

Out[ ]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	date_time
0	none	0.673215	0.0	0.0	0.40	clouds	scattered clouds	2012-10-02 09:00:00
1	none	0.689412	0.0	0.0	0.75	clouds	broken clouds	2012-10-02 10:00:00
2	none	0.692711	0.0	0.0	0.90	clouds	overcast clouds	2012-10-02 11:00:00
3	none	0.700960	0.0	0.0	0.90	clouds	overcast clouds	2012-10-02 12:00:00
4	none	0.716107	0.0	0.0	0.75	clouds	broken clouds	2012-10-02 13:00:00
...	...	...	...	...	...	...	...	...
48199	none	0.600780	0.0	0.0	0.75	clouds	broken clouds	2018-09-30 19:00:00
48200	none	0.590432	0.0	0.0	0.90	clouds	overcast clouds	2018-09-30 20:00:00
48201	none	0.589982	0.0	0.0	0.90	thunderstorm	proximity thunderstorm	2018-09-30 21:00:00
48202	none	0.580384	0.0	0.0	0.90	clouds	overcast clouds	2018-09-30 22:00:00
48203	none	0.580834	0.0	0.0	0.90	clouds	overcast clouds	2018-09-30 23:00:00

48193 rows × 10 columns

Transformacija datuma

In [ ]:
```
dataset['date_time']= pd.to_datetime(dataset['date_time'])
```

In [ ]:
```
dataset['hour'] = dataset['date_time'].dt.hour
dataset['day'] = dataset['date_time'].dt.dayofweek
dataset['year'] = dataset['date_time'].dt.year
dataset
```

Out[ ]:

	holiday	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	date_time
0	none	0.673215	0.0	0.0	0.40	clouds	scattered clouds	2012-10-02 09:00:00
1	none	0.689412	0.0	0.0	0.75	clouds	broken clouds	2012-10-02 10:00:00
2	none	0.692711	0.0	0.0	0.90	clouds	overcast clouds	2012-10-02 11:00:00
3	none	0.700960	0.0	0.0	0.90	clouds	overcast clouds	2012-10-02 12:00:00
4	none	0.716107	0.0	0.0	0.75	clouds	broken clouds	2012-10-02 13:00:00
...	...	...	...	...	...	...	...	...
48199	none	0.600780	0.0	0.0	0.75	clouds	broken clouds	2018-09-30 19:00:00
48200	none	0.590432	0.0	0.0	0.90	clouds	overcast clouds	2018-09-30 20:00:00
48201	none	0.589982	0.0	0.0	0.90	thunderstorm	proximity thunderstorm	2018-09-30 21:00:00
48202	none	0.580384	0.0	0.0	0.90	clouds	overcast clouds	2018-09-30 22:00:00
48203	none	0.580834	0.0	0.0	0.90	clouds	overcast clouds	2018-09-30 23:00:00

48193 rows × 13 columns

In [ ]:

```
one_hot = LabelBinarizer()
one_hot.fit_transform(dataset['holiday'])
one_hot_encoded_data = pd.get_dummies(dataset, columns = ['holiday'])
dataset = one_hot_encoded_data
dataset['holiday'] = dataset['holiday_none'].apply(lambda x: 1 if x == 1 else 0)
dataset['weekend'] = dataset['day'].apply(lambda x: 1 if x > 4 else 0)
dataset
```

Out[ ]:

	temp	rain_1h	snow_1h	clouds_all	weather_main	weather_description	date_time	traffic_v
0	0.673215	0.0	0.0	0.40	clouds	scattered clouds	2012-10-02 09:00:00	
1	0.689412	0.0	0.0	0.75	clouds	broken clouds	2012-10-02 10:00:00	
2	0.692711	0.0	0.0	0.90	clouds	overcast clouds	2012-10-02 11:00:00	
3	0.700960	0.0	0.0	0.90	clouds	overcast clouds	2012-10-02 12:00:00	
4	0.716107	0.0	0.0	0.75	clouds	broken clouds	2012-10-02 13:00:00	
...	...	...	...	...	...	...	...	
48199	0.600780	0.0	0.0	0.75	clouds	broken clouds	2018-09-30 19:00:00	
48200	0.590432	0.0	0.0	0.90	clouds	overcast clouds	2018-09-30 20:00:00	
48201	0.589982	0.0	0.0	0.90	thunderstorm	proximity thunderstorm	2018-09-30 21:00:00	
48202	0.580384	0.0	0.0	0.90	clouds	overcast clouds	2018-09-30 22:00:00	
48203	0.580834	0.0	0.0	0.90	clouds	overcast clouds	2018-09-30 23:00:00	

48193 rows × 26 columns

In [ ]:

```
model_data = dataset.copy()
model_data.drop(['weather_main', 'weather_description', 'date_time'], axis = 1, inplac
model_data
```

Out[ ]:

	temp	rain_1h	snow_1h	clouds_all	traffic_volume	weather	hour	day	year	holiday_chri
0	0.673215	0.0	0.0	0.40	5545	0.00	9	1	2012	
1	0.689412	0.0	0.0	0.75	4516	0.25	10	1	2012	
2	0.692711	0.0	0.0	0.90	4767	0.50	11	1	2012	
3	0.700960	0.0	0.0	0.90	5026	0.50	12	1	2012	
4	0.716107	0.0	0.0	0.75	4918	0.25	13	1	2012	
...	...	...	...	...	...	...	...	...	...	
48199	0.600780	0.0	0.0	0.75	3543	0.25	19	6	2018	
48200	0.590432	0.0	0.0	0.90	2781	0.50	20	6	2018	
48201	0.589982	0.0	0.0	0.90	2159	7.00	21	6	2018	
48202	0.580384	0.0	0.0	0.90	1450	0.50	22	6	2018	
48203	0.580834	0.0	0.0	0.90	954	0.50	23	6	2018	

48193 rows × 23 columns

In [ ]:

```
def eval_metrics(actual, pred):
  rmse = np.sqrt(mean_squared_error(actual, pred))
  mae = mean_absolute_error(actual, pred)
  mse = mean_squared_error(actual, pred)
  score = r2_score(actual, pred)
  return("r2_score: ", score,  "mae: ", mae,  "mse: ", mse,"rmse: ", rmse)
```

ALGORITMI

In [ ]:

```
Y_col = 'traffic_volume'
X_cols = model_data.loc[:, model_data.columns != Y_col].columns
X_train, X_test, y_train, y_test = train_test_split(model_data[X_cols], model_data[Y_c
```

In [ ]:

```
X_train2 =  X_train.copy()
X_test2 = X_test.copy()
```

In [ ]:

```
X_train.drop(['holiday_christmas day', 'holiday_columbus day', 'holiday_martin luther
X_test.drop(['holiday_christmas day', 'holiday_columbus day', 'holiday_martin luther k
X_train
```

Out[ ]:

	temp	rain_1h	snow_1h	clouds_all	weather	hour	day	year	holiday
43102	0.477804	0.0	0.0	0.68	0.25	14	1	2018	1
180	0.550540	0.0	0.0	0.99	2.00	8	2	2012	1
32911	0.498950	0.0	0.0	0.01	4.00	1	4	2017	1
9793	0.288542	0.0	0.0	0.64	0.25	2	1	2013	1
19199	0.486953	0.0	0.0	0.90	4.00	15	2	2015	1
...	...	...	...	...	...	...	...	...	...
11284	0.080984	0.0	0.0	0.40	0.00	7	1	2014	1
44743	0.728104	0.0	0.0	0.01	1.00	0	3	2018	1
38169	0.662717	0.0	0.0	0.01	1.00	23	3	2017	1
860	0.387672	0.0	0.0	0.20	0.75	7	5	2012	1
15805	0.839082	0.0	0.0	0.01	1.00	17	2	2014	1

38554 rows × 9 columns

In [ ]:

```
X_train2
```

Out[ ]:

	temp	rain_1h	snow_1h	clouds_all	weather	hour	day	year	holiday_christmas day	holiday_
43102	0.477804	0.0	0.0	0.68	0.25	14	1	2018	0	
180	0.550540	0.0	0.0	0.99	2.00	8	2	2012	0	
32911	0.498950	0.0	0.0	0.01	4.00	1	4	2017	0	
9793	0.288542	0.0	0.0	0.64	0.25	2	1	2013	0	
19199	0.486953	0.0	0.0	0.90	4.00	15	2	2015	0	
...	...	...	...	...	...	...	...	...	...	
11284	0.080984	0.0	0.0	0.40	0.00	7	1	2014	0	
44743	0.728104	0.0	0.0	0.01	1.00	0	3	2018	0	
38169	0.662717	0.0	0.0	0.01	1.00	23	3	2017	0	
860	0.387672	0.0	0.0	0.20	0.75	7	5	2012	0	
15805	0.839082	0.0	0.0	0.01	1.00	17	2	2014	0	

38554 rows × 22 columns

In [ ]:

```
seed = 43
linear = LinearRegression(n_jobs=-1)
lasso = Lasso(random_state = seed)
ridge= Ridge(random_state=seed)
dt = DecisionTreeRegressor(random_state = seed)
```

```
rf = RandomForestRegressor(random_state = seed, n_jobs = -1)
xgb = XGBRegressor (random_state = seed, n_jobs = -1)
models = [('linear',linear),('lasso',lasso), ('ridge',ridge),('dectree',dt),('randfore
```

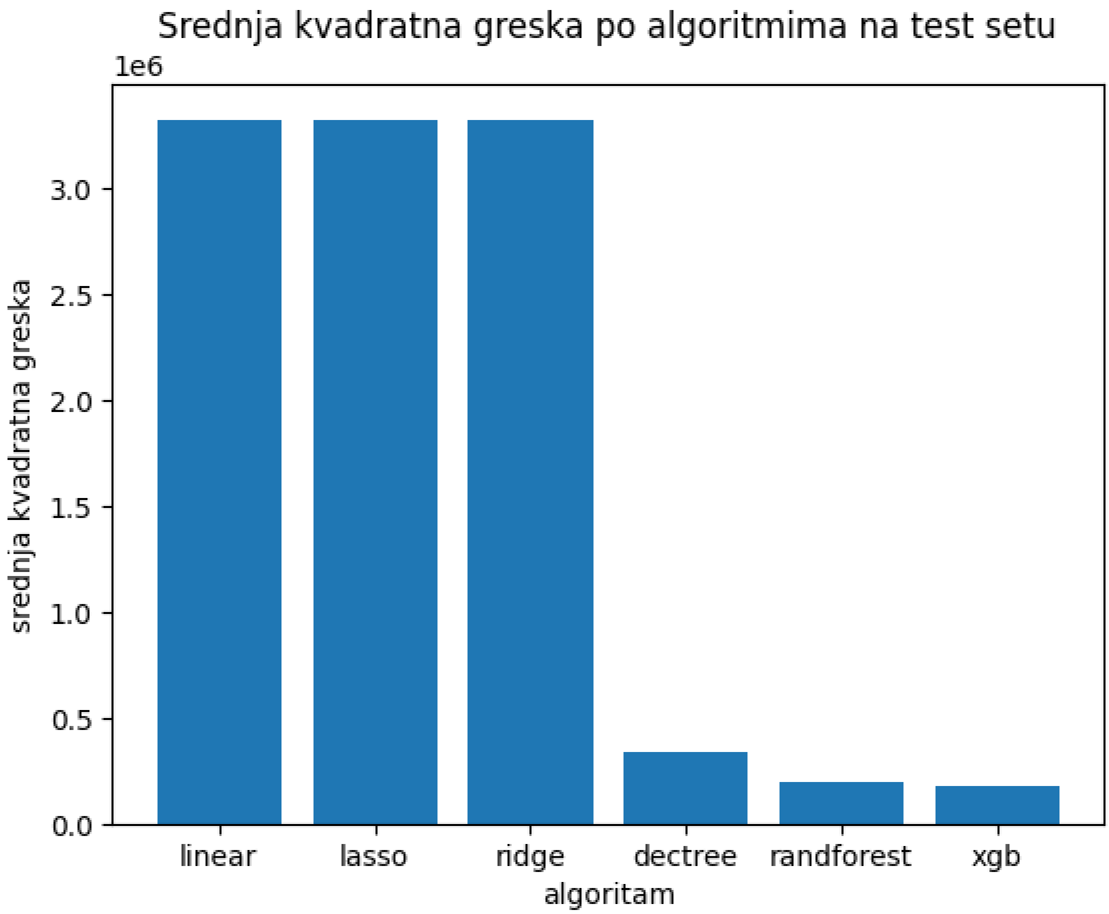
Klasicno treniranje

In [ ]:
```
def train_mse(name,model):
  train_model = model.fit(X_train,y_train)
  predicted = train_model.predict(X_test)
  print("------------------------------")
  print("model {}".format(name))
  print(eval_metrics(y_test,predicted))
  names.append(name)
  return mean_squared_error(y_test, predicted)
```

In [ ]:
```
names = []
mses = []
for name,model in models:
  mses.append(train_mse(name,model))
```

```
------------------------------
model linear
('r2_score: ', 0.1565714595580494, 'mae: ', 1597.898254924882, 'mse: ', 3317384.28300
70658, 'rmse: ', 1821.368793794125)
------------------------------
model lasso
('r2_score: ', 0.15562917552694755, 'mae: ', 1599.698242740463, 'mse: ', 3321090.4870
125265, 'rmse: ', 1822.3859325105993)
------------------------------
model ridge
('r2_score: ', 0.15659172543867272, 'mae: ', 1597.875565217174, 'mse: ', 3317304.5729
775405, 'rmse: ', 1821.346911759959)
------------------------------
model dectree
('r2_score: ', 0.9142609345531718, 'mae: ', 294.4229173150742, 'mse: ', 337230.025443
51073, 'rmse: ', 580.7150983429918)
------------------------------
model randforest
('r2_score: ', 0.951298166537967, 'mae: ', 244.92417984477743, 'mse: ', 191554.695073
4181, 'rmse: ', 437.6696186319289)
------------------------------
model xgb
('r2_score: ', 0.9541373635756439, 'mae: ', 249.24717847669456, 'mse: ', 180387.52775
866896, 'rmse: ', 424.72052900544963)
```

In [ ]:
```
plt.bar(names,mses)
plt.title("Srednja kvadratna greska po algoritmima na test setu")
plt.xlabel("algoritam")
plt.ylabel("srednja kvadratna greska")
plt.show()
```



Cross-validation mehanizam

In [ ]:
```
kfold = StratifiedKFold(n_splits = 5,random_state=1,shuffle = True)
def cross_validate(name,model):
  neg_score = cross_val_score(model,X_train,y_train,cv=kfold,n_jobs=-1,scoring="neg_me
  print("--------------------------------")
  print("model %s %f" %(name,-neg_score.mean()))
  names.append(name)
  return -neg_score.mean()
```

In [ ]:
```
cross_mses = []
names = []
for name,model in models:
  cross_mses.append(cross_validate(name,model))
plt.bar(names,cross_mses)
plt.title("Srednja kvadratna greska po algoritmima primenom unakrsne validacije")
plt.xlabel("algoritam")
plt.ylabel("srednja kvadratna greska")
plt.show()
```

```
--------------------------------
model linear 3305585.351752
--------------------------------
model lasso 3308965.207768
--------------------------------
model ridge 3305532.367398
--------------------------------
model dectree 365157.206148
--------------------------------
model randforest 205465.272315
--------------------------------
model xgb 192719.340349
```

Odredjivanje hiperparametara

In [ ]:
```python
def grid_search_cv(model,params):
  grid_search_model = GridSearchCV(estimator = model,param_grid = params, cv = 5,scori
  grid_search_model.fit(X_train, y_train)
  best_params = grid_search_model.best_params_
  best_score = -1*grid_search_model.best_score_
  best_estimator = grid_search_model.best_estimator_
  return best_estimator,best_params,best_score
```

In [ ]:
```python
predictions_mse_score = []
predictions_mse_short_score = []
results_short = []
```

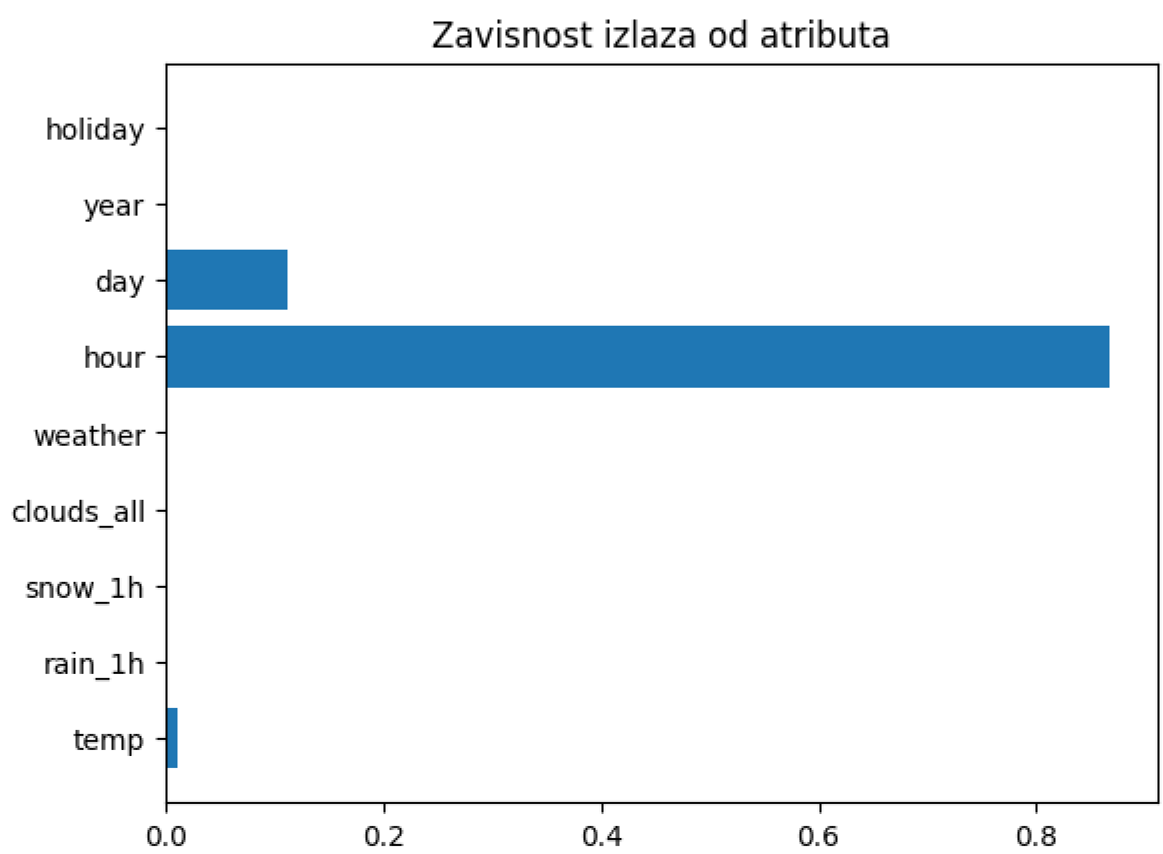
Decision Tree algoritam

In [ ]:
```
max_depth = np.arange(1,25,5)
min_samples_split = np.arange(2,10,2)
min_samples_leaf = [1,2,4]
params_dt={
    "splitter" : ["best","random"],
    "max_depth": max_depth,
    "min_samples_split":min_samples_split,
    "min_samples_leaf":min_samples_leaf
}
model,best_params_dt,best_score_dt = grid_search_cv(dt,params_dt)
features_importances = model.feature_importances_
```

In [ ]:
```
model.fit(X_train,y_train)
predictions = model.predict(X_test)
met = eval_metrics(predictions,y_test)
print(met)
predictions_mse_score.append(met[5])
```

```
('r2_score: ', 0.9342502883791372, 'mae: ', 282.57992658295643, 'mse: ', 245469.59443
146733, 'rmse: ', 495.44888175417987)
```

In [ ]:
```
y = np.arange(len(X_train.columns))
plt.barh(y=X_train.columns,width = features_importances)
plt.title("Zavisnost izlaza od atributa")
plt.show()
```



Na osnovu prikazanog grafikona moze se utvrditi da su najznacajniji atributi **hour**,**day**,**temp**,**year**, pa se za kreira novi model sa najboljim parametrima i trenira se nad nabrojanim atributima

In [ ]:
```
X_train_short = X_train[["hour","day","temp","year"]]
X_test_short = X_test[["hour","day","temp","year"]]
model = DecisionTreeRegressor(**best_params_dt)
cv_results= cross_val_score(model,X_train_short,y_train,cv = 5,scoring = "neg_mean_squ
print("Decision tree nad najbitnijim atributima: %f (%f)"%(-1*cv_results.mean(),cv_res
model.fit(X_train_short,y_train)
results_short.append(-1*cv_results.mean())
predictions = model.predict(X_test_short)
met = eval_metrics(predictions,y_test)
print(met)
predictions_mse_short_score.append(met[5])
```

```
Decision tree nad najbitnijim atributima: 258736.977473 (14412.354851)
('r2_score: ', 0.9359234136406563, 'mae: ', 281.827612944563, 'mse: ', 238454.5914874
947, 'rmse: ', 488.3181252907726)
```

In [ ]:
```
data_predictions = {
    "klasicno treniranje":[mses[3],cross_mses[3]],
    "najbolji hiperparametri":[predictions_mse_score[0],best_score_dt],
    "redukcija dimenzionalnosti":[predictions_mse_short_score[0],results_short[0]]
  }
df_decisiontree = pd.DataFrame(data_predictions)
df_decisiontree.index=["test set","cross validacija"]
df_decisiontree
```

Out[ ]:

	klasicno treniranje	najbolji hiperparametri	redukcija dimenzionalnosti
test set	337230.025444	245469.594431	238454.591487
cross validacija	365157.206148	251926.197428	258736.977473

Prilikom primene Decision Tree algoritma najmanja srednja kvadratna greska se postiza sa najbolje odredjenim hiperparametrima i redukcijom dimenzionalnosti podataka na svodjenjem na 4 karakteristike.

Random Forest algoritam

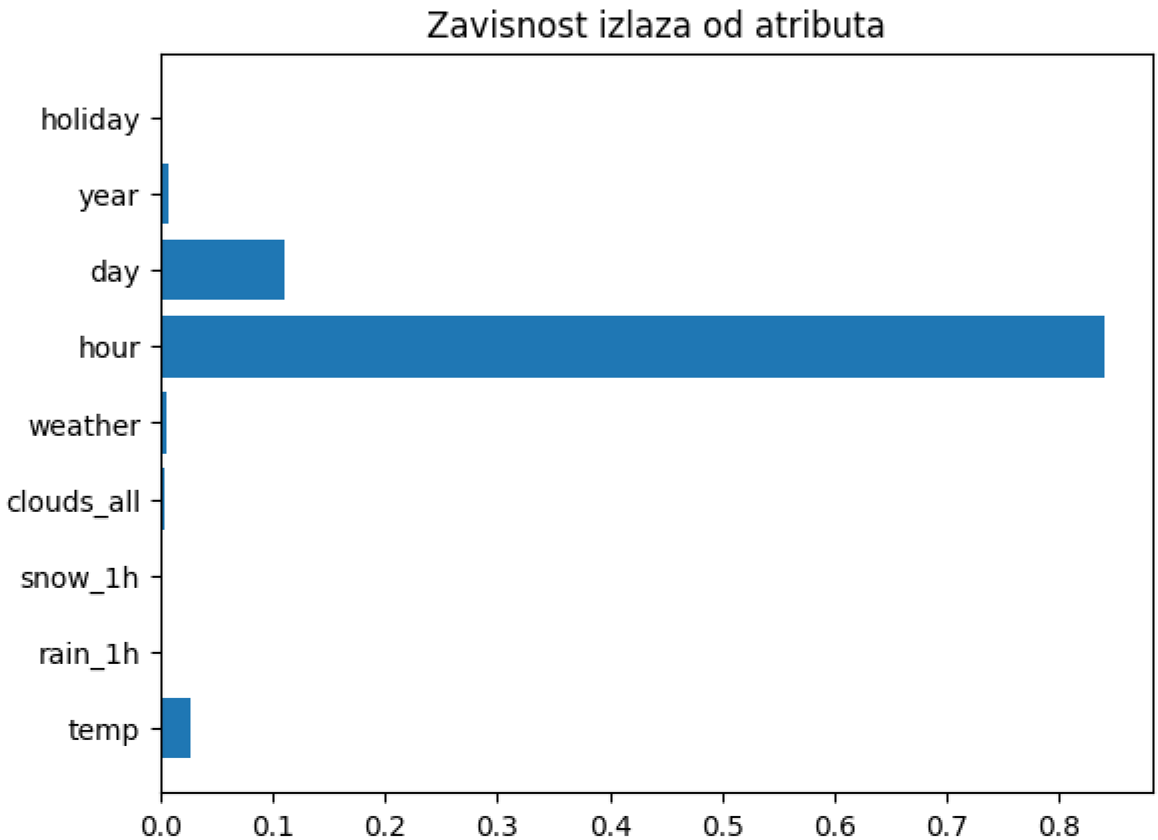
In [ ]:
```
params_rf= {
    'n_estimators': np.arange(10,25,10),
    'max_depth': np.arange(1,25,10),
    'min_samples_split': np.arange(2,10,2),
    'min_samples_leaf': [1, 2, 4]
}
best_model_rf,best_params_rf,best_score_rf = grid_search_cv(rf,params_rf)
```

In [ ]:
```
best_model_rf.fit(X_train,y_train)
predictions = best_model_rf.predict(X_test)
met = eval_metrics(predictions,y_test)
print(met)
predictions_mse_score.append(met[5])
```

```
('r2_score: ', 0.9478141189575251, 'mae: ', 249.0622923808842, 'mse: ', 194355.883236
5884, 'rmse: ', 440.8581214365778)
```

In [ ]:
```
features_importances_rf = best_model_rf.feature_importances_
y = np.arange(len(X_train.columns))
plt.barh(y=X_train.columns,width = features_importances_rf)
```

```
plt.title("Zavisnost izlaza od atributa")
plt.show()
```



In [ ]:
```
X_train_short = X_train[["hour","day","temp"]]
X_test_short = X_test[["hour","day","temp"]]
model = DecisionTreeRegressor(**best_params_dt)
cv_results= cross_val_score(model,X_train_short,y_train,cv = 5,scoring = "neg_mean_squ
print("Random forest nad najbitnijim atributima: %f (%f)"%(-1*cv_results.mean(),cv_res
model.fit(X_train_short,y_train)
results_short.append(-1*cv_results.mean())
met = eval_metrics(predictions,y_test)
print(met)
predictions_mse_short_score.append(met[5])
```

```
Random forest nad najbitnijim atributima: 264799.571337 (17666.766382)
('r2_score: ', 0.9478141189575251, 'mae: ', 249.0622923808842, 'mse: ', 194355.883236
5884, 'rmse: ', 440.8581214365778)
```

In [ ]:
```
data_predictions = {
    "klasicno treniranje":[mses[4],cross_mses[4]],
    "najbolji hiperparametri":[predictions_mse_score[1],best_score_rf],
    "redukcija dimenzionalnosti":[predictions_mse_short_score[1],results_short[1]]
  }
df_randomforest = pd.DataFrame(data_predictions)
df_randomforest.index=["test set","cross validacija"]
df_randomforest
```

Out[ ]:

	klasicno treniranje	najbolji hiperparametri	redukcija dimenzionalnosti
test set	191554.695073	194355.883237	194355.883237
cross validacija	205465.272315	213952.332603	264799.571337

Primenom random forest algoritma postize se ista srednja kvadratna greska na test skupu sa i bez redukcije dimenzionalnosti podataka kod modela sa najboljim hipeparametrima, a kako je primenom unakrsne validacija manja greska je kada se ne vrsi redukcija dimenzionalnosti dataseta, najbolje resenje je primena modela sa najboljim hiperparametrima bez redukcije dimenzionalnosti podataka

Lasso regresija

In [ ]:

```
alpha = np.arange(0,1,0.1)
params_lasso= {
    'alpha':alpha

}
best_model_lasso,best_params_lasso,best_score_lasso = grid_search_cv(lasso,params_lass
```

Kod ovog algoritma moze se primeniti SelectFromModel za izdvajanje nenula koeficijenata, zbog osobine Lasso regresije.

In [ ]:

```
best_model_lasso.fit(X_train,y_train)
predictions = best_model_lasso.predict(X_test)
met = eval_metrics(predictions,y_test)
print(met)
predictions_mse_score.append(met[5])
best_model_lasso.coef_
```

```
('r2_score: ', -4.101123025106862, 'mae: ', 1597.9055989426422, 'mse: ', 3317285.2217
728887, 'rmse: ', 1821.3415994186507)
```

Out[ ]:

```
array([ 9.95867810e+02, -2.92261491e+03,  0.00000000e+00,  3.86790355e+02,
       -5.25220940e+01,  9.46900634e+01, -1.47735949e+02,  2.63343401e-01,
        1.41223161e+03])
```

Na osnovu prikazanih koeficijenata odlucuje se da je bolje izabrati 5 najznacajnijih nego nenula

In [ ]:

```
features_resizer= SelectFromModel(best_model_lasso,prefit=True,max_features = 5)
X_train_short = features_resizer.transform(X_train)
```

In [ ]:

```
X_test_short = features_resizer.transform(X_test)
```

In [ ]:

```
model = Lasso(**best_params_lasso)
cv_results= cross_val_score(model,X_train_short,y_train,cv = 5,scoring = "neg_mean_squ
print("Lasso regresija nad najbitnijim atributima: %f (%f)"%(-1*cv_results.mean(),cv_r
model.fit(X_train_short,y_train)
results_short.append(-1*cv_results.mean())
predictions = model.predict(X_test_short)
met = eval_metrics(predictions,y_test)
print(met)
predictions_mse_short_score.append(met[5])
```

```
Lasso regresija nad najbitnijim atributima: 3751983.369670 (58067.260081)
('r2_score: ', -17.90585199090799, 'mae: ', 1689.6510788505207, 'mse: ', 3755574.8331
38277, 'rmse: ', 1937.930554260982)
```

In [ ]:
```
predictions_mse_score
```

Out[ ]:
```
[245469.59443146733, 194355.8832365884, 3317285.2217728887]
```

In [ ]:
```
data_predictions = {
    "klasicno treniranje":[mses[1],cross_mses[1]],
    "najbolji hiperparametri":[predictions_mse_score[2],best_score_lasso],
    "redukcija dimenzionalnosti":[predictions_mse_short_score[2],results_short[2]]
  }
df_lasso = pd.DataFrame(data_predictions)
df_lasso.index=["test set","cross validacija"]
df_lasso
```

Out[ ]:

	klasicno treniranje	najbolji hiperparametri	redukcija dimenzionalnosti
test set	3.321090e+06	3.317285e+06	3.755575e+06
cross validacija	3.308965e+06	3.305359e+06	3.751983e+06

Kod Lasso regresije najbolji rezultati se postizu primenom modela sa najboljim hiperparametrima na trening setu cija je redukcija dimenzionalnosti izvrsena.

Ridge regresija

In [ ]:
```
params_ridge= {
    'alpha':np.arange(1,3,0.1)
}
best_model_ridge,best_params_ridge,best_score_ridge = grid_search_cv(ridge,params_ridg
```

In [ ]:
```
best_model_ridge.fit(X_train,y_train)
predictions = best_model_ridge.predict(X_test)
met = eval_metrics(predictions,y_test)
print(met)
predictions_mse_score.append(met[5])
```

```
('r2_score: ', -4.097171947908378, 'mae: ', 1597.8717091229028, 'mse: ', 3317296.4246
41154, 'rmse: ', 1821.3446748600754)
```

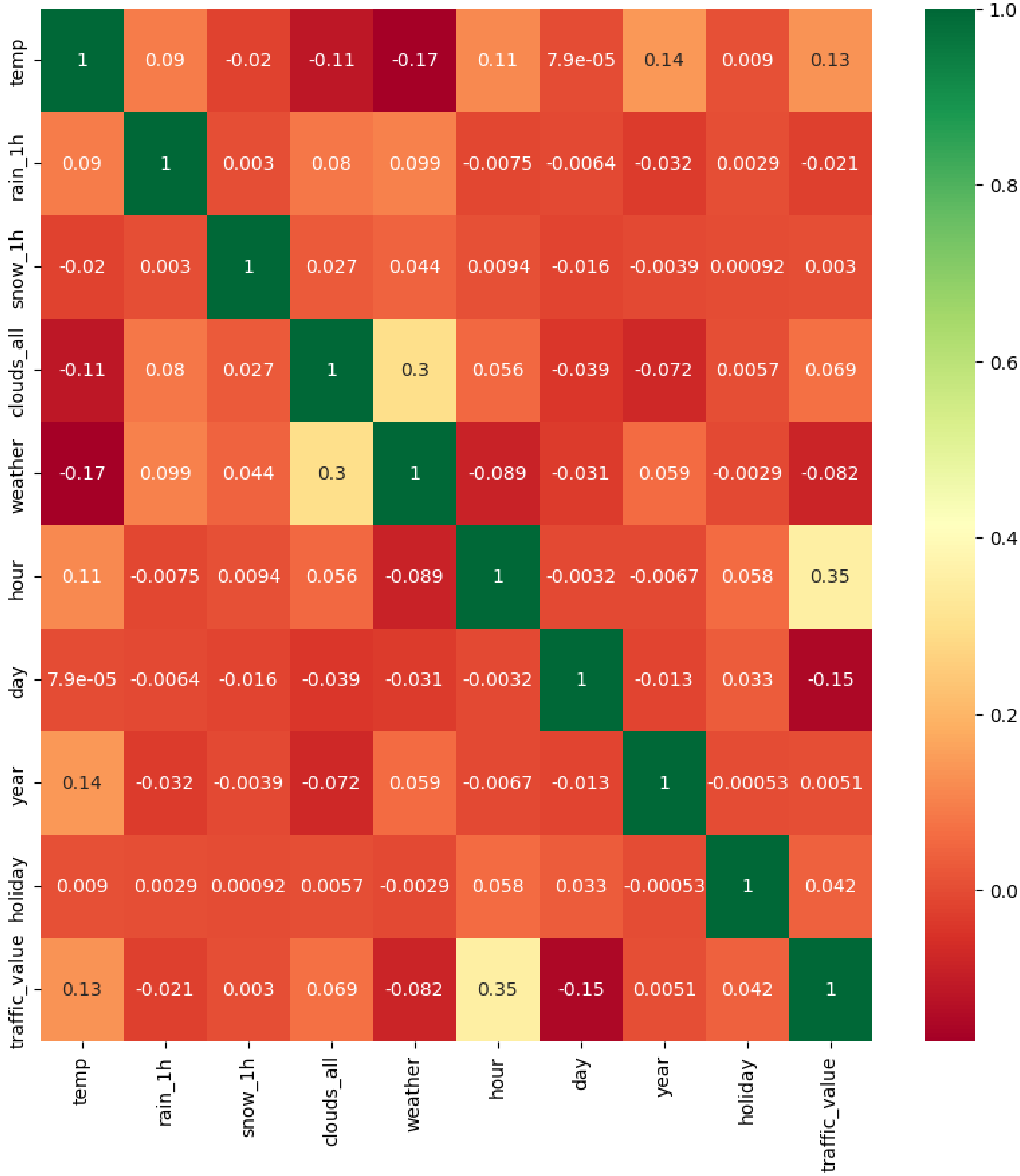
In [ ]:
```
dataset_tmp = X_train.copy()
dataset_tmp["traffic_value"]=y_train.values
dataset_tmp.head()
```

Out[ ]:

	temp	rain_1h	snow_1h	clouds_all	weather	hour	day	year	holiday	traffic_value
43102	0.477804	0.0	0.0	0.68	0.25	14	1	2018	1	5315
180	0.550540	0.0	0.0	0.99	2.00	8	2	2012	1	6283
32911	0.498950	0.0	0.0	0.01	4.00	1	4	2017	1	444
9793	0.288542	0.0	0.0	0.64	0.25	2	1	2013	1	206
19199	0.486953	0.0	0.0	0.90	4.00	15	2	2015	1	5691

In [ ]:

```
corrmat = dataset_tmp.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(10,10))
g = sns.heatmap(dataset_tmp[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```



In [ ]:
```
target_corr = dataset_tmp[top_corr_features].corr()['traffic_value'].abs().sort_values
print(target_corr)
```

```
traffic_value    1.000000
hour             0.352775
day              0.150571
temp             0.133214
weather          0.081713
clouds_all       0.069450
holiday          0.042164
rain_1h          0.021313
year             0.005147
snow_1h          0.002971
Name: traffic_value, dtype: float64
```

Na osnovu odredjenih korelacija atrubuti **hour**,**day**,**temp** najvise uticu na izlaz, pa se treniranje modela ponavlja nad tim atributima

In [ ]:
```
X_train_short = X_train[["hour","day","temp"]]
X_test_short = X_test[["hour","day","temp"]]
```

In [ ]:
```
model = Ridge(**best_params_ridge)
cv_results= cross_val_score(model,X_train_short,y_train,cv = 5,scoring = "neg_mean_squ
print("Ridge regresija nad najbitnijim atributima: %f (%f)"%(-1*cv_results.mean(),cv_r
model.fit(X_train_short,y_train)
results_short.append(-1*cv_results.mean())
predictions = model.predict(X_test_short)
met = eval_metrics(predictions,y_test)
print(met)
predictions_mse_short_score.append(met[5])
```

```
Ridge regresija nad najbitnijim atributima: 3336651.800602 (47606.551299)
('r2_score: ', -4.3758887478779, 'mae: ', 1608.6018199104276, 'mse: ', 3341500.650004
969, 'rmse: ', 1827.9772017191485)
```

In [ ]:
```
data_predictions = {
    "klasicno treniranje":[mses[2],cross_mses[2]],
    "najbolji hiperparametri":[predictions_mse_score[3],best_score_ridge],
    "redukcija dimenzionalnosti":[predictions_mse_short_score[3],results_short[3]]
  }
df_ridge = pd.DataFrame(data_predictions)
df_ridge.index=["test set","cross validacija"]
df_ridge
```

Out[ ]:

	klasicno treniranje	najbolji hiperparametri	redukcija dimenzionalnosti
test set	3.317305e+06	3.317296e+06	3.341501e+06
cross validacija	3.305532e+06	3.305567e+06	3.336652e+06

Kod primene Ridge regresije najbolji rezultati se postizu prilikom primene modela sa najboljim hiperparametrima na test setu neredukovanih dimenzija.

XGBoost algoritam

In [ ]:
```
params_xgb= {
    'learning_rate':[0.01,0.1,0.3],
    'max_depth':[3,5,7],
    'subsample': [0.8, 0.9, 1.0]

}
best_model_xgb,best_params_xgb,best_score_xgb = grid_search_cv(xgb,params_xgb)
```

In [ ]:
```
best_model_xgb.fit(X_train,y_train)
predictions = best_model_xgb.predict(X_test)
met = eval_metrics(predictions,y_test)
print(met)
predictions_mse_score.append(met[5])
```

```
('r2_score: ', 0.9537305421895477, 'mae: ', 245.29347514538537, 'mse: ', 174635.55856
616568, 'rmse: ', 417.8941954205223)
```

Za ovoj algoritam iskoristicemo **PCA** metode za redukciju dimenzionalnosti. Na osnovu odabira atributa za prethodne algoritme pretpostavlja se da je 4 glavne komponente dovoljno.

In [ ]:
```
pca = PCA(n_components = 4)
pca.fit(X_train)
X_train_short = pca.transform(X_train)
X_test_short = pca.transform(X_test)
```

In [ ]:
```
model = XGBRegressor(**best_params_xgb)
cv_results= cross_val_score(model,X_train_short,y_train,cv = 5,scoring = "neg_mean_squ
print("XGBoost nad najbitnijim atributima: %f (%f)"%(-1*cv_results.mean(),cv_results.s
model.fit(X_train_short,y_train)
results_short.append(-1*cv_results.mean())
predictions = model.predict(X_test_short)
met = eval_metrics(predictions,y_test)
print(met)
predictions_mse_short_score.append(met[5])
```

```
XGBoost nad najbitnijim atributima: 276334.810120 (16798.689071)
('r2_score: ', 0.9310904510279692, 'mae: ', 294.46144571773294, 'mse: ', 256625.17576
811134, 'rmse: ', 506.58185495348266)
```

In [ ]:
```
data_predictions = {
    "klasicno treniranje":[mses[4],cross_mses[4]],
    "najbolji hiperparametri":[predictions_mse_score[4],best_score_xgb],
    "redukcija dimenzionalnosti":[predictions_mse_short_score[4],results_short[4]]
  }
df_xgb = pd.DataFrame(data_predictions)
df_xgb.index=["test set","cross validacija"]
df_xgb
```

Out[ ]:

	klasicno treniranje	najbolji hiperparametri	redukcija dimenzionalnosti
test set	191554.695073	174635.558566	256625.175768
cross validacija	205465.272315	185324.214910	276334.810120

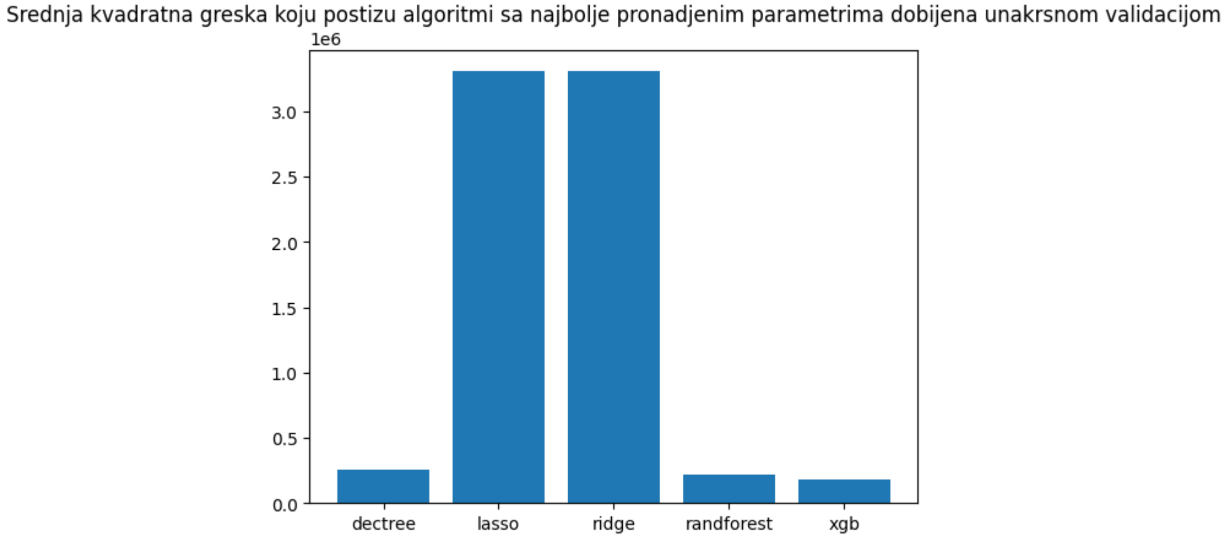
Najbolje rezultate dahe XGBoost kad se primenjuje sa najbolje odredjenim hiperparamtrima na setu kad nije izvrsena redukcija dimenzionalnosti.

Rezultati

Modeli sa najbolje odredjenim hiperparametrima

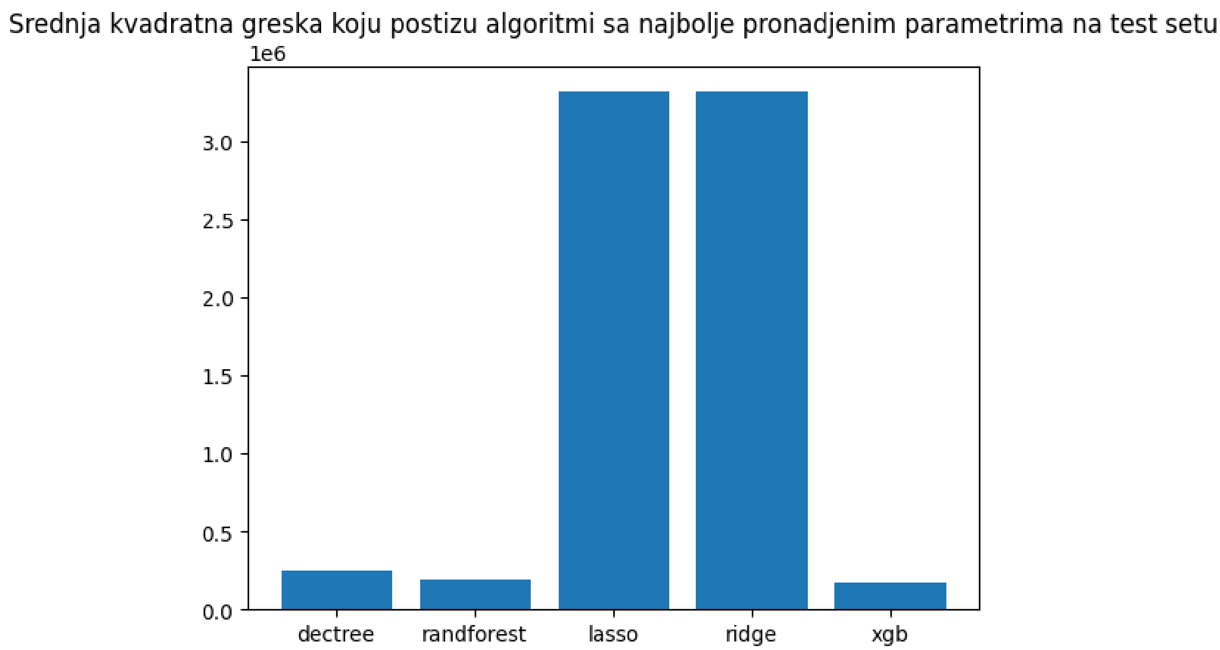
Dat je grafikon MSE kod algortama sa najbolje pronadjenim hiperparametrima na trening setu

In [ ]:
```
y = [best_score_dt,best_score_lasso,best_score_ridge,best_score_rf,best_score_xgb]
plt.bar([ 'dectree','lasso', 'ridge','randforest','xgb'],y)
plt.title("Srednja kvadratna greska koju postizu algoritmi sa najbolje pronadjenim par
plt.show()
```



Dat je grafikon MSE dobijenih primenom algoritama sa najbolje pronadjenim hiperparametrima na test setu

In [ ]:
```
plt.bar([ 'dectree','randforest','lasso', 'ridge','xgb'],predictions_mse_score)
plt.title("Srednja kvadratna greska koju postizu algoritmi sa najbolje pronadjenim par
plt.show()
```

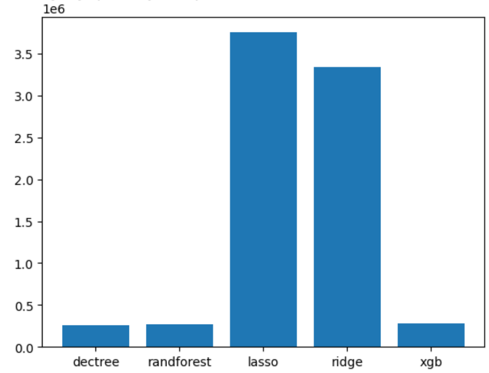


Modeli trenirani na podacima redukovanih dimenzija

Dat je grafikon MSE kod algortama sa najbolje pronadjenim hiperparametrima na najznacajnijim atributima trening seta

In [ ]:
```
plt.bar([ 'dectree','randforest','lasso', 'ridge','xgb'],results_short)
plt.title("Srednja kvadratna greska koju postizu algoritmi sa najbolje pronadjenim par
plt.show()
```

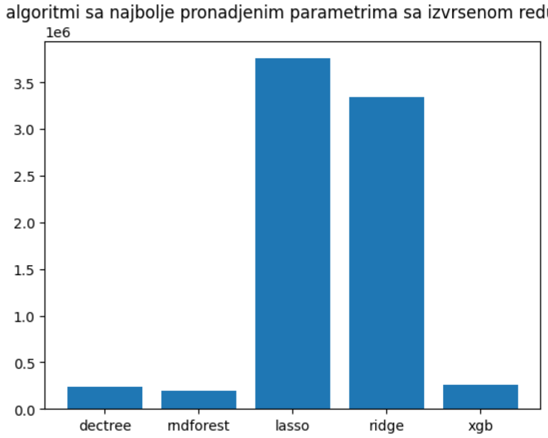
Srednja kvadratna greska koju postizu algoritmi sa najbolje pronadjenim parametrima nakon odabira nekoliko najznacajnih atributa dobijena unakrsnom validacijom



Dat je grafikon MSE dobijenih primenom algoritama sa najbolje pronadjenim hiperparametrima na datasetu redukovane dimenzionalnosti na test setu

In [ ]:
```
plt.bar([ 'dectree','rndforest','lasso', 'ridge','xgb'],predictions_mse_short_score)
plt.title("Srednja kvadratna greska koju postizu algoritmi sa najbolje pronadjenim par
plt.show()
```

Srednja kvadratna greska koju postizu algoritmi sa najbolje pronadjenim parametrima sa izvrsenom redukcijom dimenzionalnosti seta na test setu



Kao zakljucak se moze izvesti da prilikom odredjivanja hiperparametara modela, najmanja greska se postize koriscenjem **XGBoost-a** nad datasetom, a nakon sto se izvrsi redukcija dimenzionalnosti dataseta **RandomForest**

Ensamble learning

Vrsi se kombinacija ovih algoritama **Decision Tree**,**Random Forest** i **XGBoost**, s obzirom da daju najbolje rezultate. Prvo je izvrsena kombinacija svih model sa hiperparametrima koji daju najbolje rezultate.

In [ ]:
```
dectree = DecisionTreeRegressor(**best_params_dt)
randforest = RandomForestRegressor(**best_params_rf)
xgb = XGBRegressor(**best_params_xgb)
```

In [ ]:
```
dectree.fit(X_train, y_train)
randforest.fit(X_train,y_train)
xgb.fit(X_train, y_train)
pred_dectree = dectree.predict(X_test)
pred_randforest = randforest.predict(X_test)
pred_xgb = xgb.predict(X_test)
```

In [ ]:
```
met_xgb = eval_metrics(pred_xgb,y_test)
met_rand = eval_metrics(pred_randforest,y_test)
met_dt = eval_metrics(pred_dectree,y_test)
compare_df = pd.DataFrame({
    "decision tree":[met_dt[1],met_dt[3],met_dt[5],met_dt[7]],
    "random forest":[met_rand[1],met_rand[3],met_rand[5],met_rand[7]],
    "xgboost":[met_xgb[1],met_xgb[3],met_xgb[5],met_xgb[7]]
})
compare_df.index = ["r2_score","mae","mse","rmse"]
compare_df
```

Out[ ]:

	decision tree	random forest	xgboost
r2_score	0.934251	0.946393	0.953731
mae	282.585462	251.805339	245.293475
mse	245470.843488	199816.814877	174635.558566
rmse	495.450142	447.008741	417.894195

In [ ]:
```
voting_reg_1 = VotingRegressor(estimators=[("dectree",dectree),("randomforest",randfor
voting_reg_1.fit(X_train,y_train)
```

Out[ ]:

```
VotingRegressor
dectree                  randomforest             xgb
DecisionTreeRegressor    RandomForestRegressor    XGBRegressor
```

In [ ]:
```
predictions_1 = voting_reg_1.predict(X_test)
met = eval_metrics(predictions_1,y_test)
compare_df["dectree&randforest&xgb"] = [met[1],met[3],met[5],met[7]]
compare_df
```

Out[ ]:

	decision tree	random forest	xgboost	dectree&randforest&xgb
r2_score	0.934251	0.946393	0.953731	0.950506
mae	282.585462	251.805339	245.293475	243.706963
mse	245470.843488	199816.814877	174635.558566	184368.679219
rmse	495.450142	447.008741	417.894195	429.381741

Kombinacijom ne dobija se poboljsanje,pa ce se isprobati kombinacije svaka dva od tri navedena algoritma

In [ ]:
```
voting_reg_2 = VotingRegressor(estimators=[("dectree",dectree),("randomforest",randfor
voting_reg_2.fit(X_train,y_train)
```

Out[ ]:

VotingRegressor

dectree | randomforest

DecisionTreeRegressor | RandomForestRegressor

In [ ]:
```
predictions_2 = voting_reg_2.predict(X_test)
met = eval_metrics(predictions_2,y_test)
compare_df["dectree&randforest"] = [met[1],met[3],met[5],met[7]]
compare_df
```

Out[ ]:

	decision tree	random forest	xgboost	dectree&randforest&xgb	dectree&randforest
r2_score	0.934251	0.946393	0.953731	0.950506	0.944309
mae	282.585462	251.805339	245.293475	243.706963	256.940246
mse	245470.843488	199816.814877	174635.558566	184368.679219	206906.098567
rmse	495.450142	447.008741	417.894195	429.381741	454.869320

In [ ]:
```
voting_reg_3 = VotingRegressor(estimators=[("dectree",dectree),("xgb",xgb)])
voting_reg_3.fit(X_train,y_train)
```

Out[ ]:

VotingRegressor

dectree | xgb

DecisionTreeRegressor | XGBRegressor

In [ ]:
```
predictions_3 = voting_reg_3.predict(X_test)
met = eval_metrics(predictions_3,y_test)
compare_df["dectree&xgb"] = [met[1],met[3],met[5],met[7]]
compare_df
```

Out[ ]:

	decision tree	random forest	xgboost	dectree&randforest&xgb	dectree&randforest
r2_score	0.934251	0.946393	0.953731	0.950506	0.944309
mae	282.585462	251.805339	245.293475	243.706963	256.940246
mse	245470.843488	199816.814877	174635.558566	184368.679219	206906.098567
rmse	495.450142	447.008741	417.894195	429.381741	454.869320

In [ ]:
```
voting_reg_4 = VotingRegressor(estimators=[("randforest",randforest),("xgb",xgb)])
voting_reg_4.fit(X_train,y_train)
```

```
Out[ ]:
VotingRegressor
randforest                 xgb
RandomForestRegressor      XGBRegressor
```

```
In [ ]: predictions_4 = voting_reg_4.predict(X_test)
met = eval_metrics(predictions_4,y_test)
compare_df["randforest&xgb"] = [met[1],met[3],met[5],met[7]]
compare_df
```

Out[ ]:

	decision tree	random forest	xgboost	dectree&randforest&xgb	dectree&randforest
r2_score	0.934251	0.946393	0.953731	0.950506	0.944309
mae	282.585462	251.805339	245.293475	243.706963	256.940246
mse	245470.843488	199816.814877	174635.558566	184368.679219	206906.098567
rmse	495.450142	447.008741	417.894195	429.381741	454.869320

Na osnovu prikazane tabele gde su navedene metrike modela i njihovih kombinacija biramo MSE kao meru uporedjivanja, dobija se da najbolje rezultate daje kombinacija **Random Forest** i **XGBoost** .

ALGORITMI - RAZLICITE VARIJANTE

Primenjuju se kombinacija algoritama **Random Forest** i **XGBoost**, kako se pokazala kao najbolja, na razlicitim varijantama dataseta, kako bi se pronaslo sto bolje resenje problema.

```
In [ ]: r2_scores = []
mae_scores = []
mse_scores = []
rmse_scores = []
```

```
In [ ]: randforest = RandomForestRegressor(**best_params_rf)
xgb = XGBRegressor(**best_params_xgb)
voting_reg = VotingRegressor(estimators=[("randforest",randforest),("xgb",xgb)])
voting_reg.fit(X_train2,y_train)
```

```
Out[ ]:
VotingRegressor
randforest                 xgb
RandomForestRegressor      XGBRegressor
```

```
In [ ]: predictions = voting_reg.predict(X_test2)
met = eval_metrics(predictions,y_test)
r2_scores.append(met[1])
```

```
mae_scores.append(met[3])
mse_scores.append(met[5])
rmse_scores.append(met[7])
```

In [ ]:
```
X_train3 = X_train2.copy()
X_train4 = X_train2.copy()
X_train5 = X_train2.copy()
X_test3 = X_test2.copy()
X_test4 = X_test2.copy()
X_test5 = X_test2.copy()
```

Prva varijanta izmenjenog dataseta je kada se koristi one-hot metoda za kodiranje kategorickih vrednosti polaznog atributa holiday

In [ ]:
```
X_train3.drop(['holiday', 'weekend'], axis = 1, inplace = True)
X_test3.drop(['holiday', 'weekend'], axis = 1, inplace = True)
X_train3
```

Out[ ]:

	temp	rain_1h	snow_1h	clouds_all	weather	hour	day	year	holiday_christmas day	holiday_
43102	0.477804	0.0	0.0	0.68	0.25	14	1	2018	0	
180	0.550540	0.0	0.0	0.99	2.00	8	2	2012	0	
32911	0.498950	0.0	0.0	0.01	4.00	1	4	2017	0	
9793	0.288542	0.0	0.0	0.64	0.25	2	1	2013	0	
19199	0.486953	0.0	0.0	0.90	4.00	15	2	2015	0	
...	...	...	...	...	...	...	...	...	...	
11284	0.080984	0.0	0.0	0.40	0.00	7	1	2014	0	
44743	0.728104	0.0	0.0	0.01	1.00	0	3	2018	0	
38169	0.662717	0.0	0.0	0.01	1.00	23	3	2017	0	
860	0.387672	0.0	0.0	0.20	0.75	7	5	2012	0	
15805	0.839082	0.0	0.0	0.01	1.00	17	2	2014	0	

38554 rows × 20 columns

In [ ]:
```
voting_reg = VotingRegressor(estimators=[("randforest",randforest),("xgb",xgb)])
voting_reg.fit(X_train3,y_train)
predictions = voting_reg.predict(X_test3)
met = eval_metrics(predictions,y_test)
r2_scores.append(met[1])
mae_scores.append(met[3])
mse_scores.append(met[5])
rmse_scores.append(met[7])
```

Naredna varijanta je kada se polazni atributi **holiday** i **date_time** zamenjuju, tako da atribut **holiday** ima vrednosti 0 i 1, gde 1 oznacava da je praznik u pitanju, a 0 suprotno i uvodi se nova kolona **weekend** koja takodje ima vrednosti 0 i 1, gde 1 oznacava da je vikend u pitanju, a 0 suprotno.

In [ ]:
```
X_train4.drop(['holiday_christmas day', 'holiday_columbus day', 'holiday_martin luther
X_test4.drop(['holiday_christmas day', 'holiday_columbus day', 'holiday_martin luther
X_train4
```

Out[ ]:

	temp	rain_1h	snow_1h	clouds_all	weather	hour	year	holiday	weekend
43102	0.477804	0.0	0.0	0.68	0.25	14	2018	1	0
180	0.550540	0.0	0.0	0.99	2.00	8	2012	1	0
32911	0.498950	0.0	0.0	0.01	4.00	1	2017	1	0
9793	0.288542	0.0	0.0	0.64	0.25	2	2013	1	0
19199	0.486953	0.0	0.0	0.90	4.00	15	2015	1	0
...	...	...	...	...	...	...	...	...	...
11284	0.080984	0.0	0.0	0.40	0.00	7	2014	1	0
44743	0.728104	0.0	0.0	0.01	1.00	0	2018	1	0
38169	0.662717	0.0	0.0	0.01	1.00	23	2017	1	0
860	0.387672	0.0	0.0	0.20	0.75	7	2012	1	1
15805	0.839082	0.0	0.0	0.01	1.00	17	2014	1	0

38554 rows × 9 columns

In [ ]:
```
voting_reg = VotingRegressor(estimators=[("randforest",randforest),("xgb",xgb)])
voting_reg.fit(X_train4,y_train)
predictions = voting_reg.predict(X_test4)
met = eval_metrics(predictions,y_test)
r2_scores.append(met[1])
mae_scores.append(met[3])
mse_scores.append(met[5])
rmse_scores.append(met[7])
```

Poslednja varijanta dataseta transformise sve numericke podatke u preprocesiranom datasetu, tako da vrednosti atributa prate normalnu raspodelu

In [ ]:
```
X_train5.drop(['holiday_christmas day', 'holiday_columbus day', 'holiday_martin luther
X_test5.drop(['holiday_christmas day', 'holiday_columbus day', 'holiday_martin luther
X_train5
```

Out[ ]:

	temp	rain_1h	snow_1h	clouds_all	weather	hour	day	year	holiday
43102	0.477804	0.0	0.0	0.68	0.25	14	1	2018	1
180	0.550540	0.0	0.0	0.99	2.00	8	2	2012	1
32911	0.498950	0.0	0.0	0.01	4.00	1	4	2017	1
9793	0.288542	0.0	0.0	0.64	0.25	2	1	2013	1
19199	0.486953	0.0	0.0	0.90	4.00	15	2	2015	1
...	...	...	...	...	...	...	...	...	...
11284	0.080984	0.0	0.0	0.40	0.00	7	1	2014	1
44743	0.728104	0.0	0.0	0.01	1.00	0	3	2018	1
38169	0.662717	0.0	0.0	0.01	1.00	23	3	2017	1
860	0.387672	0.0	0.0	0.20	0.75	7	5	2012	1
15805	0.839082	0.0	0.0	0.01	1.00	17	2	2014	1

38554 rows × 9 columns

In [ ]:

```
from sklearn.preprocessing import QuantileTransformer
qt = QuantileTransformer(output_distribution='normal')
X_train5 = pd.DataFrame(qt.fit_transform(X_train5), columns=X_train5.columns)
X_test5 = pd.DataFrame(qt.fit_transform(X_test5), columns=X_train5.columns)
X_test5
```

Out[ ]:

	temp	rain_1h	snow_1h	clouds_all	weather	hour	day	year	holiday
0	-1.300216	-5.199338	-5.199338	-0.180377	1.204935	-0.352151	0.360172	5.199338	5.199338
1	-1.703666	-5.199338	-5.199338	-0.008782	2.043115	-0.593940	-0.373591	-0.579039	5.199338
2	-0.744529	-5.199338	-5.199338	-0.444534	-0.116941	0.599937	-0.373591	0.605955	5.199338
3	-0.051460	-5.199338	-5.199338	0.869846	0.645631	-0.593940	-0.373591	-0.321611	5.199338
4	-1.083201	-5.199338	-5.199338	0.869846	-0.763030	0.266584	0.798769	0.605955	5.199338
...	...	...	...	...	...	...	...	...	...
9634	-0.239380	-5.199338	-5.199338	0.869846	0.326900	-0.243255	5.199338	-1.064091	5.199338
9635	-0.486480	-5.199338	-5.199338	0.869846	0.326900	1.513589	0.798769	-1.064091	5.199338
9636	0.694311	-5.199338	-5.199338	-0.941700	-0.116941	-5.199338	5.199338	0.605955	5.199338
9637	-0.670557	-5.199338	-5.199338	0.869846	-0.763030	-0.035135	0.798769	0.605955	5.199338
9638	0.548644	-5.199338	-5.199338	-0.941700	-0.116941	-0.723343	0.360172	-0.321611	5.199338

9639 rows × 9 columns

In [ ]:

```
voting_reg = VotingRegressor(estimators=[("randforest",randforest),("xgb",xgb)])
voting_reg.fit(X_train5,y_train)
predictions = voting_reg.predict(X_test5)
```

```
met = eval_metrics(predictions,y_test)
r2_scores.append(met[1])
mae_scores.append(met[3])
mse_scores.append(met[5])
rmse_scores.append(met[7])
```

In [ ]:
```
data= {
    "r2":r2_scores,
    "mae":mae_scores,
    "mse":mse_scores,
    "rmse":rmse_scores
}
df = pd.DataFrame(data, index=['1.varijanta',
                               '2.varijanta',
                               '3.varijanta',
                               '4.varijanta'])
df
```

Out[ ]:

	r2	mae	mse	rmse
1.varijanta	0.953475	237.807464	174168.846006	417.335412
2.varijanta	0.953667	237.703973	173223.959862	416.201826
3.varijanta	0.940302	290.011057	220598.596654	469.679249
4.varijanta	0.934552	310.748478	236350.583631	486.159011

Nakon testiranja četiri različite varijante zaključili smo da su prve dve veoma slične po performansama dok su druge dve značajno gore. Iz tog razloga smo testirali i vreme izvršenja algoritama za prvu i drugu varijantu.

ANAIZA VREMENA IZVRSENJA

In [ ]:
```
import time
seed = 43
dt = DecisionTreeRegressor(random_state = seed)
rf = RandomForestRegressor(random_state = seed, n_jobs = -1)
xgb = XGBRegressor (random_state = seed, n_jobs = -1)
models_vreme = [('dectree',dt),('randforest',rf),('xgb',xgb)]
```

In [ ]:
```
def train_mse_vreme(name,model):
  train_model = model.fit(X_train,y_train)
  predicted = train_model.predict(X_test)
  names.append(name)
  return mean_squared_error(y_test, predicted)
```

In [ ]:
```
def train_mse_vreme2(name,model):
  train_model = model.fit(X_train2,y_train)
  predicted = train_model.predict(X_test2)
  names.append(name)
  return mean_squared_error(y_test, predicted)
```

In [ ]:
```
names_vreme = []
mses_vreme = []
```

```
print("Varijanta prva\n")
t0 = time.perf_counter()
for name,model in models_vreme:
  t1 = time.perf_counter()
  mses_vreme.append(train_mse_vreme(name,model))
  t2 = time.perf_counter()
  print(name + ' vreme:',t2-t1)
t3 = time.perf_counter()
print('Ukupno prva varijanta:',t3-t0)

print("\n Varijanta druga\n")
t0 = time.perf_counter()
for name,model in models_vreme:
  t1 = time.perf_counter()
  mses_vreme.append(train_mse_vreme2(name,model))
  t2 = time.perf_counter()
  print(name + ' vreme:',t2-t1)
t3 = time.perf_counter()
print('Ukupno druga varijanta:',t3-t0)
```

```
Varijanta prva

dectree vreme: 0.2050977930011868
randforest vreme: 11.861293038997246
xgb vreme: 0.40993177499694866
Ukupno prva varijanta: 12.478902785998798

 Varijanta druga

dectree vreme: 0.23109916600151337
randforest vreme: 11.335700597999676
xgb vreme: 2.049507943000208
Ukupno druga varijanta: 13.624736582998594
```

Kada se model trenira i testira nad prvom varijantom podataka manje vremena je neophodno nego kada se trenira i testira nad drugom varijantom. Treba uzeti u obzir da bi razlika bila veća da se meri i vreme određivanja hiperparametara. S toga možemo zaključiti da najbolje rezultate postiže kombinacija **xgb** i **randforest** nad prvom varijantom podataka.