Modeling-Nonlinear-Reg

May 26, 2021

1 Modeling

in previous notebook we investigated the linear algorithms for regression problem which we discussed previously. in this notebook we are going to discuss non-linear approaches for regression problem. the non-linear algorithms which we will check in this notebook are: - k-nearest neighbor - decision tree - random forest

and in the next notebooks we will discuss classification and clustering algorithms.

the reason behind the dividing the notebooks is making the understanding of principles more easily.

an imortant fact to have in mind in contrast of plotting the trained model is that in order to minimizing the effect of simpson's paradox on dataset, for plotting we are training a single variable regression based on the algorithm and then plotting it. the final model will be multivariate.

---

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.patches as patches
import warnings
import matplotlib
warnings.filterwarnings("ignore")
pd.set_option('display.max_rows', 200)
import seaborn as sns
from openpyxl import load_workbook
np.set_printoptions(suppress=True)
pd.set_option('display.float_format', lambda x: '%.2f' % x)
from sklearn import preprocessing
from sklearn.model_selection import KFold, cross_val_score, train_test_split
from tqdm import tqdm_notebook, tqdm
```

[2]:
```
xls = pd.ExcelFile('data/Main Dataset V3.0 .xlsx')
ad_post = pd.read_excel(xls, 'Ad-Post')
ad_story = pd.read_excel(xls, 'Ad-Story')
influencer = pd.read_excel(xls, 'Influencer')
leaders_post = pd.read_excel(xls, 'Leaders-Post')
leaders_story = pd.read_excel(xls, 'Leaders-Story')
post = pd.read_excel(xls, 'Post')
```

```
story = pd.read_excel(xls, 'Story')
print('Datasets Loaded Completely.')
```

```
Datasets Loaded Completely.
```

[3]:
```
#dummying dataset

# advertising posts
dummy_field = pd.get_dummies(ad_post['field'], prefix='field')
ad_post_dummy = pd.concat([ad_post, dummy_field], axis=1)
ad_post_dummy.drop(['field'], axis=1, inplace=True)

# advertising stories
dummy_field = pd.get_dummies(ad_story['field'], prefix='field')
ad_story_dummy = pd.concat([ad_story, dummy_field], axis=1)
ad_story_dummy.drop(['field'], axis=1, inplace=True)

#influencer
dummy_gender = pd.get_dummies(influencer['gender'], prefix='gender')
dummy_field = pd.get_dummies(influencer['field'], prefix='field')
influencer_dummy = pd.concat([influencer, dummy_gender, dummy_field], axis=1)
influencer_dummy.drop(['gender', 'field'], axis=1, inplace=True)

#leaders posts
dummy_gender = pd.get_dummies(leaders_post['gender'], prefix='gender')
leaders_post_dummy = pd.concat([leaders_post, dummy_gender], axis=1)
leaders_post_dummy.drop(['gender'], axis=1, inplace=True)
```

[4]:
```
# label encoding dataset

# advertising posts
labels, _ = pd.factorize(ad_post['field'])
ad_post_labelencoded = ad_post
ad_post_labelencoded['field_labelencoded'] = labels.tolist()

# advertising stories
labels, _ = pd.factorize(ad_story['field'])
ad_story_labelencoded = ad_story
ad_story_labelencoded['field_labelencoded'] = labels.tolist()

# influencer
labels, _ = pd.factorize(influencer['gender'])
influencer_labelencoded = influencer
influencer_labelencoded['gender_labelencoded'] = labels.tolist()
labels, _ = pd.factorize(influencer['field'])
influencer_labelencoded['field_labelencoded'] = labels.tolist()

# leaders post
```

```
labels, _ = pd.factorize(leaders_post['gender'])
leaders_post_labelencoded = leaders_post
leaders_post_labelencoded['gender_labelencoded'] = labels.tolist()
```

[5]:
```
ad_post_y = np.asarray(ad_post_dummy[['cost']])
ad_post_x = np.asarray(ad_post_dummy[['follower', 'view', 'field_art &␣
↪culture', 'field_fact', 'field_video', 'field_women']])


ad_story_y = np.asarray(ad_story_dummy[['cost']])
ad_story_x = np.asarray(ad_story_dummy[['view', 'follower', 'action',␣
↪'interaction', 'impression', 'field_art & culture', 'field_fact',␣
↪'field_health',
                                        'field_news', 'field_video',␣
↪'field_women']])

influencer_y = np.asarray(influencer_dummy[['cost']])
influencer_x = np.asarray(influencer_dummy[['follower', 'view', 'action',␣
↪'impression', 'cta', 'interaction', 'gender_family', 'gender_female',␣
↪'gender_male',
                                            'field_cooking', 'field_health',␣
↪'field_lifestyle', 'field_sport', 'field_tourism']])

leaders_post_y = np.asarray(leaders_post_dummy[['cost']])
leaders_post_x = np.asarray(leaders_post_dummy[['follower', 'view', 'like',␣
↪'comment', 'share', 'save', 'profile_visit', 'reach', 'impression',␣
↪'gender_family',
                                                'gender_female', 'gender_male']])
```

1.0.1 K-Nearest Neighbor Regressor

Advertising Posts

[6]:
```
from sklearn.neighbors import KNeighborsRegressor, RadiusNeighborsRegressor
```

[7]:
```
weights = ['uniform', 'distance']
```

[8]:
```
temp_lst = []
neighbors = np.arange(2, 10)
for i in tqdm_notebook(range(2, 9)):
    kf = KFold(n_splits = i)
    for train_index, test_index in kf.split(ad_post_x):
        X_train, X_test = ad_post_x[train_index], ad_post_x[test_index]
        y_train, y_test = ad_post_y[train_index], ad_post_y[test_index]
        for n in np.arange(2, 9):
            for w in weights:
                knr = KNeighborsRegressor(n_neighbors = n, weights = w)
                knr.fit(X_train, y_train)
```

```
                temp_lst2 = []
                temp_lst2.append(i)
                temp_lst2.append(n)
                temp_lst2.append(w)
                temp_lst2.append(knr.score(X_train, y_train))
                temp_lst2.append(knr.score(X_test, y_test))
                temp_lst.append(temp_lst2)

temp_df = pd.DataFrame(temp_lst, columns=['k', '# of Neighbors', 'Weights',␣
 ↪'KNR Train Score', 'KNR Test Score'])

temp_lst = []
for k in range(2, 9):
    for n_ in np.arange(2, 9):
        for w_ in weights:
            temp_lst2 = []
            temp_lst2.append(k)
            temp_lst2.append(n_)
            temp_lst2.append(w_)
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
 ↪(temp_df['# of Neighbors'] == n_) &
                                                   (temp_df['Weights'] ==␣
 ↪w_)]['KNR Train Score']), decimals=4))
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
 ↪(temp_df['# of Neighbors'] == n_) &
                                                   (temp_df['Weights'] ==␣
 ↪w_)]['KNR Test Score']), decimals=4))
            temp_lst.append(temp_lst2)

nn_reg_eval_df = pd.DataFrame(temp_lst, columns=['k', '# of Neighbors',␣
 ↪'Weights', 'KNR Train Score', 'KNR Test Score'])
nn_reg_eval_df
```

```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=7.0),␣
 ↪HTML(value='')))
```

[8]:

	k	# of Neighbors	Weights	KNR Train Score	KNR Test Score
0	2	2	uniform	0.75	0.09
1	2	2	distance	1.00	0.02
2	2	3	uniform	0.57	0.18
3	2	3	distance	1.00	0.12
4	2	4	uniform	0.51	0.19
5	2	4	distance	1.00	0.16
6	2	5	uniform	0.48	0.22
7	2	5	distance	1.00	0.20

8	2	6	uniform	0.43	0.20
9	2	6	distance	1.00	0.20
10	2	7	uniform	0.38	0.21
11	2	7	distance	1.00	0.24
12	2	8	uniform	0.34	0.16
13	2	8	distance	1.00	0.23
14	3	2	uniform	0.83	0.32
15	3	2	distance	1.00	0.37
16	3	3	uniform	0.67	0.23
17	3	3	distance	1.00	0.32
18	3	4	uniform	0.63	0.26
19	3	4	distance	1.00	0.33
20	3	5	uniform	0.55	0.26
21	3	5	distance	1.00	0.31
22	3	6	uniform	0.52	0.25
23	3	6	distance	1.00	0.31
24	3	7	uniform	0.46	0.27
25	3	7	distance	1.00	0.31
26	3	8	uniform	0.42	0.27
27	3	8	distance	1.00	0.30
28	4	2	uniform	0.85	0.12
29	4	2	distance	1.00	-0.06
30	4	3	uniform	0.72	0.04
31	4	3	distance	1.00	0.08
32	4	4	uniform	0.68	0.14
33	4	4	distance	1.00	0.14
34	4	5	uniform	0.60	0.20
35	4	5	distance	1.00	0.16
36	4	6	uniform	0.54	0.25
37	4	6	distance	1.00	0.20
38	4	7	uniform	0.49	0.23
39	4	7	distance	1.00	0.19
40	4	8	uniform	0.46	0.25
41	4	8	distance	1.00	0.22
42	5	2	uniform	0.87	0.21
43	5	2	distance	1.00	0.06
44	5	3	uniform	0.74	0.02
45	5	3	distance	1.00	0.16
46	5	4	uniform	0.69	0.20
47	5	4	distance	1.00	0.26
48	5	5	uniform	0.61	0.16
49	5	5	distance	1.00	0.23
50	5	6	uniform	0.56	0.21
51	5	6	distance	1.00	0.26
52	5	7	uniform	0.51	0.23
53	5	7	distance	1.00	0.26
54	5	8	uniform	0.47	0.15

55	5	8	distance	1.00	0.22
56	6	2	uniform	0.88	0.44
57	6	2	distance	1.00	0.43
58	6	3	uniform	0.76	-0.18
59	6	3	distance	1.00	0.18
60	6	4	uniform	0.70	-0.20
61	6	4	distance	1.00	0.22
62	6	5	uniform	0.63	-0.29
63	6	5	distance	1.00	0.10
64	6	6	uniform	0.58	-0.10
65	6	6	distance	1.00	0.15
66	6	7	uniform	0.53	0.06
67	6	7	distance	1.00	0.20
68	6	8	uniform	0.48	-0.10
69	6	8	distance	1.00	0.09
70	7	2	uniform	0.89	0.22
71	7	2	distance	1.00	0.05
72	7	3	uniform	0.77	-0.40
73	7	3	distance	1.00	-0.03
74	7	4	uniform	0.69	-0.04
75	7	4	distance	1.00	0.11
76	7	5	uniform	0.64	-0.15
77	7	5	distance	1.00	0.05
78	7	6	uniform	0.59	0.06
79	7	6	distance	1.00	0.13
80	7	7	uniform	0.54	0.17
81	7	7	distance	1.00	0.18
82	7	8	uniform	0.49	0.02
83	7	8	distance	1.00	0.09
84	8	2	uniform	0.89	-0.13
85	8	2	distance	1.00	-0.33
86	8	3	uniform	0.78	-0.65
87	8	3	distance	1.00	-0.41
88	8	4	uniform	0.70	-0.26
89	8	4	distance	1.00	-0.22
90	8	5	uniform	0.64	-0.32
91	8	5	distance	1.00	-0.19
92	8	6	uniform	0.59	-0.14
93	8	6	distance	1.00	-0.10
94	8	7	uniform	0.54	-0.14
95	8	7	distance	1.00	-0.03
96	8	8	uniform	0.50	-0.46
97	8	8	distance	1.00	-0.11

[9]:
```
nn_reg_eval_df.nlargest(3, 'KNR Test Score')
```

[9]:

	k	# of Neighbors	Weights	KNR Train Score	KNR Test Score
56	6	2	uniform	0.88	0.44
57	6	2	distance	1.00	0.43
15	3	2	distance	1.00	0.37

[10]:
```
nn_reg_eval_df.nsmallest(3, 'KNR Test Score')
```

[10]:

	k	# of Neighbors	Weights	KNR Train Score	KNR Test Score
86	8	3	uniform	0.78	-0.65
96	8	8	uniform	0.50	-0.46
87	8	3	distance	1.00	-0.41

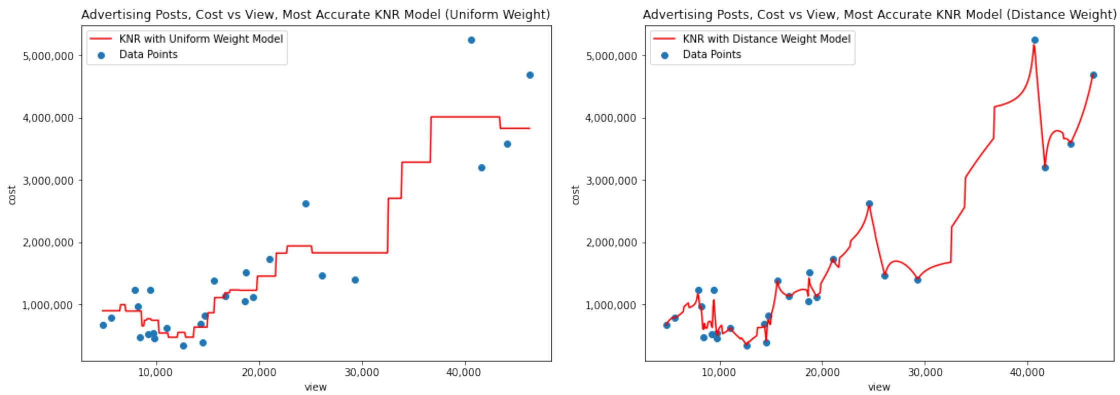
as you can see in the table above this approach didn't perform very well on advertising posts dataset. it's good to check its fitted model on dataset.

[11]:
```
knr_uniform = KNeighborsRegressor(n_neighbors=3, weights='uniform')
knr_distance = KNeighborsRegressor(n_neighbors=3, weights='distance')
knr_uniform = knr_uniform.fit(ad_post_x, ad_post_y)
knr_distance = knr_distance.fit(ad_post_x, ad_post_y)
```

[12]:
```
fig = plt.figure(figsize=(18,6))
ax1 = fig.add_subplot(1,2,1)
ax2 = fig.add_subplot(1,2,2)

ax1.scatter(ad_post_dummy['view'], ad_post_dummy['cost'], label='Data Points')
ax2.scatter(ad_post_dummy['view'], ad_post_dummy['cost'], label='Data Points')
X_plot = np.linspace(ad_post_dummy['view'].min(), ad_post_dummy['view'].max(),␣
 ↪500).reshape(-1, 1)
y_plot_uniform = knr_uniform.fit(ad_post_x[:, 1].reshape(-1, 1), ad_post_y).
 ↪predict(X_plot)
y_plot_distance = knr_distance.fit(ad_post_x[:, 1].reshape(-1, 1), ad_post_y).
 ↪predict(X_plot)
ax1.plot(X_plot, y_plot_uniform, '-r', label='KNR with Uniform Weight Model')
ax2.plot(X_plot, y_plot_distance, '-r', label='KNR with Distance Weight Model')
ax1.get_yaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
 ↪ format(int(x), ',')))
ax1.get_xaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
 ↪ format(int(x), ',')))
ax1.set_title(f'Advertising Posts, Cost vs View, Most Accurate KNR Model␣
 ↪(Uniform Weight)')
ax1.set_xlabel('view')
ax1.set_ylabel('cost')
ax1.legend()
ax2.get_yaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
 ↪ format(int(x), ',')))
ax2.get_xaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
 ↪ format(int(x), ',')))
```

```python
ax2.set_title(f'Advertising Posts, Cost vs View, Most Accurate KNR Model (Distance Weight)')
ax2.set_xlabel('view')
ax2.set_ylabel('cost')
ax2.legend()
plt.show()
```



Advertising Stories

[13]:
```python
temp_lst = []
neighbors = np.arange(2, 10)
for i in tqdm_notebook(range(2, 9)):
    kf = KFold(n_splits = i)
    for train_index, test_index in kf.split(ad_story_x):
        X_train, X_test = ad_story_x[train_index], ad_story_x[test_index]
        y_train, y_test = ad_story_y[train_index], ad_story_y[test_index]
        for n in np.arange(2, 9):
            for w in weights:
                knr = KNeighborsRegressor(n_neighbors = n, weights = w)
                knr.fit(X_train, y_train)
                temp_lst2 = []
                temp_lst2.append(i)
                temp_lst2.append(n)
                temp_lst2.append(w)
                temp_lst2.append(knr.score(X_train, y_train))
                temp_lst2.append(knr.score(X_test, y_test))
                temp_lst.append(temp_lst2)

temp_df = pd.DataFrame(temp_lst, columns=['k', '# of Neighbors', 'Weights', 'KNR Train Score', 'KNR Test Score'])

temp_lst = []
for k in range(2, 9):
```

```
    for n_ in np.arange(2, 9):
        for w_ in weights:
            temp_lst2 = []
            temp_lst2.append(k)
            temp_lst2.append(n_)
            temp_lst2.append(w_)
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
 ↪(temp_df['# of Neighbors'] == n_) &
                                                      (temp_df['Weights'] ==␣
 ↪w_)]['KNR Train Score']), decimals=4))
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
 ↪(temp_df['# of Neighbors'] == n_) &
                                                      (temp_df['Weights'] ==␣
 ↪w_)]['KNR Test Score']), decimals=4))
            temp_lst.append(temp_lst2)

nn_reg_eval_df = pd.DataFrame(temp_lst, columns=['k', '# of Neighbors',␣
 ↪'Weights', 'KNR Train Score', 'KNR Test Score'])
nn_reg_eval_df
```

```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=7.0),␣
 ↪HTML(value='')))
```

[13]:

	k	# of Neighbors	Weights	KNR Train Score	KNR Test Score
0	2	2	uniform	0.80	0.38
1	2	2	distance	1.00	0.44
2	2	3	uniform	0.57	0.33
3	2	3	distance	1.00	0.42
4	2	4	uniform	0.54	0.36
5	2	4	distance	1.00	0.43
6	2	5	uniform	0.43	0.33
7	2	5	distance	1.00	0.40
8	2	6	uniform	0.40	0.31
9	2	6	distance	1.00	0.39
10	2	7	uniform	0.30	0.30
11	2	7	distance	1.00	0.37
12	2	8	uniform	0.26	0.27
13	2	8	distance	1.00	0.35
14	3	2	uniform	0.83	0.17
15	3	2	distance	1.00	0.17
16	3	3	uniform	0.61	0.18
17	3	3	distance	1.00	0.24
18	3	4	uniform	0.55	0.14
19	3	4	distance	1.00	0.21
20	3	5	uniform	0.49	0.07
21	3	5	distance	1.00	0.16

22	3	6	uniform	0.44	-0.01
23	3	6	distance	1.00	0.10
24	3	7	uniform	0.39	-0.05
25	3	7	distance	1.00	0.07
26	3	8	uniform	0.35	-0.03
27	3	8	distance	1.00	0.05
28	4	2	uniform	0.85	-3.97
29	4	2	distance	1.00	-3.64
30	4	3	uniform	0.69	-2.83
31	4	3	distance	1.00	-2.84
32	4	4	uniform	0.60	-2.33
33	4	4	distance	1.00	-2.49
34	4	5	uniform	0.53	-1.94
35	4	5	distance	1.00	-2.31
36	4	6	uniform	0.50	-1.68
37	4	6	distance	1.00	-2.12
38	4	7	uniform	0.44	-1.52
39	4	7	distance	1.00	-1.98
40	4	8	uniform	0.39	-1.59
41	4	8	distance	1.00	-1.97
42	5	2	uniform	0.85	-0.98
43	5	2	distance	1.00	-0.82
44	5	3	uniform	0.70	-0.75
45	5	3	distance	1.00	-0.37
46	5	4	uniform	0.60	-0.72
47	5	4	distance	1.00	-0.35
48	5	5	uniform	0.55	-0.58
49	5	5	distance	1.00	-0.32
50	5	6	uniform	0.50	-0.54
51	5	6	distance	1.00	-0.33
52	5	7	uniform	0.46	-0.56
53	5	7	distance	1.00	-0.37
54	5	8	uniform	0.41	-0.53
55	5	8	distance	1.00	-0.39
56	6	2	uniform	0.86	-10.50
57	6	2	distance	1.00	-10.49
58	6	3	uniform	0.73	-8.09
59	6	3	distance	1.00	-7.91
60	6	4	uniform	0.62	-7.82
61	6	4	distance	1.00	-7.43
62	6	5	uniform	0.57	-7.12
63	6	5	distance	1.00	-6.91
64	6	6	uniform	0.52	-6.45
65	6	6	distance	1.00	-6.62
66	6	7	uniform	0.48	-5.50
67	6	7	distance	1.00	-6.23
68	6	8	uniform	0.43	-5.20

69	6	8	distance	1.00	-6.16
70	7	2	uniform	0.87	-1.62
71	7	2	distance	1.00	-1.43
72	7	3	uniform	0.74	-0.65
73	7	3	distance	1.00	-0.65
74	7	4	uniform	0.64	-0.67
75	7	4	distance	1.00	-0.64
76	7	5	uniform	0.56	-0.55
77	7	5	distance	1.00	-0.60
78	7	6	uniform	0.53	-0.57
79	7	6	distance	1.00	-0.57
80	7	7	uniform	0.49	-0.64
81	7	7	distance	1.00	-0.61
82	7	8	uniform	0.45	-0.58
83	7	8	distance	1.00	-0.61
84	8	2	uniform	0.88	-12.10
85	8	2	distance	1.00	-12.33
86	8	3	uniform	0.74	-10.53
87	8	3	distance	1.00	-9.51
88	8	4	uniform	0.65	-9.78
89	8	4	distance	1.00	-8.33
90	8	5	uniform	0.57	-6.52
91	8	5	distance	1.00	-6.78
92	8	6	uniform	0.55	-6.45
93	8	6	distance	1.00	-6.45
94	8	7	uniform	0.50	-6.60
95	8	7	distance	1.00	-6.62
96	8	8	uniform	0.46	-5.31
97	8	8	distance	1.00	-6.01

[14]:
```
nn_reg_eval_df.nlargest(3, 'KNR Test Score')
```

[14]:

	k	# of Neighbors	Weights	KNR Train Score	KNR Test Score
1	2	2	distance	1.00	0.44
5	2	4	distance	1.00	0.43
3	2	3	distance	1.00	0.42

[15]:
```
nn_reg_eval_df.nsmallest(3, 'KNR Test Score')
```

[15]:

	k	# of Neighbors	Weights	KNR Train Score	KNR Test Score
85	8	2	distance	1.00	-12.33
84	8	2	uniform	0.88	-12.10
86	8	3	uniform	0.74	-10.53

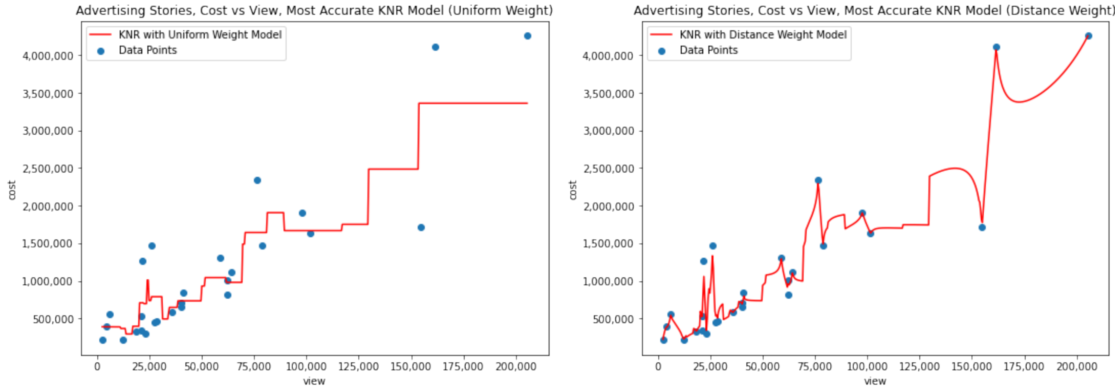
[16]:
```
knr_uniform = KNeighborsRegressor(n_neighbors=3, weights='uniform')
knr_distance = KNeighborsRegressor(n_neighbors=3, weights='distance')
knr_uniform = knr_uniform.fit(ad_story_x, ad_story_y)
```

```
knr_distance = knr_distance.fit(ad_story_x, ad_story_y)
```

[17]:

```
fig = plt.figure(figsize=(18,6))
ax1 = fig.add_subplot(1,2,1)
ax2 = fig.add_subplot(1,2,2)

ax1.scatter(ad_story_dummy['view'], ad_story_dummy['cost'], label='Data Points')
ax2.scatter(ad_story_dummy['view'], ad_story_dummy['cost'], label='Data Points')
X_plot = np.linspace(ad_story_dummy['view'].min(), ad_story_dummy['view'].
 ↪max(), 500).reshape(-1, 1)
y_plot_uniform = knr_uniform.fit(ad_story_x[:, 0].reshape(-1, 1), ad_story_y).
 ↪predict(X_plot)
y_plot_distance = knr_distance.fit(ad_story_x[:, 0].reshape(-1, 1), ad_story_y).
 ↪predict(X_plot)
ax1.plot(X_plot, y_plot_uniform, '-r', label='KNR with Uniform Weight Model')
ax2.plot(X_plot, y_plot_distance, '-r', label='KNR with Distance Weight Model')
ax1.get_yaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
 ↪ format(int(x), ',')))
ax1.get_xaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
 ↪ format(int(x), ',')))
ax1.set_title(f'Advertising Stories, Cost vs View, Most Accurate KNR Model␣
 ↪(Uniform Weight)')
ax1.set_xlabel('view')
ax1.set_ylabel('cost')
ax1.legend()
ax2.get_yaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
 ↪ format(int(x), ',')))
ax2.get_xaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
 ↪ format(int(x), ',')))
ax2.set_title(f'Advertising Stories, Cost vs View, Most Accurate KNR Model␣
 ↪(Distance Weight)')
ax2.set_xlabel('view')
ax2.set_ylabel('cost')
ax2.legend()
plt.show()
```



Influencers

[18]:
```
temp_lst = []
neighbors = np.arange(2, 10)
for i in tqdm_notebook(range(2, 9)):
    kf = KFold(n_splits = i)
    for train_index, test_index in kf.split(influencer_x):
        X_train, X_test = influencer_x[train_index], influencer_x[test_index]
        y_train, y_test = influencer_y[train_index], influencer_y[test_index]
        for n in np.arange(2, 9):
            for w in weights:
                knr = KNeighborsRegressor(n_neighbors = n, weights = w)
                knr.fit(X_train, y_train)
                temp_lst2 = []
                temp_lst2.append(i)
                temp_lst2.append(n)
                temp_lst2.append(w)
                temp_lst2.append(knr.score(X_train, y_train))
                temp_lst2.append(knr.score(X_test, y_test))
                temp_lst.append(temp_lst2)

temp_df = pd.DataFrame(temp_lst, columns=['k', '# of Neighbors', 'Weights',␣
↪'KNR Train Score', 'KNR Test Score'])

temp_lst = []
for k in range(2, 9):
    for n_ in np.arange(2, 9):
        for w_ in weights:
            temp_lst2 = []
            temp_lst2.append(k)
            temp_lst2.append(n_)
            temp_lst2.append(w_)
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
↪(temp_df['# of Neighbors'] == n_) &
                                                   (temp_df['Weights'] ==␣
↪w_)]['KNR Train Score']), decimals=4))
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
↪(temp_df['# of Neighbors'] == n_) &
                                                   (temp_df['Weights'] ==␣
↪w_)]['KNR Test Score']), decimals=4))
            temp_lst.append(temp_lst2)

nn_reg_eval_df = pd.DataFrame(temp_lst, columns=['k', '# of Neighbors',␣
↪'Weights', 'KNR Train Score', 'KNR Test Score'])
nn_reg_eval_df
```

```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=7.0),␣
↪HTML(value='')))
```

[18]:

	k	# of Neighbors	Weights	KNR Train Score	KNR Test Score
0	2	2	uniform	1.00	0.09
1	2	2	distance	1.00	0.09
2	2	3	uniform	1.00	0.09
3	2	3	distance	1.00	0.09
4	2	4	uniform	1.00	0.31
5	2	4	distance	1.00	0.29
6	2	5	uniform	0.97	0.42
7	2	5	distance	1.00	0.39
8	2	6	uniform	0.92	0.39
9	2	6	distance	1.00	0.38
10	2	7	uniform	0.87	0.35
11	2	7	distance	1.00	0.37
12	2	8	uniform	0.81	0.31
13	2	8	distance	1.00	0.35
14	3	2	uniform	1.00	-0.38
15	3	2	distance	1.00	-0.38
16	3	3	uniform	1.00	-0.38
17	3	3	distance	1.00	-0.38
18	3	4	uniform	0.99	0.05
19	3	4	distance	1.00	-0.01
20	3	5	uniform	0.98	0.25
21	3	5	distance	1.00	0.19
22	3	6	uniform	0.97	0.34
23	3	6	distance	1.00	0.30
24	3	7	uniform	0.94	0.37
25	3	7	distance	1.00	0.36
26	3	8	uniform	0.91	0.38
27	3	8	distance	1.00	0.39
28	4	2	uniform	1.00	0.23
29	4	2	distance	1.00	0.22
30	4	3	uniform	1.00	0.26
31	4	3	distance	1.00	0.27
32	4	4	uniform	0.99	0.50
33	4	4	distance	1.00	0.49
34	4	5	uniform	0.98	0.60
35	4	5	distance	1.00	0.60
36	4	6	uniform	0.96	0.63
37	4	6	distance	1.00	0.65
38	4	7	uniform	0.94	0.59
39	4	7	distance	1.00	0.64
40	4	8	uniform	0.91	0.55
41	4	8	distance	1.00	0.63

42	5	2	uniform	1.00	-0.50
43	5	2	distance	1.00	-0.50
44	5	3	uniform	1.00	-0.50
45	5	3	distance	1.00	-0.50
46	5	4	uniform	1.00	-0.18
47	5	4	distance	1.00	-0.21
48	5	5	uniform	0.98	0.04
49	5	5	distance	1.00	0.00
50	5	6	uniform	0.97	0.12
51	5	6	distance	1.00	0.11
52	5	7	uniform	0.95	0.15
53	5	7	distance	1.00	0.16
54	5	8	uniform	0.92	0.14
55	5	8	distance	1.00	0.18
56	6	2	uniform	1.00	-0.07
57	6	2	distance	1.00	-0.03
58	6	3	uniform	1.00	-0.11
59	6	3	distance	1.00	-0.05
60	6	4	uniform	1.00	0.20
61	6	4	distance	1.00	0.23
62	6	5	uniform	0.99	0.35
63	6	5	distance	1.00	0.38
64	6	6	uniform	0.98	0.46
65	6	6	distance	1.00	0.47
66	6	7	uniform	0.96	0.51
67	6	7	distance	1.00	0.52
68	6	8	uniform	0.93	0.55
69	6	8	distance	1.00	0.56
70	7	2	uniform	1.00	-1.22
71	7	2	distance	1.00	-0.68
72	7	3	uniform	1.00	-2.16
73	7	3	distance	1.00	-1.26
74	7	4	uniform	0.99	-2.73
75	7	4	distance	1.00	-1.65
76	7	5	uniform	0.98	-3.12
77	7	5	distance	1.00	-1.92
78	7	6	uniform	0.97	-3.37
79	7	6	distance	1.00	-2.13
80	7	7	uniform	0.95	-3.58
81	7	7	distance	1.00	-2.32
82	7	8	uniform	0.93	-3.63
83	7	8	distance	1.00	-2.38
84	8	2	uniform	1.00	0.30
85	8	2	distance	1.00	0.31
86	8	3	uniform	1.00	0.25
87	8	3	distance	1.00	0.31
88	8	4	uniform	1.00	0.45

```
89   8                4  distance            1.00            0.53
90   8                5   uniform            0.98            0.47
91   8                5  distance            1.00            0.62
92   8                6   uniform            0.97            0.35
93   8                6  distance            1.00            0.61
94   8                7   uniform            0.95            0.23
95   8                7  distance            1.00            0.56
96   8                8   uniform            0.93            0.11
97   8                8  distance            1.00            0.49
```

[19]:
```
nn_reg_eval_df.nlargest(3, 'KNR Test Score')
```

[19]:
```
    k  # of Neighbors   Weights  KNR Train Score  KNR Test Score
37  4               6  distance             1.00            0.65
39  4               7  distance             1.00            0.64
36  4               6   uniform             0.96            0.63
```

[20]:
```
nn_reg_eval_df.nsmallest(3, 'KNR Test Score')
```

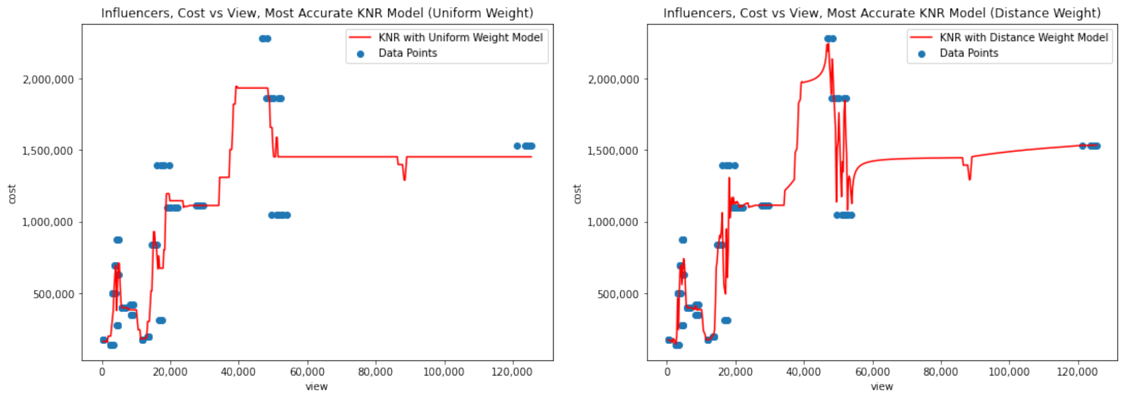
[20]:
```
    k  # of Neighbors  Weights  KNR Train Score  KNR Test Score
82  7               8  uniform             0.93           -3.63
80  7               7  uniform             0.95           -3.58
78  7               6  uniform             0.97           -3.37
```

[21]:
```
knr_uniform = KNeighborsRegressor(n_neighbors=6, weights='uniform')
knr_distance = KNeighborsRegressor(n_neighbors=6, weights='distance')
knr_uniform = knr_uniform.fit(influencer_x, influencer_y)
knr_distance = knr_distance.fit(influencer_x, influencer_y)
```

[22]:
```
fig = plt.figure(figsize=(18,6))
ax1 = fig.add_subplot(1,2,1)
ax2 = fig.add_subplot(1,2,2)

ax1.scatter(influencer_dummy['view'], influencer_dummy['cost'], label='Data␣
 ↪Points')
ax2.scatter(influencer_dummy['view'], influencer_dummy['cost'], label='Data␣
 ↪Points')
X_plot = np.linspace(influencer_dummy['view'].min(), influencer_dummy['view'].
 ↪max(), 500).reshape(-1, 1)
y_plot_uniform = knr_uniform.fit(influencer_x[:, 1].reshape(-1, 1),␣
 ↪influencer_y).predict(X_plot)
y_plot_distance = knr_distance.fit(influencer_x[:, 1].reshape(-1, 1),␣
 ↪influencer_y).predict(X_plot)
ax1.plot(X_plot, y_plot_uniform, '-r', label='KNR with Uniform Weight Model')
ax2.plot(X_plot, y_plot_distance, '-r', label='KNR with Distance Weight Model')
ax1.get_yaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
 ↪ format(int(x), ',')))
```

```
ax1.get_xaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
↪ format(int(x), ',')))
ax1.set_title(f'Influencers, Cost vs View, Most Accurate KNR Model (Uniform␣
↪Weight)')
ax1.set_xlabel('view')
ax1.set_ylabel('cost')
ax1.legend()
ax2.get_yaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
↪ format(int(x), ',')))
ax2.get_xaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
↪ format(int(x), ',')))
ax2.set_title(f'Influencers, Cost vs View, Most Accurate KNR Model (Distance␣
↪Weight)')
ax2.set_xlabel('view')
ax2.set_ylabel('cost')
ax2.legend()
plt.show()
```



Leaders Posts

[23]:
```
temp_lst = []
neighbors = np.arange(2, 10)
for i in tqdm_notebook(range(2, 9)):
    kf = KFold(n_splits = i)
    for train_index, test_index in kf.split(leaders_post_x):
        X_train, X_test = leaders_post_x[train_index],␣
↪leaders_post_x[test_index]
        y_train, y_test = leaders_post_y[train_index],␣
↪leaders_post_y[test_index]
        for n in np.arange(2, 5):
            for w in weights:
                knr = KNeighborsRegressor(n_neighbors = n, weights = w)
                knr.fit(X_train, y_train)
```

```
                temp_lst2 = []
                temp_lst2.append(i)
                temp_lst2.append(n)
                temp_lst2.append(w)
                temp_lst2.append(knr.score(X_train, y_train))
                temp_lst2.append(knr.score(X_test, y_test))
                temp_lst.append(temp_lst2)

temp_df = pd.DataFrame(temp_lst, columns=['k', '# of Neighbors', 'Weights',␣
 ↪'KNR Train Score', 'KNR Test Score'])

temp_lst = []
for k in range(2, 9):
    for n_ in np.arange(2, 5):
        for w_ in weights:
            temp_lst2 = []
            temp_lst2.append(k)
            temp_lst2.append(n_)
            temp_lst2.append(w_)
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
 ↪(temp_df['# of Neighbors'] == n_) &
                                                   (temp_df['Weights'] ==␣
 ↪w_)]['KNR Train Score']), decimals=4))
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
 ↪(temp_df['# of Neighbors'] == n_) &
                                                   (temp_df['Weights'] ==␣
 ↪w_)]['KNR Test Score']), decimals=4))
            temp_lst.append(temp_lst2)

nn_reg_eval_df = pd.DataFrame(temp_lst, columns=['k', '# of Neighbors',␣
 ↪'Weights', 'KNR Train Score', 'KNR Test Score'])
nn_reg_eval_df
```

```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=7.0),␣
 ↪HTML(value='')))
```

[23]:

	k	# of Neighbors	Weights	KNR Train Score	KNR Test Score
0	2	2	uniform	0.65	0.43
1	2	2	distance	1.00	0.49
2	2	3	uniform	0.48	0.34
3	2	3	distance	1.00	0.51
4	2	4	uniform	0.15	-0.03
5	2	4	distance	1.00	0.47
6	3	2	uniform	0.73	0.29
7	3	2	distance	1.00	0.32

	k	# of Neighbors	Weights	KNR Train Score	KNR Test Score
8	3	3	uniform	0.48	0.02
9	3	3	distance	1.00	0.25
10	3	4	uniform	0.45	0.23
11	3	4	distance	1.00	0.34
12	4	2	uniform	0.73	-70.69
13	4	2	distance	1.00	-158.40
14	4	3	uniform	0.59	-69.88
15	4	3	distance	1.00	-142.79
16	4	4	uniform	0.46	-43.12
17	4	4	distance	1.00	-120.69
18	5	2	uniform	0.76	0.06
19	5	2	distance	1.00	0.22
20	5	3	uniform	0.63	-0.05
21	5	3	distance	1.00	0.25
22	5	4	uniform	0.53	-0.11
23	5	4	distance	1.00	0.22
24	6	2	uniform	0.76	-0.15
25	6	2	distance	1.00	-0.03
26	6	3	uniform	0.67	-0.12
27	6	3	distance	1.00	0.02
28	6	4	uniform	0.52	-0.21
29	6	4	distance	1.00	-0.00
30	7	2	uniform	0.77	-0.02
31	7	2	distance	1.00	0.21
32	7	3	uniform	0.68	0.26
33	7	3	distance	1.00	0.46
34	7	4	uniform	0.53	0.11
35	7	4	distance	1.00	0.42
36	8	2	uniform	0.78	0.67
37	8	2	distance	1.00	0.97
38	8	3	uniform	0.68	0.52
39	8	3	distance	1.00	0.92
40	8	4	uniform	0.53	0.26
41	8	4	distance	1.00	0.85

[24]:
```
nn_reg_eval_df.nlargest(3, 'KNR Test Score')
```

[24]:

	k	# of Neighbors	Weights	KNR Train Score	KNR Test Score
37	8	2	distance	1.00	0.97
39	8	3	distance	1.00	0.92
41	8	4	distance	1.00	0.85

[25]:
```
nn_reg_eval_df.nsmallest(3, 'KNR Test Score')
```

[25]:

	k	# of Neighbors	Weights	KNR Train Score	KNR Test Score
13	4	2	distance	1.00	-158.40
15	4	3	distance	1.00	-142.79

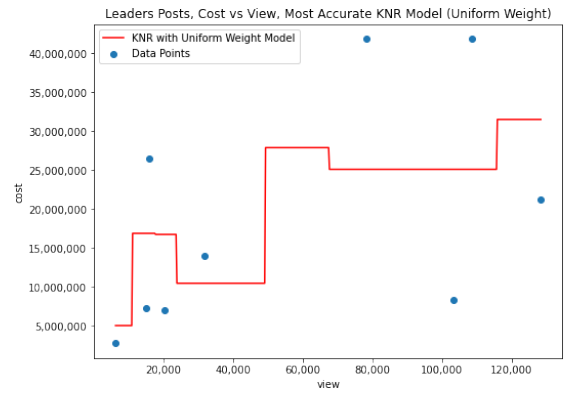
```
17  4              4  distance            1.00         -120.69
```

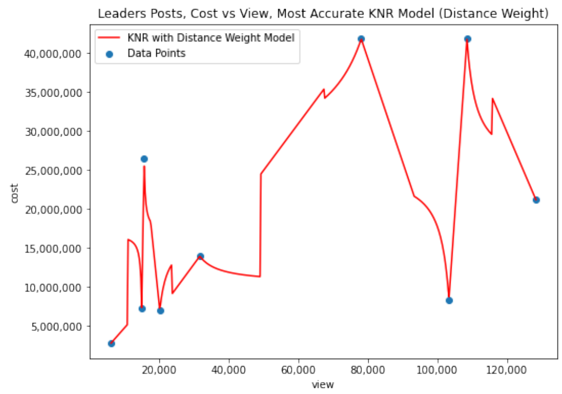
it seems like that the k-nearest regression is best perfroming algorithm for this dataset since it got 97% accuracy on test set.

[26]:
```
knr_uniform = KNeighborsRegressor(n_neighbors=2, weights='uniform')
knr_distance = KNeighborsRegressor(n_neighbors=2, weights='distance')
knr_uniform = knr_uniform.fit(leaders_post_x, leaders_post_y)
knr_distance = knr_distance.fit(leaders_post_x, leaders_post_y)
```

[27]:
```
fig = plt.figure(figsize=(18,6))
ax1 = fig.add_subplot(1,2,1)
ax2 = fig.add_subplot(1,2,2)

ax1.scatter(leaders_post_dummy['view'], leaders_post_dummy['cost'], label='Data␣
↪Points')
ax2.scatter(leaders_post_dummy['view'], leaders_post_dummy['cost'], label='Data␣
↪Points')
X_plot = np.linspace(leaders_post_dummy['view'].min(),␣
↪leaders_post_dummy['view'].max(), 500).reshape(-1, 1)
y_plot_uniform = knr_uniform.fit(leaders_post_x[:, 1].reshape(-1, 1),␣
↪leaders_post_y).predict(X_plot)
y_plot_distance = knr_distance.fit(leaders_post_x[:, 1].reshape(-1, 1),␣
↪leaders_post_y).predict(X_plot)
ax1.plot(X_plot, y_plot_uniform, '-r', label='KNR with Uniform Weight Model')
ax2.plot(X_plot, y_plot_distance, '-r', label='KNR with Distance Weight Model')
ax1.get_yaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
↪ format(int(x), ',')))
ax1.get_xaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
↪ format(int(x), ',')))
ax1.set_title(f'Leaders Posts, Cost vs View, Most Accurate KNR Model (Uniform␣
↪Weight)')
ax1.set_xlabel('view')
ax1.set_ylabel('cost')
ax1.legend()
ax2.get_yaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
↪ format(int(x), ',')))
ax2.get_xaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:
↪ format(int(x), ',')))
ax2.set_title(f'Leaders Posts, Cost vs View, Most Accurate KNR Model (Distance␣
↪Weight)')
ax2.set_xlabel('view')
ax2.set_ylabel('cost')
ax2.legend()
plt.show()
```





1.0.2 Decision Tree Regressor

Advertising Posts

[28]:
```
from sklearn.tree import DecisionTreeRegressor
```

[29]:
```
criterion = ['mse', 'friedman_mse', 'mae']
```

[30]:
```
temp_lst = []
for i in tqdm_notebook(range(2, 9)):
    kf = KFold(n_splits = i)
    for train_index, test_index in kf.split(ad_post_x):
        X_train, X_test = ad_post_x[train_index], ad_post_x[test_index]
        y_train, y_test = ad_post_y[train_index], ad_post_y[test_index]
        for c in criterion:
            dtr = DecisionTreeRegressor(criterion = c, max_features = 'auto')
            dtr.fit(X_train, y_train)
            temp_lst2 = []
            temp_lst2.append(i)
            temp_lst2.append(c)
            temp_lst2.append(dtr.score(X_train, y_train))
            temp_lst2.append(dtr.score(X_test, y_test))
            temp_lst.append(temp_lst2)

temp_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', 'DTR Train Score',␣
 ↪'DTR Test Score'])

temp_lst = []
for k in range(2, 9):
    for c_ in criterion:
        temp_lst2 = []
        temp_lst2.append(k)
        temp_lst2.append(c_)
```

```
        temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
↪(temp_df['Criterion'] == c_)]['DTR Train Score']), decimals=4))
        temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
↪(temp_df['Criterion'] == c_)]['DTR Test Score']), decimals=4))
        temp_lst.append(temp_lst2)

dt_reg_eval_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', 'DTR Train␣
↪Score', 'DTR Test Score'])
dt_reg_eval_df
```

```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=7.0),␣
↪HTML(value='')))
```

[30]:

	k	Criterion	DTR Train Score	DTR Test Score
0	2	mse	1.00	0.45
1	2	friedman_mse	1.00	0.40
2	2	mae	1.00	0.50
3	3	mse	1.00	0.46
4	3	friedman_mse	1.00	0.61
5	3	mae	1.00	0.51
6	4	mse	1.00	0.69
7	4	friedman_mse	1.00	0.66
8	4	mae	1.00	0.74
9	5	mse	1.00	0.53
10	5	friedman_mse	1.00	0.64
11	5	mae	1.00	0.72
12	6	mse	1.00	0.49
13	6	friedman_mse	1.00	0.49
14	6	mae	1.00	-0.51
15	7	mse	1.00	0.70
16	7	friedman_mse	1.00	0.67
17	7	mae	1.00	0.49
18	8	mse	1.00	0.31
19	8	friedman_mse	1.00	0.22
20	8	mae	1.00	-0.51

[31]:
```
dt_reg_eval_df.nlargest(3, 'DTR Test Score')
```

[31]:

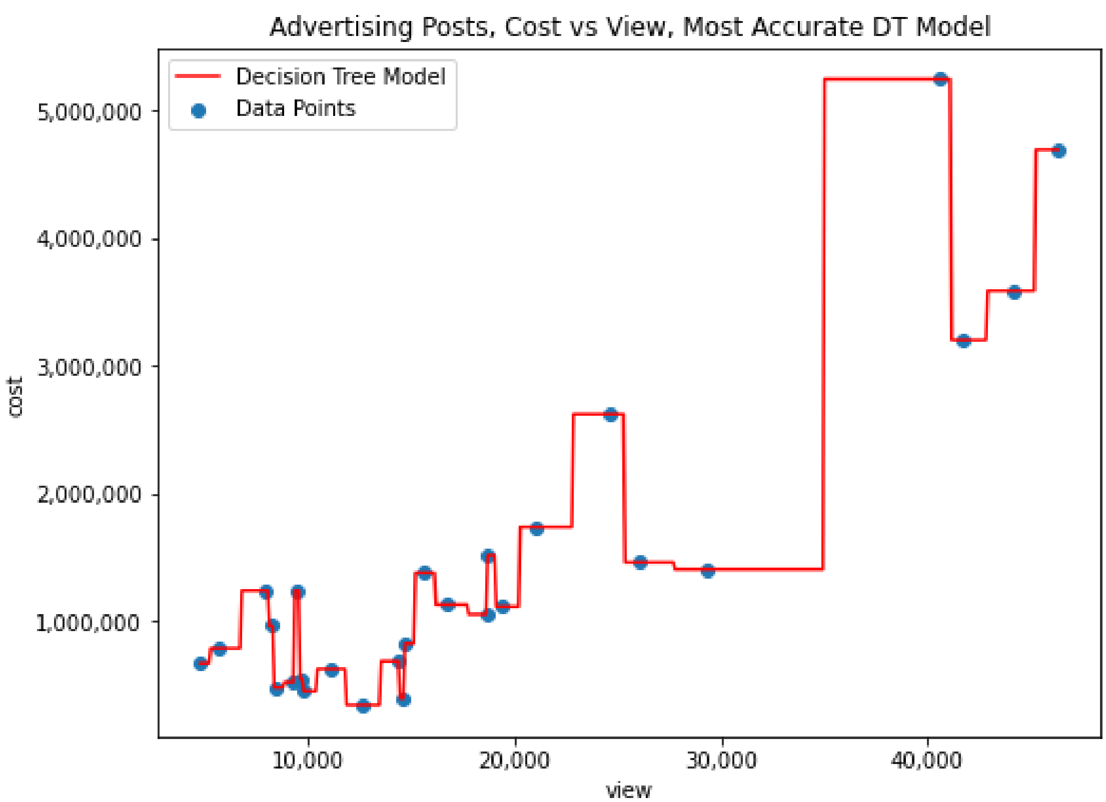
	k	Criterion	DTR Train Score	DTR Test Score
8	4	mae	1.00	0.74
11	5	mae	1.00	0.72
15	7	mse	1.00	0.70

[32]:
```
dtr = DecisionTreeRegressor(max_features='auto', criterion='mse')
```

[33]:

```
fig = plt.figure(figsize=(8,6))
ax = fig.add_subplot()

ax.scatter(ad_post_dummy['view'], ad_post_dummy['cost'], label='Data Points')
X_plot = np.linspace(ad_post_dummy['view'].min(), ad_post_dummy['view'].max(),␣
↪500).reshape(-1, 1)
y_plot = dtr.fit(ad_post_x[:, 1].reshape(-1, 1), ad_post_y).predict(X_plot)
ax.plot(X_plot, y_plot, '-r', label='Decision Tree Model')
ax.get_yaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:␣
↪format(int(x), ',')))
ax.get_xaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:␣
↪format(int(x), ',')))
ax.set_title(f'Advertising Posts, Cost vs View, Most Accurate DT Model')
ax.set_xlabel('view')
ax.set_ylabel('cost')
ax.legend()
plt.show()
```



Advertising Story

[34]:
```python
temp_lst = []
for i in tqdm_notebook(range(2, 9)):
    kf = KFold(n_splits = i)
    for train_index, test_index in kf.split(ad_story_x):
        X_train, X_test = ad_story_x[train_index], ad_story_x[test_index]
        y_train, y_test = ad_story_y[train_index], ad_story_y[test_index]
        for c in criterion:
            dtr = DecisionTreeRegressor(criterion = c, max_features = 'auto')
            dtr.fit(X_train, y_train)
            temp_lst2 = []
            temp_lst2.append(i)
            temp_lst2.append(c)
            temp_lst2.append(dtr.score(X_train, y_train))
            temp_lst2.append(dtr.score(X_test, y_test))
            temp_lst.append(temp_lst2)

temp_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', 'DTR Train Score',␣
 ↪'DTR Test Score'])

temp_lst = []
for k in range(2, 9):
    for c_ in criterion:
        temp_lst2 = []
        temp_lst2.append(k)
        temp_lst2.append(c_)
        temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
 ↪(temp_df['Criterion'] == c_)]['DTR Train Score']), decimals=4))
        temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
 ↪(temp_df['Criterion'] == c_)]['DTR Test Score']), decimals=4))
        temp_lst.append(temp_lst2)

dt_reg_eval_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', 'DTR Train␣
 ↪Score', 'DTR Test Score'])
dt_reg_eval_df
```

```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=7.0),␣
 ↪HTML(value='')))
```

[34]:

	k	Criterion	DTR Train Score	DTR Test Score
0	2	mse	1.00	0.67
1	2	friedman_mse	1.00	0.42
2	2	mae	1.00	0.69
3	3	mse	1.00	0.79
4	3	friedman_mse	1.00	0.78
5	3	mae	1.00	0.64
6	4	mse	1.00	0.70

```
7   4  friedman_mse             1.00            0.73
8   4           mae             1.00            0.75
9   5           mse             1.00            0.28
10  5  friedman_mse             1.00            0.42
11  5           mae             1.00            0.45
12  6           mse             1.00            0.21
13  6  friedman_mse             1.00            0.12
14  6           mae             1.00           -0.15
15  7           mse             1.00            0.34
16  7  friedman_mse             1.00            0.27
17  7           mae             1.00            0.34
18  8           mse             1.00           -0.72
19  8  friedman_mse             1.00            0.16
20  8           mae             1.00           -1.23
```

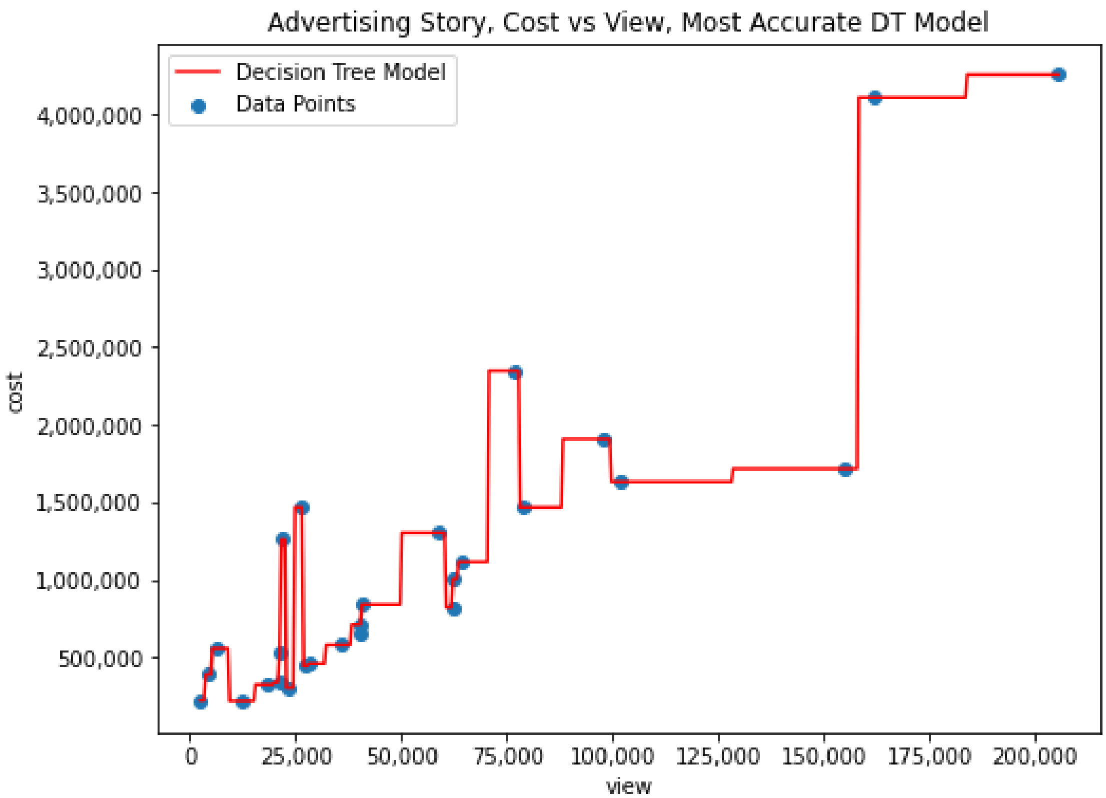
[35]:
```python
dt_reg_eval_df.nlargest(3, 'DTR Test Score')
```

[35]:
```
   k     Criterion  DTR Train Score  DTR Test Score
3  3           mse             1.00            0.79
4  3  friedman_mse             1.00            0.78
8  4           mae             1.00            0.75
```

[36]:
```python
dtr = DecisionTreeRegressor(max_features='auto', criterion='mae')
```

[37]:
```python
fig = plt.figure(figsize=(8,6))
ax = fig.add_subplot()

ax.scatter(ad_story_dummy['view'], ad_story_dummy['cost'], label='Data Points')
X_plot = np.linspace(ad_story_dummy['view'].min(), ad_story_dummy['view'].
 ↪max(), 500).reshape(-1, 1)
y_plot = dtr.fit(ad_story_x[:, 0].reshape(-1, 1), ad_story_y).predict(X_plot)
ax.plot(X_plot, y_plot, '-r', label='Decision Tree Model')
ax.get_yaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:␣
 ↪format(int(x), ',')))
ax.get_xaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:␣
 ↪format(int(x), ',')))
ax.set_title(f'Advertising Story, Cost vs View, Most Accurate DT Model')
ax.set_xlabel('view')
ax.set_ylabel('cost')
ax.legend()
plt.show()
```



Influencers

[38]:
```
temp_lst = []
for i in tqdm_notebook(range(2, 9)):
    kf = KFold(n_splits = i)
    for train_index, test_index in kf.split(influencer_x):
        X_train, X_test = influencer_x[train_index], influencer_x[test_index]
        y_train, y_test = influencer_y[train_index], influencer_y[test_index]
        for c in criterion:
            dtr = DecisionTreeRegressor(criterion = c, max_features = 'auto')
            dtr.fit(X_train, y_train)
            temp_lst2 = []
            temp_lst2.append(i)
            temp_lst2.append(c)
            temp_lst2.append(dtr.score(X_train, y_train))
            temp_lst2.append(dtr.score(X_test, y_test))
            temp_lst.append(temp_lst2)

temp_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', 'DTR Train Score',␣
↪'DTR Test Score'])

temp_lst = []
```

```
for k in range(2, 9):
    for c_ in criterion:
        temp_lst2 = []
        temp_lst2.append(k)
        temp_lst2.append(c_)
        temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
↪(temp_df['Criterion'] == c_)]['DTR Train Score']), decimals=4))
        temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
↪(temp_df['Criterion'] == c_)]['DTR Test Score']), decimals=4))
        temp_lst.append(temp_lst2)

dt_reg_eval_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', 'DTR Train␣
↪Score', 'DTR Test Score'])
dt_reg_eval_df
```

```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=7.0),␣
↪HTML(value='')))
```

[38]:

	k	Criterion	DTR Train Score	DTR Test Score
0	2	mse	1.00	0.28
1	2	friedman_mse	1.00	-0.11
2	2	mae	1.00	-0.64
3	3	mse	1.00	-0.61
4	3	friedman_mse	1.00	-0.60
5	3	mae	1.00	-0.52
6	4	mse	1.00	0.02
7	4	friedman_mse	1.00	-0.02
8	4	mae	1.00	-0.42
9	5	mse	1.00	-1.28
10	5	friedman_mse	1.00	-0.11
11	5	mae	1.00	-1.08
12	6	mse	1.00	-0.19
13	6	friedman_mse	1.00	-0.45
14	6	mae	1.00	0.21
15	7	mse	1.00	-4.76
16	7	friedman_mse	1.00	-4.65
17	7	mae	1.00	-2.68
18	8	mse	1.00	-0.87
19	8	friedman_mse	1.00	-0.07
20	8	mae	1.00	-1.06

[39]:

```
dt_reg_eval_df.nlargest(3, 'DTR Test Score')
```

[39]:

	k	Criterion	DTR Train Score	DTR Test Score
0	2	mse	1.00	0.28
14	6	mae	1.00	0.21

```
6   4        mse              1.00            0.02
```

as you can see in the table above, decision tree regressoris not a good fit for influencers dataset.

Leaders Post

[40]:
```
temp_lst = []
for i in tqdm_notebook(range(2, 9)):
    kf = KFold(n_splits = i)
    for train_index, test_index in kf.split(leaders_post_x):
        X_train, X_test = leaders_post_x[train_index],␣
↪leaders_post_x[test_index]
        y_train, y_test = leaders_post_y[train_index],␣
↪leaders_post_y[test_index]
        for c in criterion:
            dtr = DecisionTreeRegressor(criterion = c, max_features = 'auto')
            dtr.fit(X_train, y_train)
            temp_lst2 = []
            temp_lst2.append(i)
            temp_lst2.append(c)
            temp_lst2.append(dtr.score(X_train, y_train))
            temp_lst2.append(dtr.score(X_test, y_test))
            temp_lst.append(temp_lst2)

temp_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', 'DTR Train Score',␣
↪'DTR Test Score'])

temp_lst = []
for k in range(2, 9):
    for c_ in criterion:
        temp_lst2 = []
        temp_lst2.append(k)
        temp_lst2.append(c_)
        temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
↪(temp_df['Criterion'] == c_)]['DTR Train Score']), decimals=4))
        temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
↪(temp_df['Criterion'] == c_)]['DTR Test Score']), decimals=4))
        temp_lst.append(temp_lst2)

dt_reg_eval_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', 'DTR Train␣
↪Score', 'DTR Test Score'])
dt_reg_eval_df
```

```
HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=7.0),␣
↪HTML(value='')))
```

[40]:

	k	Criterion	DTR Train Score	DTR Test Score
0	2	mse	1.00	-0.15
1	2	friedman_mse	1.00	-0.60
2	2	mae	1.00	-0.34
3	3	mse	1.00	-0.12
4	3	friedman_mse	1.00	-0.39
5	3	mae	1.00	-0.45
6	4	mse	1.00	-162.24
7	4	friedman_mse	1.00	-162.30
8	4	mae	1.00	-162.28
9	5	mse	1.00	-4.64
10	5	friedman_mse	1.00	-0.42
11	5	mae	1.00	-4.31
12	6	mse	1.00	-6.27
13	6	friedman_mse	1.00	0.07
14	6	mae	1.00	-5.95
15	7	mse	1.00	-8.39
16	7	friedman_mse	1.00	-8.39
17	7	mae	1.00	0.49
18	8	mse	1.00	0.97
19	8	friedman_mse	1.00	1.00
20	8	mae	1.00	0.97

[41]:
```
dt_reg_eval_df.nlargest(3, 'DTR Test Score')
```

[41]:

	k	Criterion	DTR Train Score	DTR Test Score
19	8	friedman_mse	1.00	1.00
18	8	mse	1.00	0.97
20	8	mae	1.00	0.97

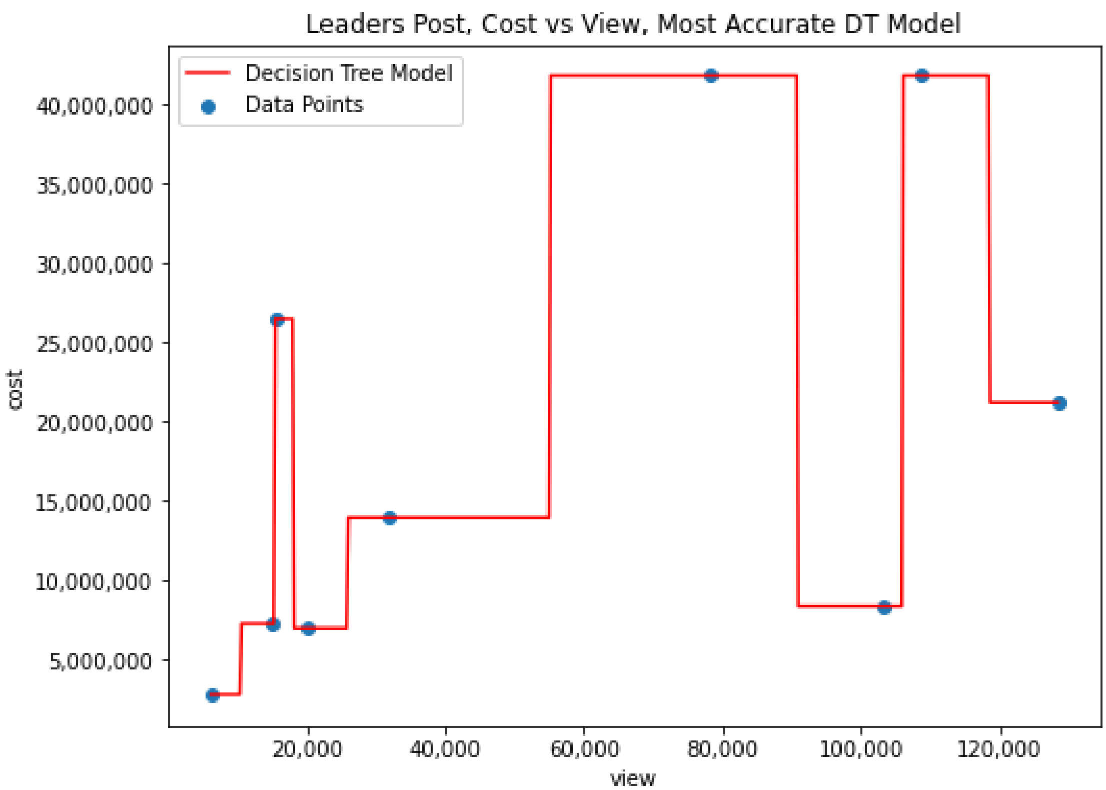
as you can see in the tables above, decision tree algorithm managed to achieve the perfect score on this dataset.

[42]:
```
dtr = DecisionTreeRegressor(max_features='auto', criterion='friedman_mse')
```

[43]:
```
fig = plt.figure(figsize=(8,6))
ax = fig.add_subplot()

ax.scatter(leaders_post_dummy['view'], leaders_post_dummy['cost'], label='Data␣
 ↪Points')
X_plot = np.linspace(leaders_post_dummy['view'].min(),␣
 ↪leaders_post_dummy['view'].max(), 500).reshape(-1, 1)
y_plot = dtr.fit(leaders_post_x[:, 1].reshape(-1, 1), leaders_post_y).
 ↪predict(X_plot)
ax.plot(X_plot, y_plot, '-r', label='Decision Tree Model')
ax.get_yaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:␣
 ↪format(int(x), ',')))
```

```
ax.get_xaxis().set_major_formatter(matplotlib.ticker.FuncFormatter(lambda x, p:␣
↪format(int(x), ',')))
ax.set_title(f'Leaders Post, Cost vs View, Most Accurate DT Model')
ax.set_xlabel('view')
ax.set_ylabel('cost')
ax.legend()
plt.show()
```



1.0.3 Random Forrest Regression

Advertising Posts

[44]:
```
from sklearn.ensemble import RandomForestRegressor
```

[45]:
```
criterion = ['mse', 'mae']
n_estimators = np.arange(10, 210, 10, dtype='int16')
```

[46]:
```
temp_lst = []
for i in tqdm(range(2, 9)):
    kf = KFold(n_splits = i)
    for train_index, test_index in kf.split(ad_post_x):
        X_train, X_test = ad_post_x[train_index], ad_post_x[test_index]
```

```
        y_train, y_test = ad_post_y[train_index], ad_post_y[test_index]
        for c in criterion:
            for n in n_estimators:
                rfr = RandomForestRegressor(criterion = c, n_estimators = n)
                rfr.fit(X_train, y_train)
                temp_lst2 = []
                temp_lst2.append(i)
                temp_lst2.append(c)
                temp_lst2.append(n)
                temp_lst2.append(rfr.score(X_train, y_train))
                temp_lst2.append(rfr.score(X_test, y_test))
                temp_lst.append(temp_lst2)

temp_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', '# of Trees', 'RFR␣
↪Train Score', 'RFR Test Score'])

temp_lst = []
for k in range(2, 9):
    for c_ in criterion:
        for n_ in n_estimators:
            temp_lst2 = []
            temp_lst2.append(k)
            temp_lst2.append(c_)
            temp_lst2.append(n_)
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
↪(temp_df['Criterion'] == c_) &
                                                      (temp_df['# of Trees'] ==␣
↪n_)]['RFR Train Score']), decimals=4))
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
↪(temp_df['Criterion'] == c_) &
                                                      (temp_df['# of Trees'] ==␣
↪n_)]['RFR Test Score']), decimals=4))
            temp_lst.append(temp_lst2)

rfr_reg_eval_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', '# of Trees␣
↪in Forest', 'RFR Train Score', 'RFR Test Score'])
rfr_reg_eval_df
```

```
100%|      | 7/7 [03:28<00:00, 29.74s/it]
```

[46]:

	k	Criterion	# of Trees in Forest	RFR Train Score	RFR Test Score
0	2	mse	10	0.96	0.77
1	2	mse	20	0.93	0.73
2	2	mse	30	0.91	0.74
3	2	mse	40	0.89	0.69
4	2	mse	50	0.92	0.76
..	..	…	…	…	…

```
275  8        mae                    160          0.98          0.54
276  8        mae                    170          0.98          0.60
277  8        mae                    180          0.98          0.58
278  8        mae                    190          0.98          0.63
279  8        mae                    200          0.98          0.60

[280 rows x 5 columns]
```

[47]:
```
rfr_reg_eval_df.nlargest(3, 'RFR Test Score')
```

[47]:
```
    k Criterion  # of Trees in Forest  RFR Train Score  RFR Test Score
86  4       mse                    70             0.97            0.83
63  3       mae                    40             0.97            0.82
65  3       mae                    60             0.97            0.82
```

Advertising Stories

[48]:
```
temp_lst = []
for i in tqdm(range(2, 9)):
    kf = KFold(n_splits = i)
    for train_index, test_index in kf.split(ad_story_x):
        X_train, X_test = ad_story_x[train_index], ad_story_x[test_index]
        y_train, y_test = ad_story_y[train_index], ad_story_y[test_index]
        for c in criterion:
            for n in n_estimators:
                rfr = RandomForestRegressor(criterion = c, n_estimators = n)
                rfr.fit(X_train, y_train)
                temp_lst2 = []
                temp_lst2.append(i)
                temp_lst2.append(c)
                temp_lst2.append(n)
                temp_lst2.append(rfr.score(X_train, y_train))
                temp_lst2.append(rfr.score(X_test, y_test))
                temp_lst.append(temp_lst2)

temp_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', '# of Trees', 'RFR␣
 ↪Train Score', 'RFR Test Score'])

temp_lst = []
for k in range(2, 9):
    for c_ in criterion:
        for n_ in n_estimators:
            temp_lst2 = []
            temp_lst2.append(k)
            temp_lst2.append(c_)
            temp_lst2.append(n_)
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
 ↪(temp_df['Criterion'] == c_) &
```

```
                                                            (temp_df['# of Trees'] ==␣
↪n_)]['RFR Train Score']), decimals=4))
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
↪(temp_df['Criterion'] == c_) &
                                                            (temp_df['# of Trees'] ==␣
↪n_)]['RFR Test Score']), decimals=4))
            temp_lst.append(temp_lst2)

rfr_reg_eval_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', '# of Trees␣
↪in Forest', 'RFR Train Score', 'RFR Test Score'])
rfr_reg_eval_df
```

100%| | 7/7 [03:28<00:00, 29.76s/it]

[48]:

	k	Criterion	# of Trees in Forest	RFR Train Score	RFR Test Score
0	2	mse	10	0.96	0.86
1	2	mse	20	0.96	0.79
2	2	mse	30	0.94	0.85
3	2	mse	40	0.94	0.82
4	2	mse	50	0.93	0.84
..	..	…	…	…	…
275	8	mae	160	0.97	0.51
276	8	mae	170	0.97	0.49
277	8	mae	180	0.97	0.48
278	8	mae	190	0.97	0.50
279	8	mae	200	0.97	0.47

[280 rows x 5 columns]

[49]:

```
rfr_reg_eval_df.nlargest(3, 'RFR Test Score')
```

[49]:

	k	Criterion	# of Trees in Forest	RFR Train Score	RFR Test Score
9	2	mse	100	0.95	0.88
29	2	mae	100	0.94	0.87
24	2	mae	50	0.94	0.87

Influencers

[50]:

```
temp_lst = []
for i in tqdm(range(2, 9)):
    kf = KFold(n_splits = i)
    for train_index, test_index in kf.split(influencer_x):
        X_train, X_test = influencer_x[train_index], influencer_x[test_index]
        y_train, y_test = influencer_y[train_index], influencer_y[test_index]
        for c in criterion:
            for n in n_estimators:
                rfr = RandomForestRegressor(criterion = c, n_estimators = n)
                rfr.fit(X_train, y_train)
```

```
                temp_lst2 = []
                temp_lst2.append(i)
                temp_lst2.append(c)
                temp_lst2.append(n)
                temp_lst2.append(rfr.score(X_train, y_train))
                temp_lst2.append(rfr.score(X_test, y_test))
                temp_lst.append(temp_lst2)

temp_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', '# of Trees', 'RFR␣
 ↪Train Score', 'RFR Test Score'])

temp_lst = []
for k in range(2, 9):
    for c_ in criterion:
        for n_ in n_estimators:
            temp_lst2 = []
            temp_lst2.append(k)
            temp_lst2.append(c_)
            temp_lst2.append(n_)
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
 ↪(temp_df['Criterion'] == c_) &
                                                      (temp_df['# of Trees'] ==␣
 ↪n_)]['RFR Train Score']), decimals=4))
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
 ↪(temp_df['Criterion'] == c_) &
                                                      (temp_df['# of Trees'] ==␣
 ↪n_)]['RFR Test Score']), decimals=4))
            temp_lst.append(temp_lst2)

rfr_reg_eval_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', '# of Trees␣
 ↪in Forest', 'RFR Train Score', 'RFR Test Score'])
rfr_reg_eval_df
```

```
100%|      | 7/7 [04:02<00:00, 34.58s/it]
```

[50]:

	k	Criterion	# of Trees in Forest	RFR Train Score	RFR Test Score
0	2	mse	10	0.99	-0.00
1	2	mse	20	1.00	-0.09
2	2	mse	30	1.00	-0.02
3	2	mse	40	1.00	-0.07
4	2	mse	50	1.00	-0.02
..	..	…	…	…	…
275	8	mae	160	1.00	-0.11
276	8	mae	170	1.00	-0.07
277	8	mae	180	1.00	-0.17
278	8	mae	190	1.00	-0.17
279	8	mae	200	1.00	-0.20

```
[280 rows x 5 columns]
```

[51]:
```
rfr_reg_eval_df.nlargest(3, 'RFR Test Score')
```

[51]:
```
    k Criterion  # of Trees in Forest  RFR Train Score  RFR Test Score
85  4       mse                    60             0.99            0.27
84  4       mse                    50             1.00            0.26
89  4       mse                   100             1.00            0.23
```

as it was obvious, since the tree-based algorithms didn't perform well on influencer dataset, random forest won't change this fact.

Leaders Post

[52]:
```
temp_lst = []
for i in tqdm(range(2, 9)):
    kf = KFold(n_splits = i)
    for train_index, test_index in kf.split(leaders_post_x):
        X_train, X_test = leaders_post_x[train_index],␣
 ↪leaders_post_x[test_index]
        y_train, y_test = leaders_post_y[train_index],␣
 ↪leaders_post_y[test_index]
        for c in criterion:
            for n in n_estimators:
                rfr = RandomForestRegressor(criterion = c, n_estimators = n)
                rfr.fit(X_train, y_train)
                temp_lst2 = []
                temp_lst2.append(i)
                temp_lst2.append(c)
                temp_lst2.append(n)
                temp_lst2.append(rfr.score(X_train, y_train))
                temp_lst2.append(rfr.score(X_test, y_test))
                temp_lst.append(temp_lst2)

temp_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', '# of Trees', 'RFR␣
 ↪Train Score', 'RFR Test Score'])

temp_lst = []
for k in range(2, 9):
    for c_ in criterion:
        for n_ in n_estimators:
            temp_lst2 = []
            temp_lst2.append(k)
            temp_lst2.append(c_)
            temp_lst2.append(n_)
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
 ↪(temp_df['Criterion'] == c_) &
```

```
                                                          (temp_df['# of Trees'] ==␣
↪n_)]['RFR Train Score']), decimals=4))
            temp_lst2.append(np.round(np.mean(temp_df[(temp_df['k'] == k) &␣
↪(temp_df['Criterion'] == c_) &
                                                          (temp_df['# of Trees'] ==␣
↪n_)]['RFR Test Score']), decimals=4))
            temp_lst.append(temp_lst2)

rfr_reg_eval_df = pd.DataFrame(temp_lst, columns=['k', 'Criterion', '# of Trees␣
↪in Forest', 'RFR Train Score', 'RFR Test Score'])
rfr_reg_eval_df
```

```
100%|      | 7/7 [03:04<00:00, 26.41s/it]
```

[52]:

	k	Criterion	# of Trees in Forest	RFR Train Score	RFR Test Score
0	2	mse	10	0.89	0.24
1	2	mse	20	0.72	0.10
2	2	mse	30	0.80	0.12
3	2	mse	40	0.78	0.21
4	2	mse	50	0.81	0.16
..	..	…	…	…	…
275	8	mae	160	0.88	0.74
276	8	mae	170	0.88	0.78
277	8	mae	180	0.87	0.84
278	8	mae	190	0.88	0.81
279	8	mae	200	0.88	0.75

[280 rows x 5 columns]

[53]:
```
rfr_reg_eval_df.nlargest(3, 'RFR Test Score')
```

[53]:

	k	Criterion	# of Trees in Forest	RFR Train Score	RFR Test Score
261	8	mae	20	0.84	0.88
268	8	mae	90	0.87	0.84
253	8	mse	140	0.87	0.84

1.1 Regression Algorithms Summary

in the table below you can see the performance summary of most accurate regression model which we tested and discussed in this notebook and previous one.

[54]:
```
data = {
    'Regression Algorithms': ['Linear', 'Polynomial', 'Ridge', 'Lasso',␣
↪'Support Vector Machine', 'k-Nearest', 'Decision Tree', 'Random Forest'],
    'Advertising Post - Train Score': [0.93, 0.86, 0.93, 0.93, 0.86, 0.88, 1, 0.
↪97],
```

```
    'Advertising Post - Test Score': [0.77, 0.70, 0.77, 0.80, 0.74, 0.44, 0.74,␣
↪0.83],
    'Advertising Story - Train Score': [1, 0.81, 1, 1, 0.97, 1, 1, 0.95],
    'Advertising Story - Test Score': [0.96, 0.71, 0.96, 0.96, 0.94, 0.44, 0.
↪79, 0.88],
    'Influencers - Train Score': [0.22, '-', 0.86, 0.86, 0.72, 1, 1, 0.99],
    'Influencers - Test Score': [0.25, '-', 0.43, 0.40, 0.65, 0.65, 0.28, 0.27],
    'Leaders Post - Train Score': ['-', 0.41, '-', '-', 0.80, 1, 1, 0.84],
    'Leaders Post - Test Score': ['-', 0.40, '-', '-', 0.16, 0.97, 1, 0.88]}
score_df = pd.DataFrame(data=data)
score_df
```

[54]:

```
     Regression Algorithms  Advertising Post - Train Score  \
0                   Linear                            0.93
1               Polynomial                            0.86
2                    Ridge                            0.93
3                    Lasso                            0.93
4   Support Vector Machine                            0.86
5                k-Nearest                            0.88
6            Decision Tree                            1.00
7            Random Forest                            0.97

   Advertising Post - Test Score  Advertising Story - Train Score  \
0                           0.77                             1.00
1                           0.70                             0.81
2                           0.77                             1.00
3                           0.80                             1.00
4                           0.74                             0.97
5                           0.44                             1.00
6                           0.74                             1.00
7                           0.83                             0.95

   Advertising Story - Test Score Influencers - Train Score  \
0                            0.96                      0.22
1                            0.71                         -
2                            0.96                      0.86
3                            0.96                      0.86
4                            0.94                      0.72
5                            0.44                         1
6                            0.79                         1
7                            0.88                      0.99

  Influencers - Test Score Leaders Post - Train Score  \
0                     0.25                          -
1                        -                       0.41
2                     0.43                          -
3                     0.40                          -
```

```
4                      0.65                           0.80
5                      0.65                              1
6                      0.28                              1
7                      0.27                           0.84

  Leaders Post - Test Score
0                          -
1                       0.40
2                          -
3                          -
4                       0.16
5                       0.97
6                          1
7                       0.88
```

lowest accuracy for datasets is for influencers dataset, in more technical wording, the variance of these models are higher than normal and thus, in orderto fix that, we are in need of more data. without additional data this accuracy couldn't be increased significantly. on other data sets we managed to achieve high score and accuracy.

---

2 Notebook by Ramin F. - @simplyramin

[ ]:

```
```