```
In [1]: %matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
pd.set_option('precision', 4)
np.set_printoptions(precision=3)

import warnings
warnings.filterwarnings('ignore')
plt.style.use('seaborn-paper')
```

목차

1. Read the dataset (after extracting)
2. Preprocessing
3. EDA
4. Modeling
5. Evaluation

Read the dataset

- 데이터셋: 유저별(iduser) 문서 사용행동에 대한 횟수와 그룹 특성(group)를 처리한 데이터
    - 3개의 테이블 소스에서 Raw 데이터를 가공: `groupby("iduesr").agg(count,,,sum,,,etc)` 이후에 조인함
    - 결제 타이밍 기준(유저마다 다름)으로 이전 30일의 행동 기준으로 데이터 추출
- 간혹 csv를 불러올 때 unnamed 라는 컬럼이 자동으로 생성되므로, index_col=0 이라는 명령어를 통해 처리

```
In [2]: df = pd.read_csv("testset.csv", index_col=0)
```

```
In [3]: df.head()
```

Out[3]:

	iduser	mdutype	group	viewCount	editCount	shareCount	searchCount	cc
0	10100018739106	NaN	sdu	12.0	0.0	0.0	0.0	0.(
1	10100037810674	NaN	sdu	23.0	0.0	0.0	1.0	0.(
2	10100036273719	NaN	sdu	4.0	0.0	0.0	0.0	0.(
3	10100027752244	NaN	sdu	6.0	0.0	1.0	0.0	0.(
4	10100000624840	NaN	sdu	NaN	NaN	NaN	NaN	Na

5 rows × 22 columns

In [4]:
```
df.tail()
```

Out[4]:

	iduser	mdutype	group	viewCount	editCount	shareCount	searchCou
199995	10100014533282	NaN	sdu	37.0	0.0	2.0	0.0
199996	10100037382422	a2p	mdu	6.0	0.0	0.0	6.0
199997	10100024157271	NaN	sdu	32.0	0.0	0.0	0.0
199998	10100022150627	NaN	sdu	18.0	0.0	0.0	0.0
199999	10100021804275	NaN	sdu	3.0	0.0	0.0	0.0

5 rows × 22 columns

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 200000 entries, 0 to 199999
Data columns (total 22 columns):
iduser           200000 non-null int64
mdutype          9328 non-null object
group            200000 non-null object
viewCount        165369 non-null float64
editCount        165369 non-null float64
shareCount       165369 non-null float64
searchCount      165369 non-null float64
coworkCount      165369 non-null float64
add              63166 non-null float64
del              63166 non-null float64
move             63166 non-null float64
rename           63166 non-null float64
adddir           63166 non-null float64
movedir          63166 non-null float64
visdays          184306 non-null float64
openCount        149090 non-null float64
saveCount        149090 non-null float64
exportCount      149090 non-null float64
viewTraffic      149090 non-null float64
editTraffic      149090 non-null float64
exportTraffic    149090 non-null float64
traffic          149090 non-null float64
dtypes: float64(19), int64(1), object(2)
memory usage: 35.1+ MB
```

In [6]:
```
df.shape
```

Out[6]: (200000, 22)

Column Info.

- ★iduser: 식별값
- mdutype: 중요x
- ★★group: y, 결제(mdu) vs 비결제(sdu) 정보
- ★viewCount: 보기 횟수
- ★editCount: 편집 횟수
- ★shareCount: 공유 횟수
- ★searchCount: 검색 횟수
- ★coworkCount: 공동작업 횟수
- add: 파일 추가 횟수
- del: 파일 삭제 횟수
- move: 파일 이동 횟수
- rename: 파일명 변경 횟수
- adddir: 폴더 생성
- movedir: 폴더 이동
- ★★visdays: 방문일수
- ★openCount: 열기 횟수
- ★saveCount: 저장 횟수
- ★exportCount: 내보내기 횟수
- viewTraffic: 보기 용량(파일 사이즈)
- editTraffic: 편집 용량
- exportTraffic: 내보내기 용량
- traffic: 전체 용량

Pandas DF index 지정

- 유저ID와 같은 유니크 값(primary key)를 인덱스로 지정하는 것이 편리함 (pandas 장점)
- 그렇지 않으면, 추후 scaling 이나 모델 학습 등을 할때 매번 슬라이싱으로 처리해야함

In [7]:
```
df.set_index("iduser", inplace=True)
```

In [8]:
```
df.head()
```

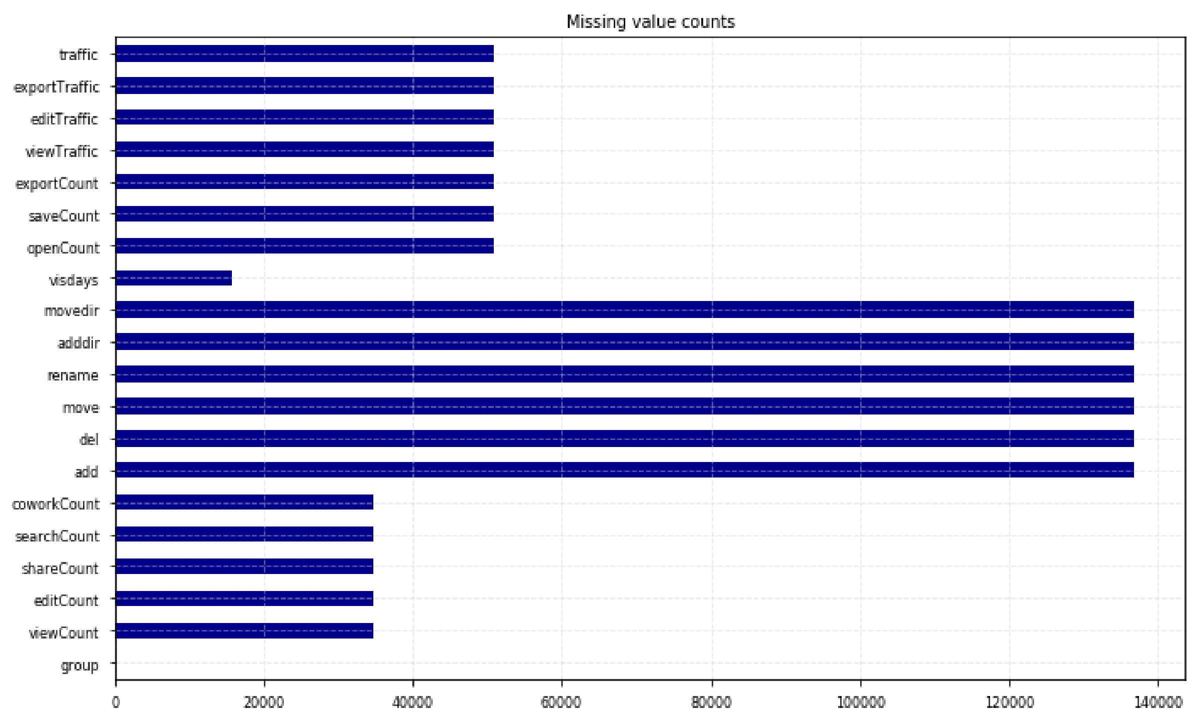
Out[8]:

	mdutype	group	viewCount	editCount	shareCount	searchCount	cow
iduser							
10100018739106	NaN	sdu	12.0	0.0	0.0	0.0	0.0
10100037810674	NaN	sdu	23.0	0.0	0.0	1.0	0.0
10100036273719	NaN	sdu	4.0	0.0	0.0	0.0	0.0
10100027752244	NaN	sdu	6.0	0.0	1.0	0.0	0.0
10100000624840	NaN	sdu	NaN	NaN	NaN	NaN	NaN

5 rows × 21 columns

In [9]:
```
df.drop("mdutype", axis=1, inplace=True)
```

In [10]:
```
# check missing values in each cols
df.isnull().sum().plot(kind='barh', color='darkblue', figsize=(10,6))

plt.title("Missing value counts")
plt.grid(color='lightgrey', alpha=0.5, linestyle='--')
plt.tight_layout()
```



결측치 처리

- 추후에는 협의를 통해 결측치 발새 이유 파악 및 예방에 노력을 기울이는 것이 필요
- 결측치 처리 방법
  - 가장 쉬운 방법은 Null이 포함 행을 모두 제거하는 것이다
  - 사례(observation)이 많다면 이 방법을 사용하는 것이 가능하다
  - 평균, 중앙치, 최빈치, 간단한 예측 모델활용해서 imputation
  - 만약 샘플수가 충분하지 않을 경우, Pandas의 fillna() 명령어로 Null 값을 채우는 것이 가능하다.
  - 연속형인 경우 Mean이나 Median을 이용하고 명목형인 경우 Mode(최빈치)나 classification 모델을 통해 Null 값을 대체할 수 있다.

```
# Null 값을 median, mean으로 대체하는 코드 예제
df.fillna(df.med())
df.fillna(df.mean())

# Scikit-learn Imputation을 이용하여 명목변수의 Null 값을 Mode로 대체한 예제
from sklearn.preprocessing import Imputer
imp = Imputer(missing_values = 'NaN', strategy='most_frequent', axis=0)
df['X'] = imp.fit_transform(df['X'])

# 참고: http://scikit-learn.org/stable/modules/generated/sklearn.preprocessin
g.Imputer.html
```

In [11]:
```
# 우선 group 컬럼이 null 경우만 선택
df[df['group'].isnull() == True].head(10)
```

Out[11]:

	group	viewCount	editCount	shareCount	searchCount	coworkCount	add	del
iduser								

In [12]:
```python
# visdays 컬럼이 null 경우만 선택
df[df['visdays'].isnull() == True].head(10)
```

Out[12]:

	group	viewCount	editCount	shareCount	searchCount	coworkCount
iduser						
10100022918449	sdu	NaN	NaN	NaN	NaN	NaN
10100009612042	sdu	NaN	NaN	NaN	NaN	NaN
10100017397956	sdu	NaN	NaN	NaN	NaN	NaN
10100030949780	sdu	NaN	NaN	NaN	NaN	NaN
10100021285047	sdu	2.0	0.0	0.0	0.0	0.0
10100025107423	sdu	NaN	NaN	NaN	NaN	NaN
10100038550949	sdu	2.0	0.0	0.0	0.0	0.0
10100013191329	sdu	NaN	NaN	NaN	NaN	NaN
10100038688226	sdu	NaN	NaN	NaN	NaN	NaN
10100014174432	sdu	NaN	NaN	NaN	NaN	NaN

In [13]:
```python
# 특정 열을 기준으로 dropna
df1 = df.dropna(subset=['visdays'])
```

In [14]:
```python
df1.head(10)
```

Out[14]:

	group	viewCount	editCount	shareCount	searchCount	coworkCount
iduser						
10100018739106	sdu	12.0	0.0	0.0	0.0	0.0
10100037810674	sdu	23.0	0.0	0.0	1.0	0.0
10100036273719	sdu	4.0	0.0	0.0	0.0	0.0
10100027752244	sdu	6.0	0.0	1.0	0.0	0.0
10100000624840	sdu	NaN	NaN	NaN	NaN	NaN
10100006151000	sdu	33.0	0.0	0.0	0.0	0.0
10100036301327	sdu	25.0	0.0	0.0	0.0	0.0
10100038731798	sdu	NaN	NaN	NaN	NaN	NaN
10100039037854	sdu	4.0	0.0	0.0	4.0	0.0
10100038701419	mdu	27.0	34.0	0.0	2.0	0.0

In [15]:
```
df1.isnull().sum()
```

Out[15]:
```
group                0
viewCount        22534
editCount        22534
shareCount       22534
searchCount      22534
coworkCount      22534
add             121225
del             121225
move            121225
rename          121225
adddir          121225
movedir         121225
visdays              0
openCount        38403
saveCount        38403
exportCount      38403
viewTraffic      38403
editTraffic      38403
exportTraffic    38403
traffic          38403
dtype: int64
```

Q) visiday, group 을 제외한 나머지 항목이 nan이면 drop 해볼까요?

In [16]:
```
# subset 용 컬럼 설정
mycols = df1.columns[1:].drop('visdays')

# mycols 컬럼들을 기준으로 drop
df2 = df1.dropna(subset=mycols, how='all')
```

In [17]:
```
df2.head(10)
```

Out[17]:

	group	viewCount	editCount	shareCount	searchCount	coworkCount
iduser						
10100018739106	sdu	12.0	0.0	0.0	0.0	0.0
10100037810674	sdu	23.0	0.0	0.0	1.0	0.0
10100036273719	sdu	4.0	0.0	0.0	0.0	0.0
10100027752244	sdu	6.0	0.0	1.0	0.0	0.0
10100006151000	sdu	33.0	0.0	0.0	0.0	0.0
10100036301327	sdu	25.0	0.0	0.0	0.0	0.0
10100039037854	sdu	4.0	0.0	0.0	4.0	0.0
10100038701419	mdu	27.0	34.0	0.0	2.0	0.0
10100034746743	sdu	5.0	0.0	0.0	0.0	0.0
10100016781863	sdu	18.0	0.0	0.0	0.0	0.0

In [18]:
```
df2.isnull().sum()
```

Out[18]:
```
group                0
viewCount         1580
editCount         1580
shareCount        1580
searchCount       1580
coworkCount       1580
add             100271
del             100271
move            100271
rename          100271
adddir          100271
movedir         100271
visdays              0
openCount        17449
saveCount        17449
exportCount      17449
viewTraffic      17449
editTraffic      17449
exportTraffic    17449
traffic          17449
dtype: int64
```

In [19]:
```
df2[df2['viewCount'].isnull() == True][:10]
```

Out[19]:

	group	viewCount	editCount	shareCount	searchCount	coworkCount
iduser						
10100028912459	sdu	NaN	NaN	NaN	NaN	NaN
10100022395852	sdu	NaN	NaN	NaN	NaN	NaN
10100024336048	sdu	NaN	NaN	NaN	NaN	NaN
10100031442724	sdu	NaN	NaN	NaN	NaN	NaN
10100025492049	sdu	NaN	NaN	NaN	NaN	NaN
10100011427498	sdu	NaN	NaN	NaN	NaN	NaN
10100034928127	sdu	NaN	NaN	NaN	NaN	NaN
10100031389762	sdu	NaN	NaN	NaN	NaN	NaN
10100008244902	sdu	NaN	NaN	NaN	NaN	NaN
10100019342545	sdu	NaN	NaN	NaN	NaN	NaN

In [20]:
```
df2[df2['add'].isnull() == True][:10]
```

Out[20]:

	group	viewCount	editCount	shareCount	searchCount	coworkCount
iduser						
10100018739106	sdu	12.0	0.0	0.0	0.0	0.0
10100036273719	sdu	4.0	0.0	0.0	0.0	0.0
10100027752244	sdu	6.0	0.0	1.0	0.0	0.0
10100039037854	sdu	4.0	0.0	0.0	4.0	0.0
10100038701419	mdu	27.0	34.0	0.0	2.0	0.0
10100034746743	sdu	5.0	0.0	0.0	0.0	0.0
10100023986518	sdu	3.0	0.0	0.0	0.0	0.0
10100006498305	sdu	3.0	0.0	0.0	0.0	0.0
10100038316936	mdu	13.0	0.0	0.0	0.0	0.0
10100017870216	sdu	11.0	0.0	1.0	0.0	0.0

In [21]:
```
df2[df2['openCount'].isnull() == True][:10]
```

Out[21]:

	group	viewCount	editCount	shareCount	searchCount	coworkCount
iduser						
10100026531335	sdu	18.0	0.0	0.0	0.0	0.0
10100036725270	sdu	50.0	0.0	0.0	0.0	0.0
10100019287454	sdu	9.0	0.0	0.0	0.0	0.0
10100029507725	sdu	39.0	0.0	0.0	0.0	0.0
10100012973812	sdu	10.0	0.0	0.0	0.0	0.0
10100034324468	sdu	40.0	13.0	1.0	0.0	0.0
10100036076757	sdu	11.0	0.0	0.0	0.0	0.0
10100032604810	sdu	12.0	9.0	0.0	1.0	0.0
10100027655619	sdu	13.0	0.0	0.0	0.0	0.0
10100031368883	sdu	109.0	0.0	0.0	0.0	0.0

In [22]:
```
df2[df2['traffic'].isnull() == True][:10]
```

Out[22]:

	group	viewCount	editCount	shareCount	searchCount	coworkCount
iduser						
10100026531335	sdu	18.0	0.0	0.0	0.0	0.0
10100036725270	sdu	50.0	0.0	0.0	0.0	0.0
10100019287454	sdu	9.0	0.0	0.0	0.0	0.0
10100029507725	sdu	39.0	0.0	0.0	0.0	0.0
10100012973812	sdu	10.0	0.0	0.0	0.0	0.0
10100034324468	sdu	40.0	13.0	1.0	0.0	0.0
10100036076757	sdu	11.0	0.0	0.0	0.0	0.0
10100032604810	sdu	12.0	9.0	0.0	1.0	0.0
10100027655619	sdu	13.0	0.0	0.0	0.0	0.0
10100031368883	sdu	109.0	0.0	0.0	0.0	0.0

add, del ~ movedir 까지는 파일 management 관련 변수이므로 상대적 중요도 낮음

- 변수 삭제를 고려해볼 수 있으나 우선 pass
- 우선 메꾸고 추후 제거도 고려 가능

In [23]:
```
# zero로 imputaion
df2 = df2.fillna(0)
```

In [24]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 163352 entries, 10100018739106 to 10100021804275
Data columns (total 20 columns):
group             163352 non-null object
viewCount         163352 non-null float64
editCount         163352 non-null float64
shareCount        163352 non-null float64
searchCount       163352 non-null float64
coworkCount       163352 non-null float64
add               163352 non-null float64
del               163352 non-null float64
move              163352 non-null float64
rename            163352 non-null float64
adddir            163352 non-null float64
movedir           163352 non-null float64
visdays           163352 non-null float64
openCount         163352 non-null float64
saveCount         163352 non-null float64
exportCount       163352 non-null float64
viewTraffic       163352 non-null float64
editTraffic       163352 non-null float64
exportTraffic     163352 non-null float64
traffic           163352 non-null float64
dtypes: float64(19), object(1)
memory usage: 26.2+ MB
```

In [25]:
```
df2.head()
```

Out[25]:

	group	viewCount	editCount	shareCount	searchCount	coworkCount
iduser						
10100018739106	sdu	12.0	0.0	0.0	0.0	0.0
10100037810674	sdu	23.0	0.0	0.0	1.0	0.0
10100036273719	sdu	4.0	0.0	0.0	0.0	0.0
10100027752244	sdu	6.0	0.0	1.0	0.0	0.0
10100006151000	sdu	33.0	0.0	0.0	0.0	0.0

In [26]:
```python
# 간략한 기술 통계 확인
df2.describe()
```

Out[26]:

	viewCount	editCount	shareCount	searchCount	coworkCount	add
count	163352.0000	163352.0000	163352.0000	163352.0000	163352.0000	163352.0000
mean	24.7940	1.5904	0.0760	1.0210	0.0031	12.1678
std	36.9357	19.7058	0.5361	8.9742	0.2834	109.6293
min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
25%	6.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50%	14.0000	0.0000	0.0000	0.0000	0.0000	0.0000
75%	30.0000	0.0000	0.0000	0.0000	0.0000	15.0000
max	3005.0000	5267.0000	78.0000	893.0000	63.0000	17755.0000

Missing Value 처리 가이드

- Missing Value 파악을 위해 `df.info()` 가장 처음에 이용
- 만약 np.nan으로 적절히 missing value로 불러왔다면 info() 이용 가능하지만,
- '', ' ' 이런식의 공백이나 다른 방식(.)으로 처리되어 있다면, 모두 repalce 처리해야함
- `df.info()`를 실행했을 때, 누가봐도 float or int 인데 object(string)으로 되어 있다면 이런 사례가 포함될 가능성 높음

In [27]:
```python
# 가짜 dataframe 생성
tt = df2[['group', 'viewCount']]

tt.head()
```

Out[27]:

	group	viewCount
iduser		
10100018739106	sdu	12.0
10100037810674	sdu	23.0
10100036273719	sdu	4.0
10100027752244	sdu	6.0
10100006151000	sdu	33.0

In [28]:
```
tt.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 163352 entries, 10100018739106 to 10100021804275
Data columns (total 2 columns):
group        163352 non-null object
viewCount    163352 non-null float64
dtypes: float64(1), object(1)
memory usage: 3.7+ MB
```

In [29]:
```
# np.nan 대신 ''로 수집된 경우
tt.loc[10100037810674,'viewCount'] = ''
tt.loc[10100036273719,'viewCount'] = ''

# np.nan 대신 '.'로 수집된 경우
tt.loc[10100034746743,'group'] = '. '
tt.loc[10100016781863,'group'] = '. '

# if missing is zero.......?
```

In [30]:
```
tt.head(10)
```

Out[30]:

	group	viewCount
iduser		
10100018739106	sdu	12
10100037810674	sdu	
10100036273719	sdu	
10100027752244	sdu	6
10100006151000	sdu	33
10100036301327	sdu	25
10100039037854	sdu	4
10100038701419	mdu	27
10100034746743	.	5
10100016781863	.	18

In [31]:
```
tt.info() # if continous var such as viewcount is object object?
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 163352 entries, 10100018739106 to 10100021804275
Data columns (total 2 columns):
group        163352 non-null object
viewCount    163352 non-null object
dtypes: object(2)
memory usage: 8.7+ MB
```

In [32]:
```
# 만약 큰 데이터셋에서는 찾는 경우는 정렬을 이용
tt.sort_values("viewCount", ascending=False).head(10)
```

Out[32]:

	group	viewCount
iduser		
10100036273719	sdu	
10100037810674	sdu	
10100004393355	sdu	3005
10100028865215	sdu	2373
10100001015133	sdu	1643
10100018982273	sdu	1578
10100036794381	sdu	1325
10100038699275	sdu	1178
10100038295824	mdu	1117
10100036549182	sdu	1101

In [33]:
```
tt.query("viewCount == ''")
```

Out[33]:

	group	viewCount
iduser		
10100037810674	sdu	
10100036273719	sdu	

In [34]:
```python
tt.sort_values("group", ascending=True).head(10)
```

Out[34]:

	group	viewCount
iduser		
10100034746743	.	5
10100016781863	.	18
10100038554737	mdu	6
10100036899070	mdu	3
10100032736965	mdu	123
10100021842114	mdu	6
10100037737310	mdu	74
10100010236643	mdu	20
10100023425393	mdu	46
10100016433902	mdu	36

In [35]:
```python
tt.query("group == '.'")
```

Out[35]:

	group	viewCount
iduser		

In [36]:
```python
# 공백 제거
tt['group'] = tt['group'].str.strip()
```

In [37]:
```python
tt.query("group == '.'")
```

Out[37]:

	group	viewCount
iduser		
10100034746743	.	5
10100016781863	.	18

In [38]:
```python
# 만약 변수에 공백이 있을 경우
tt.columns = ['group ', ' viewCount']
```

In [39]:
```python
tt.head()
```

Out[39]:

	group	viewCount
iduser		
10100018739106	sdu	12
10100037810674	sdu	
10100036273719	sdu	
10100027752244	sdu	6
10100006151000	sdu	33

In [40]:
```python
# strip 함수 이용
tt.columns = tt.columns.str.strip()
```

In [41]:
```python
# if no float, replace with np.nan
for i in tt.index:
    if type(tt.loc[i, 'viewCount']) == float:
        tt.loc[i, 'viewCount'] == tt.loc[i, 'viewCount']
    else:
        tt.loc[i, 'viewCount'] = np.nan
```

In [42]:
```python
tt.head()
```

Out[42]:

	group	viewCount
iduser		
10100018739106	sdu	12
10100037810674	sdu	NaN
10100036273719	sdu	NaN
10100027752244	sdu	6
10100006151000	sdu	33

In [43]:
```python
# replace 이용 방식 (단 에러 값을 정확히 알고 있어야 함)
tt['group'] = tt['group'].replace('.', np.nan)
```

In [44]:
```
tt.head(10)
```

Out[44]:

	group	viewCount
iduser		
10100018739106	sdu	12
10100037810674	sdu	NaN
10100036273719	sdu	NaN
10100027752244	sdu	6
10100006151000	sdu	33
10100036301327	sdu	25
10100039037854	sdu	4
10100038701419	mdu	27
10100034746743	NaN	5
10100016781863	NaN	18

In [45]:
```
tt.isnull().sum()
```

Out[45]:
```
group        2
viewCount    2
dtype: int64
```

In [46]:
```
# fill null with mean
tt['viewCount'] = tt['viewCount'].fillna(tt.viewCount.mean())

# fill null with mode
tt['group'] = tt['group'].fillna(tt.group.value_counts().index[0])
```

In [47]:
```
tt.head(10)
```

Out[47]:

	group	viewCount
iduser		
10100018739106	sdu	12.0000
10100037810674	sdu	24.7942
10100036273719	sdu	24.7942
10100027752244	sdu	6.0000
10100006151000	sdu	33.0000
10100036301327	sdu	25.0000
10100039037854	sdu	4.0000
10100038701419	mdu	27.0000
10100034746743	sdu	5.0000
10100016781863	sdu	18.0000

결측치를 처리할 때 고려할 점

- 결측치를 처리할 경우에도 도메인 지식은 유용하게 사용된다.
- 인적, 기계적 원인임이 판명되면, 협업자와 지속적으로 노력해 결측치를 **사전에 발생하지 않도록 조치**하는 것이 좋다
- 수치형인 경우 의미상으로 0으로 메꾸는 것이 맞는지 아니면 평균이나 중앙치, 최빈치가 맞는지 정확히 판단해야 한다.
  - 예를 들어 viewCount가 1이상인데, edit, export가 missing인 경우 (도메인 지식을 통해) 0으로 메꾸는 것이 가능하다.
  - 왜냐하면, ViewCount가 다른 행동에 선행하는 개념이기 때문에 위와 같은 의사결정이 가능하다
- 특히 **숫자 0과 null 과 같은 결측치는 완전히 다른 개념**이니 유의해야 한다.
  - 0: -1과 1 사이의 가운데 값(숫자)임. '제로'라는 의미를 지니고 있음.
  - null or nan: 미지의 값 (모름)
- 만약 y label(위 샘플 데이터에서는 'group')에 결측치가 있다면 그냥 drop\
- pandas 결측치 관련 API: https://pandas.pydata.org/pandas-docs/stable/missing_data.html (https://pandas.pydata.org/pandas-docs/stable/missing_data.html)
- 참고 블로그: https://machinelearningmastery.com/handle-missing-data-python/ (https://machinelearningmastery.com/handle-missing-data-python/)

이상치(Outlier) 처리 방법

0. 이상치란?

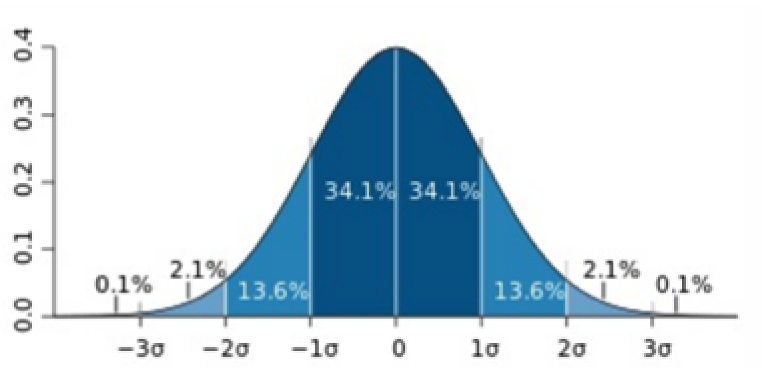
> In statistics, an outlier is a data point that differs greatly from other values in a data set. Outliers are important to keep in mind when looking at pools of data because they can sometimes affect how the data is perceived on the whole.

1. 표준편차(standard deviation) 이용

- 현재 분포에서 표준편차 기준 +3 이상이거나 -3 이하인 경우 극단치로 처리
- 정규분포일 경우 유용

2. 표준점수(z-score) 이용

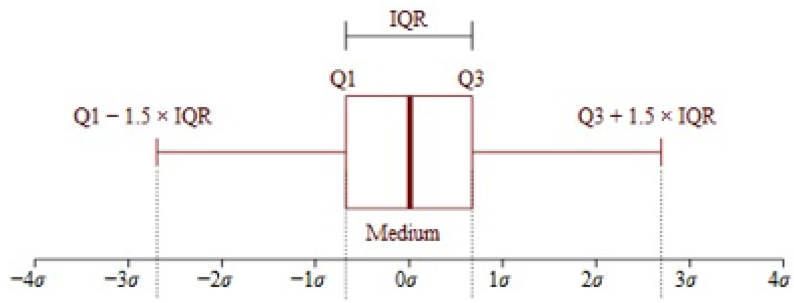
- 평균을 0, 표준편차를 1로 맞춘후 표준편차 이용 (+-3 벗어난 경우 이상치로 판정)
- 정규분포일 경우 유용



Source: Wikipedia

3. IQR 방식

- 75 percentile + IQR *1.5 이상이거나 25 percentile + IQR* 1.5 이하인 경우 극단치로 처리
- 정규분포 아닐 경우 robust한 편



In [48]:
```
# 이상치 처리 대상 데이터 (NA 제거한 dataframe)
df2.head()
```

Out[48]:

	group	viewCount	editCount	shareCount	searchCount	coworkCount
iduser						
10100018739106	sdu	12.0	0.0	0.0	0.0	0.0
10100037810674	sdu	23.0	0.0	0.0	1.0	0.0
10100036273719	sdu	4.0	0.0	0.0	0.0	0.0
10100027752244	sdu	6.0	0.0	1.0	0.0	0.0
10100006151000	sdu	33.0	0.0	0.0	0.0	0.0

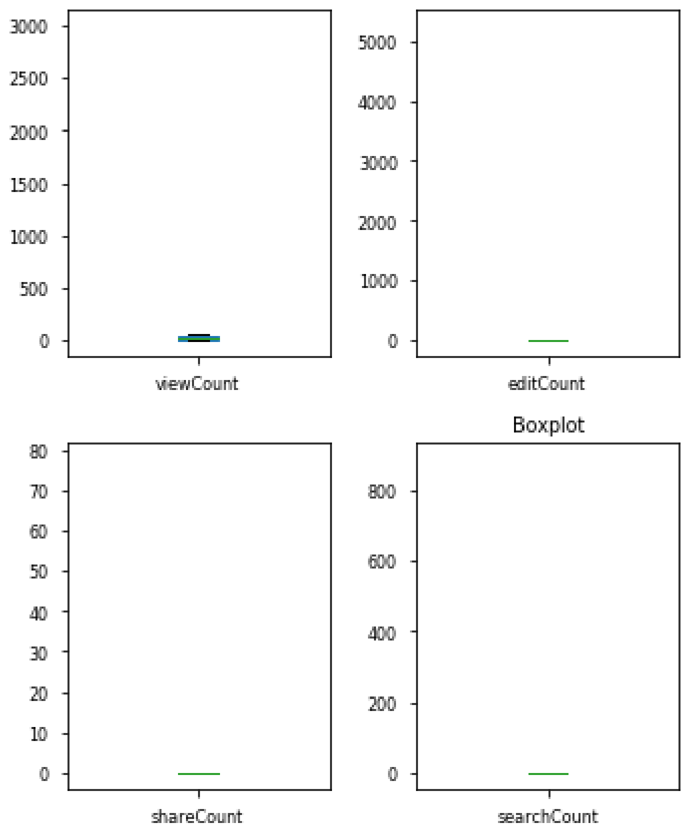
In [49]:
```
# 숫자형 변수만 선택
# df3 = df2.drop("group", axis=1)
df3 = df2._get_numeric_data()
```

In [50]:
```
df3.describe()
```

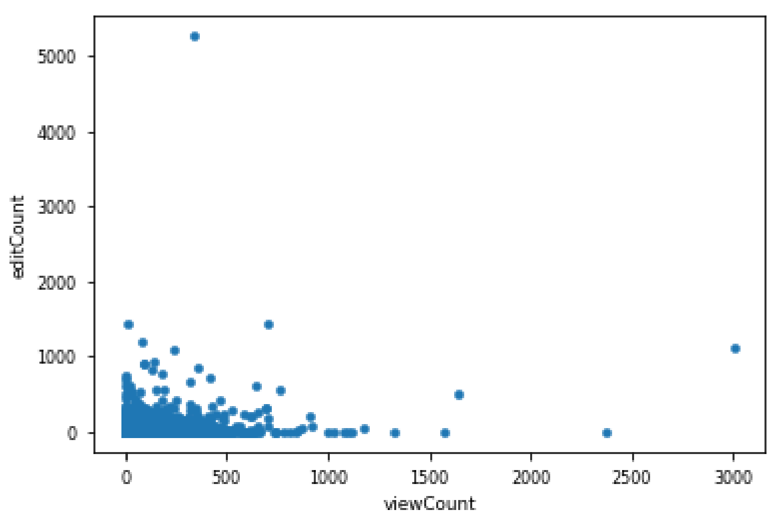
Out[50]:

	viewCount	editCount	shareCount	searchCount	coworkCount	add
count	163352.0000	163352.0000	163352.0000	163352.0000	163352.0000	163352.0000
mean	24.7940	1.5904	0.0760	1.0210	0.0031	12.1678
std	36.9357	19.7058	0.5361	8.9742	0.2834	109.6293
min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
25%	6.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50%	14.0000	0.0000	0.0000	0.0000	0.0000	0.0000
75%	30.0000	0.0000	0.0000	0.0000	0.0000	15.0000
max	3005.0000	5267.0000	78.0000	893.0000	63.0000	17755.0000

In [51]:
```
fig, ax = plt.subplots(2, 2)

df3['viewCount'].plot(kind='box', ax=ax[0, 0], figsize=(5, 6));
df3['editCount'].plot(kind='box', ax=ax[0, 1], figsize=(5, 6));
df3['shareCount'].plot(kind='box', ax=ax[1, 0], figsize=(5, 6));
df3['searchCount'].plot(kind='box', ax=ax[1, 1], figsize=(5, 6));

plt.title("Boxplot")
plt.tight_layout()
```



In [52]:
```
df3.plot(kind='scatter', x='viewCount', y='editCount');
```



In [53]:
```
# 표준편차 이용 (6-sigma): 각 컬럼별 표준편차에서 +- std 벗어난 경우 제외
def std_based_outlier(df):

    for i in range(0, len(df.iloc[1])):
        df = df[~(np.abs(df.iloc[:,i] - df.iloc[:,i].mean()) > (3*df.ilo
c[:,i].std()))]

        return(df)
```

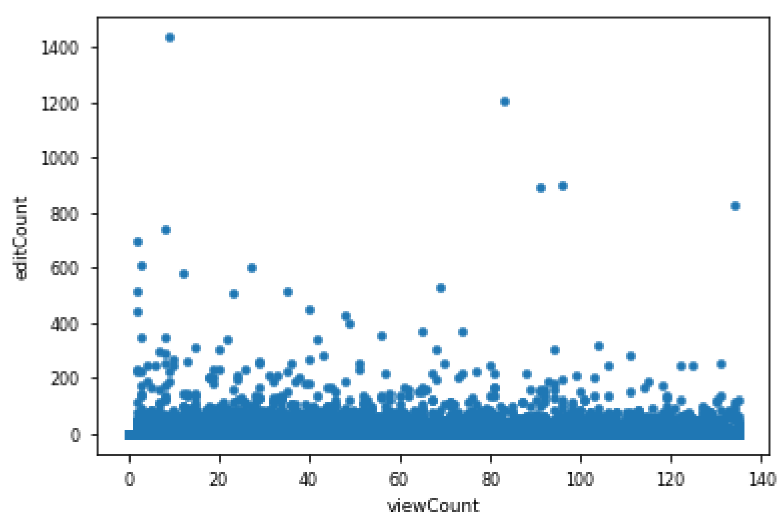
In [54]:
```
df3_std = std_based_outlier(df3)
```

In [55]:
```
df3_std.describe()
```

Out[55]:

	viewCount	editCount	shareCount	searchCount	coworkCount	add
count	160969.0000	160969.0000	160969.0000	160969.0000	160969.0000	160969.0000
mean	21.9071	1.2462	0.0708	0.8301	0.0020	11.0416
std	22.9598	11.3780	0.4535	5.6901	0.1789	108.4248
min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
25%	6.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50%	14.0000	0.0000	0.0000	0.0000	0.0000	0.0000
75%	29.0000	0.0000	0.0000	0.0000	0.0000	14.0000
max	135.0000	1436.0000	41.0000	293.0000	42.0000	17755.0000

In [56]:
```
df3_std.plot(kind='scatter', x='viewCount', y='editCount');
```



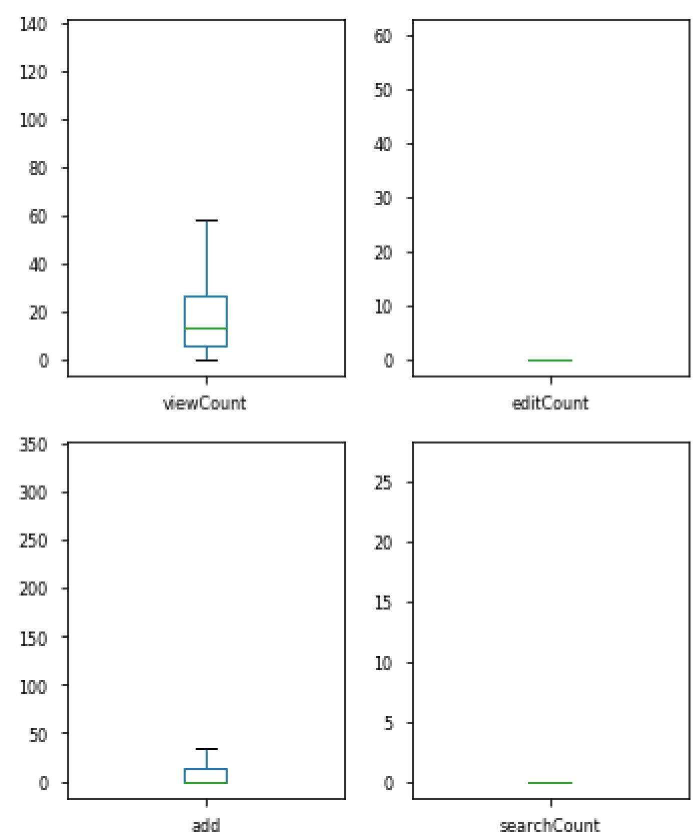
In [57]:
```
## 가장 자주 쓰이는 방식
# z-score 이용: 표준점수로 변환후 +-3 std 벗어나는 경우 제거
from scipy import stats
ore(df3)) < 3).all(axis=1)]
```

In [58]:
```
df3_zscore.describe()
```

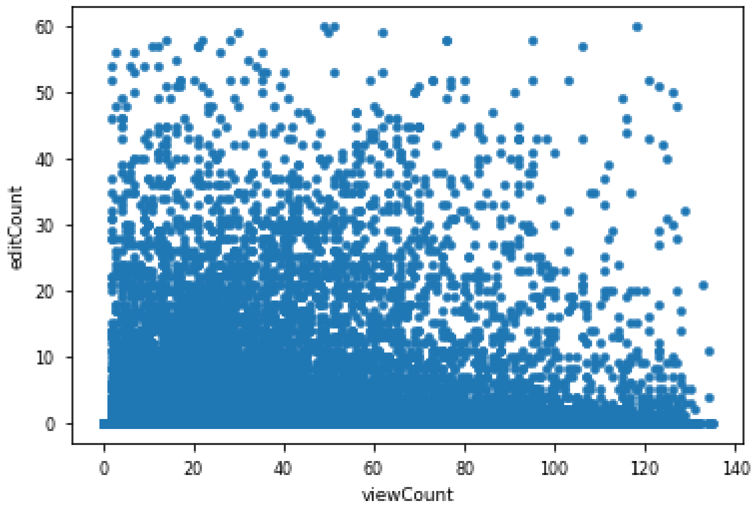
Out[58]:

	viewCount	editCount	shareCount	searchCount	coworkCount	add
count	154089.0000	154089.0000	154089.0000	154089.0000	154089.0	154089.0000
mean	20.6225	0.5710	0.0335	0.3206	0.0	8.4366
std	21.2937	3.1927	0.1800	1.9344	0.0	16.1130
min	0.0000	0.0000	0.0000	0.0000	0.0	0.0000
25%	6.0000	0.0000	0.0000	0.0000	0.0	0.0000
50%	13.0000	0.0000	0.0000	0.0000	0.0	0.0000
75%	27.0000	0.0000	0.0000	0.0000	0.0	14.0000
max	135.0000	60.0000	1.0000	27.0000	0.0	336.0000

In [59]:
```
fig, ax = plt.subplots(2, 2)

df3_zscore['viewCount'].plot(kind='box', ax=ax[0, 0], figsize=(5, 6));
df3_zscore['editCount'].plot(kind='box', ax=ax[0, 1], figsize=(5, 6));
df3_zscore['add'].plot(kind='box', ax=ax[1, 0], figsize=(5, 6));
df3_zscore['searchCount'].plot(kind='box', ax=ax[1, 1], figsize=(5, 6));

plt.tight_layout()
```



In [60]:
```
df3_zscore.plot(kind='scatter', x='viewCount', y='editCount');
```



original std vs z-score std

- 원 데이터로 처리시 매우 보수적인 결과 -> 효과가 낮아서 자주 쓰이지 않음
- 일반적으로 z-score 자주 활용, 단 정규분포에 효과적
- 정규분포가 아닐 경우, IQR 고려

In [61]:
```
# IQR
df3 = df2._get_numeric_data()

for i in range(0, len(df3.iloc[1])):

    q1 = df3.iloc[:,i].quantile(0.25)
    q3 = df3.iloc[:,i].quantile(0.75)
    iqr = q3-q1
    fence_low  = q1-1.5*iqr
    fence_high = q3+1.5*iqr

    df3 = df3[(df3.iloc[:,i] >= fence_low) & (df3.iloc[:,i] <= fence_hig
h)]
```

In [62]:
```
df3.describe()
```
Out[62]:

	viewCount	editCount	shareCount	searchCount	coworkCount	add	
count	76304.0000	76304.0	76304.0	76304.0	76304.0	76304.0000	7630
mean	10.8109	0.0	0.0	0.0	0.0	2.9787	0.0
std	8.9734	0.0	0.0	0.0	0.0	6.4260	0.0
min	0.0000	0.0	0.0	0.0	0.0	0.0000	0.0
25%	4.0000	0.0	0.0	0.0	0.0	0.0000	0.0
50%	8.0000	0.0	0.0	0.0	0.0	0.0000	0.0
75%	15.0000	0.0	0.0	0.0	0.0	0.0000	0.0
max	66.0000	0.0	0.0	0.0	0.0	30.0000	0.0

최종 검토

- IQR: 분포가 쏠려 있어서 (거의 median이 0), 조금만 벗어나도 이상치로 판정
- 최종 선정은 zscore 기준으로 우선 선택!!

In [63]:
```
df3_zscore.describe()
```
Out[63]:

	viewCount	editCount	shareCount	searchCount	coworkCount	add
count	154089.0000	154089.0000	154089.0000	154089.0000	154089.0	154089.0000
mean	20.6225	0.5710	0.0335	0.3206	0.0	8.4366
std	21.2937	3.1927	0.1800	1.9344	0.0	16.1130
min	0.0000	0.0000	0.0000	0.0000	0.0	0.0000
25%	6.0000	0.0000	0.0000	0.0000	0.0	0.0000
50%	13.0000	0.0000	0.0000	0.0000	0.0	0.0000
75%	27.0000	0.0000	0.0000	0.0000	0.0	14.0000
max	135.0000	60.0000	1.0000	27.0000	0.0	336.0000

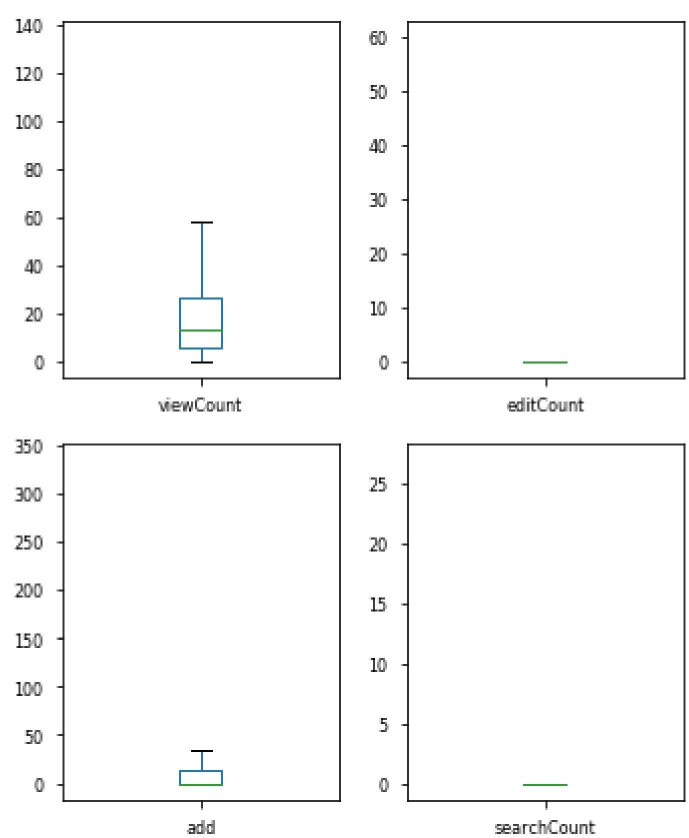
In [64]:
```
# max가 0인 컬럼은 제거
cols_max = df3_zscore.describe().loc['max']
drop_cols = cols_max[cols_max == 0]

df3_zscore.drop(drop_cols.index, axis=1, inplace=True)
```

In [65]:
```
df3_zscore.describe()
```

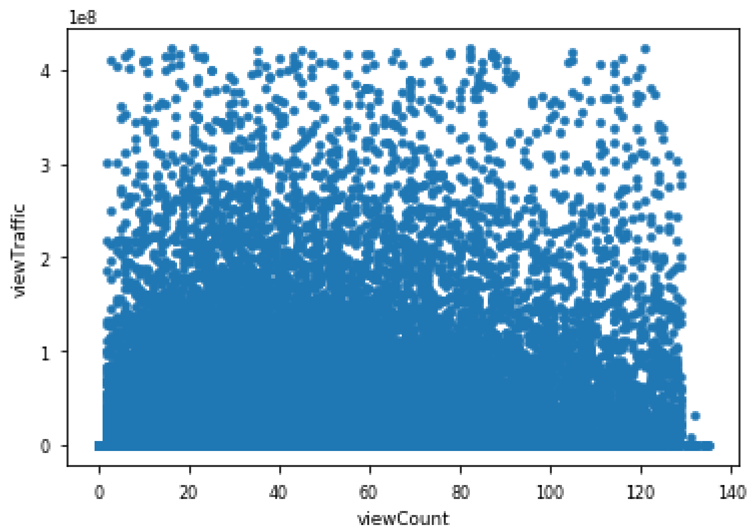
Out[65]:

	viewCount	editCount	shareCount	searchCount	add	move
count	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000
mean	20.6225	0.5710	0.0335	0.3206	8.4366	0.0059
std	21.2937	3.1927	0.1800	1.9344	16.1130	0.0906
min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
25%	6.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50%	13.0000	0.0000	0.0000	0.0000	0.0000	0.0000
75%	27.0000	0.0000	0.0000	0.0000	14.0000	0.0000
max	135.0000	60.0000	1.0000	27.0000	336.0000	2.0000

In [66]:
```
fig, ax = plt.subplots(2, 2)

df3_zscore['viewCount'].plot(kind='box', ax=ax[0, 0], figsize=(5, 6));
df3_zscore['editCount'].plot(kind='box', ax=ax[0, 1], figsize=(5, 6));
df3_zscore['add'].plot(kind='box', ax=ax[1, 0], figsize=(5, 6));
df3_zscore['searchCount'].plot(kind='box', ax=ax[1, 1], figsize=(5, 6));

plt.tight_layout()
```



In [67]:
```
df3_zscore.plot(kind='scatter', x='viewCount', y='viewTraffic');
```



분포 변환

- Transformation
  - if right skewed: Log, Sqrt, cube root functions
  - if left skwed: square
- left_distribution: X^3
- mild_left: X^2
- mild_right: sqrt(X)
- right: ln(X)
- servere right: 1/X

θ		transformation
3	x^3	cube
2	x^2	square
1	x^1	identity (no transformation)
1/2	$x^{0.5}$	square root
1/3	$x^{1/3}$	cube root
0	log(x)	logarithmic (holds the place of zero)
-1/2	$-1/x^{0.5}$	reciprocal root
-1	$-1/x$	reciprocal
-2	$-1/x^2$	reciprocal square

- source: http://seismo.berkeley.edu/~kirchner/eps_120/Toolkits/Toolkit_03.pdf (http://seismo.berkeley.edu/~kirchner/eps_120/Toolkits/Toolkit_03.pdf)
- Reference
  - http://scikit-learn.org/stable/modules/classes.html#module-sklearn.preprocessing (http://scikit-learn.org/stable/modules/classes.html#module-sklearn.preprocessing)
  - http://scikit-learn.org/stable/modules/preprocessing.html (http://scikit-learn.org/stable/modules/preprocessing.html)

In [68]:
```
df4 = df3_zscore.copy()
```

In [69]:
```
df4.head()
```

Out[69]:

	viewCount	editCount	shareCount	searchCount	add	move	rename	a
iduser								
10100018739106	12.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100037810674	23.0	0.0	0.0	1.0	13.0	0.0	0.0	(
10100036273719	4.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100027752244	6.0	0.0	1.0	0.0	0.0	0.0	0.0	(
10100006151000	33.0	0.0	0.0	0.0	16.0	0.0	0.0	(

In [70]:
```
df4.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 154089 entries, 10100018739106 to 10100021804275
Data columns (total 15 columns):
viewCount         154089 non-null float64
editCount         154089 non-null float64
shareCount        154089 non-null float64
searchCount       154089 non-null float64
add               154089 non-null float64
move              154089 non-null float64
rename            154089 non-null float64
adddir            154089 non-null float64
visdays           154089 non-null float64
openCount         154089 non-null float64
saveCount         154089 non-null float64
viewTraffic       154089 non-null float64
editTraffic       154089 non-null float64
exportTraffic     154089 non-null float64
traffic           154089 non-null float64
dtypes: float64(15)
memory usage: 18.8 MB
```

In [71]:

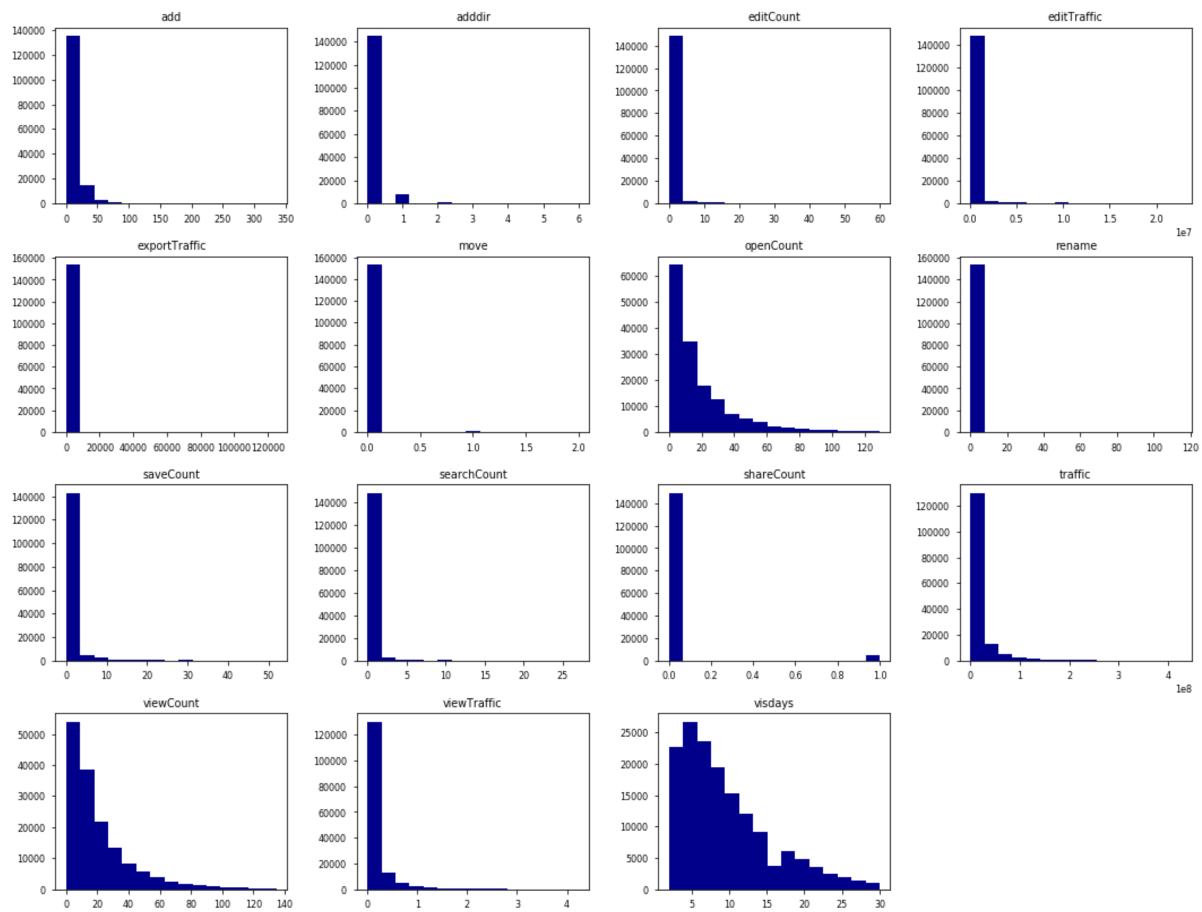
```
# 분포를 간단히 확인 with IQR, MIN, MAX, MEAN, STD
df4.describe()
```

Out[71]:

	viewCount	editCount	shareCount	searchCount	add	move
count	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000
mean	20.6225	0.5710	0.0335	0.3206	8.4366	0.0059
std	21.2937	3.1927	0.1800	1.9344	16.1130	0.0906
min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
25%	6.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50%	13.0000	0.0000	0.0000	0.0000	0.0000	0.0000
75%	27.0000	0.0000	0.0000	0.0000	14.0000	0.0000
max	135.0000	60.0000	1.0000	27.0000	336.0000	2.0000

In [72]:

```
# Outlier 미처리시 skewness 더 심해짐
df4.hist(bins=15, color='darkblue', figsize=(18,14), grid=False);

plt.grid(False)
```

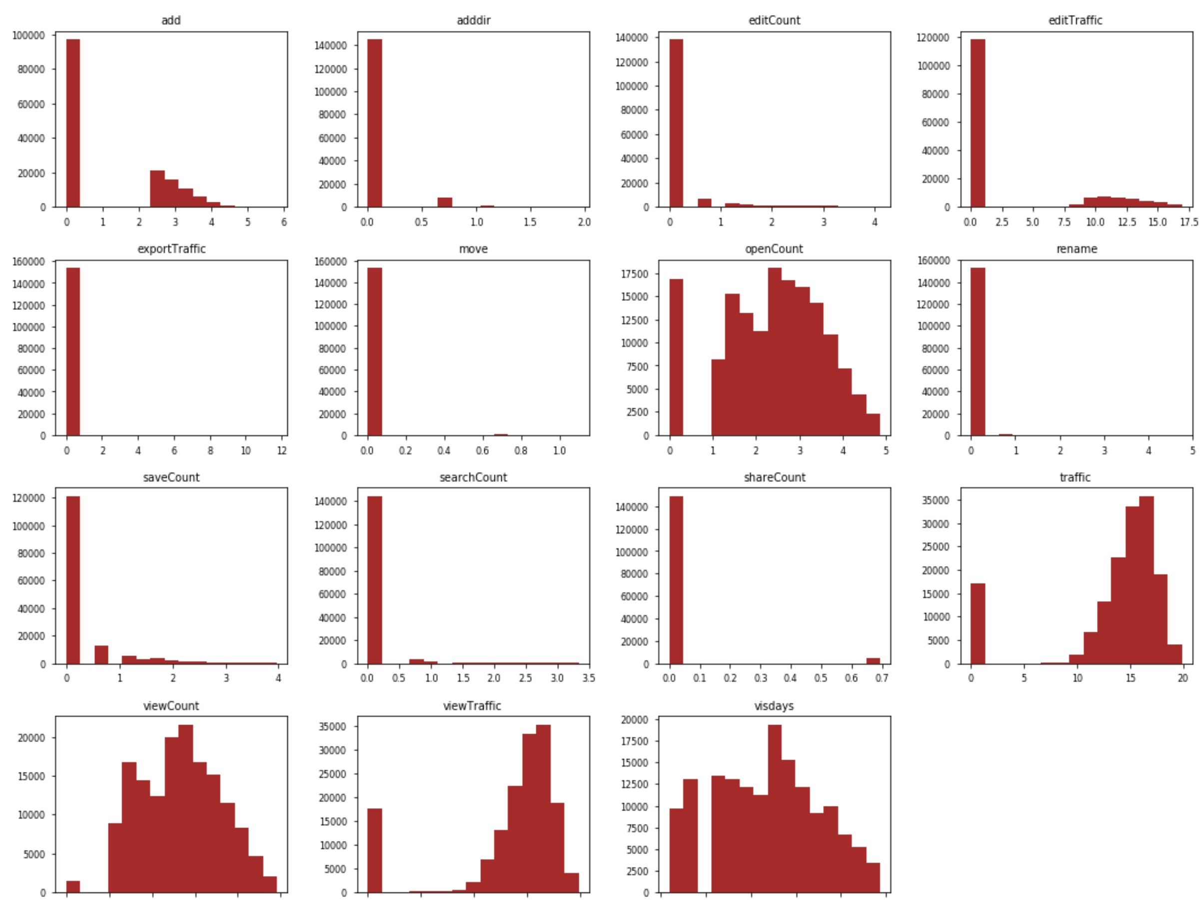


In [73]:
```python
# log 함수 적용 (if right skewed)
df4_log = df4.apply(lambda x: np.log(x+1))

df4_log.describe()
```

Out[73]:

	viewCount	editCount	shareCount	searchCount	add	move	
count	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000	1
mean	2.6544	0.1452	0.0232	0.0921	1.1105	0.0038	(
std	0.9364	0.5091	0.1248	0.4045	1.4853	0.0558	(
min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	(
25%	1.9459	0.0000	0.0000	0.0000	0.0000	0.0000	(
50%	2.6391	0.0000	0.0000	0.0000	0.0000	0.0000	(
75%	3.3322	0.0000	0.0000	0.0000	2.7081	0.0000	(
max	4.9127	4.1109	0.6931	3.3322	5.8201	1.0986	4

In [74]:
```python
df4_log.hist(bins=15, color='brown', figsize=(18,14), grid=False);
```

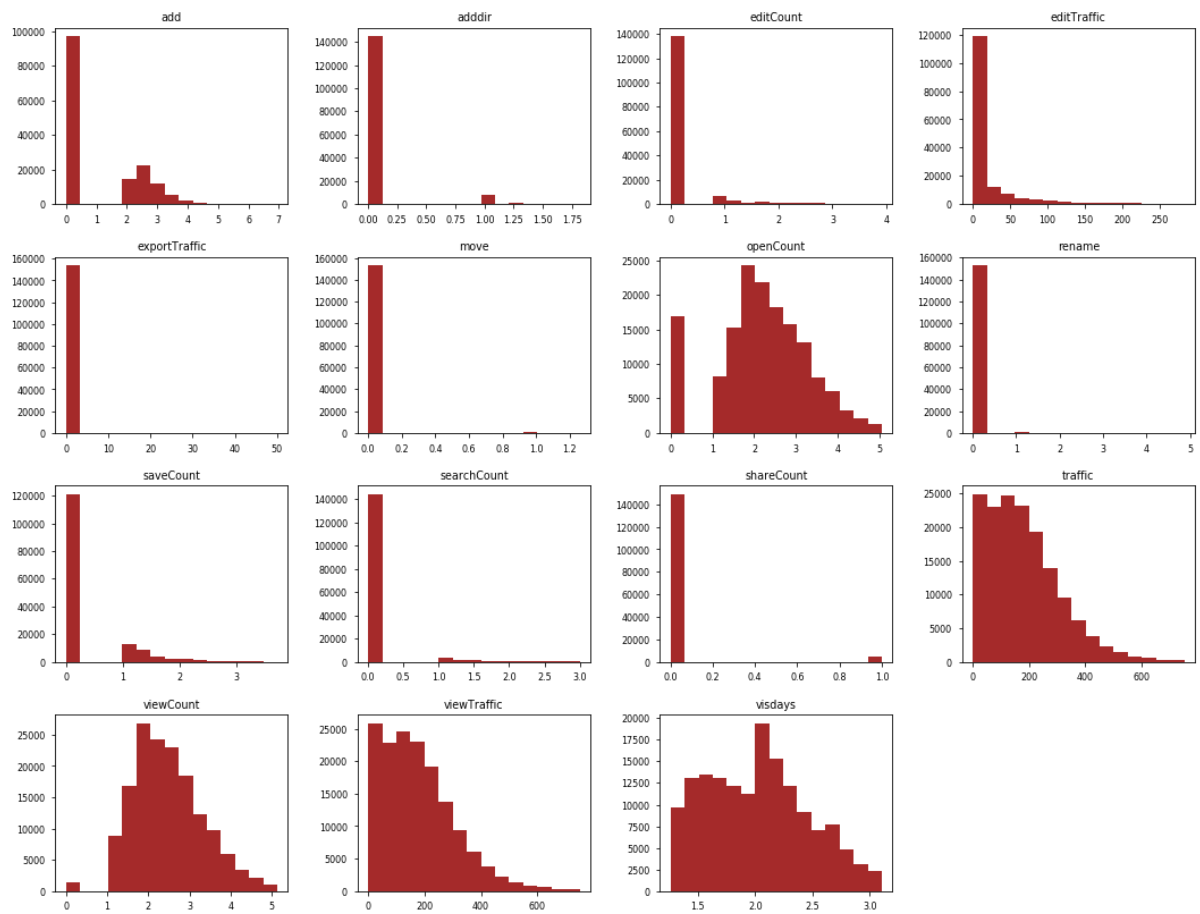


In [75]:
```
# 다른 함수 적용
df4_cube_root = df4.apply(lambda x: x ** (1. / 3))

df4_cube_root.describe()
```

Out[75]:

	viewCount	editCount	shareCount	searchCount	add	move
count	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000
mean	2.4639	0.1545	0.0335	0.0965	1.0043	0.0051
std	0.8555	0.4991	0.1800	0.3951	1.3541	0.0736
min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
25%	1.8171	0.0000	0.0000	0.0000	0.0000	0.0000
50%	2.3513	0.0000	0.0000	0.0000	0.0000	0.0000
75%	3.0000	0.0000	0.0000	0.0000	2.4101	0.0000
max	5.1299	3.9149	1.0000	3.0000	6.9521	1.2599

In [76]:
```
df4_cube_root.hist(bins=15, color='brown', figsize=(18,14), grid=False);
```



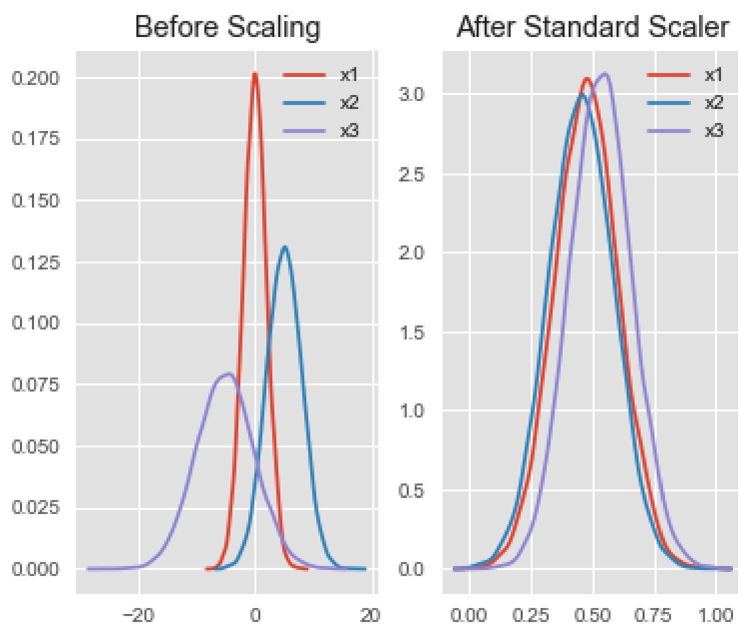
In [77]:
```
# 다른 함수 적용
```

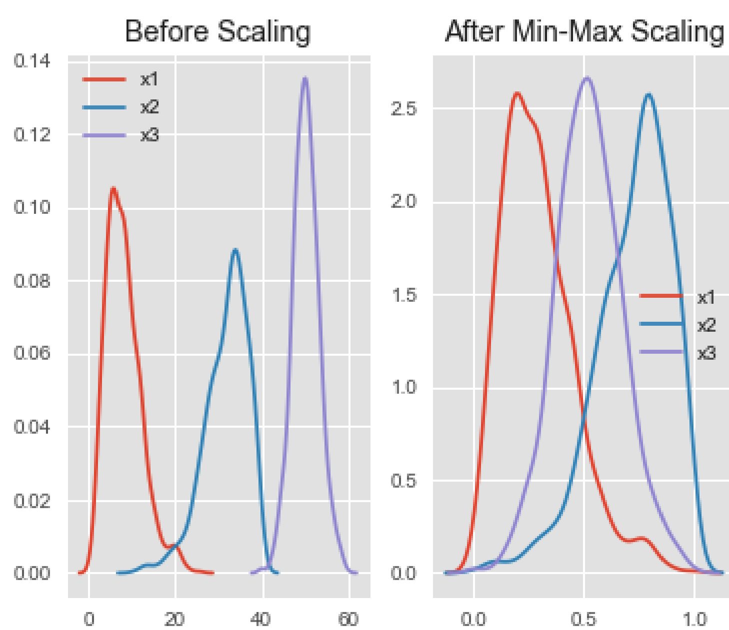
우선 분포 변환은 Pass

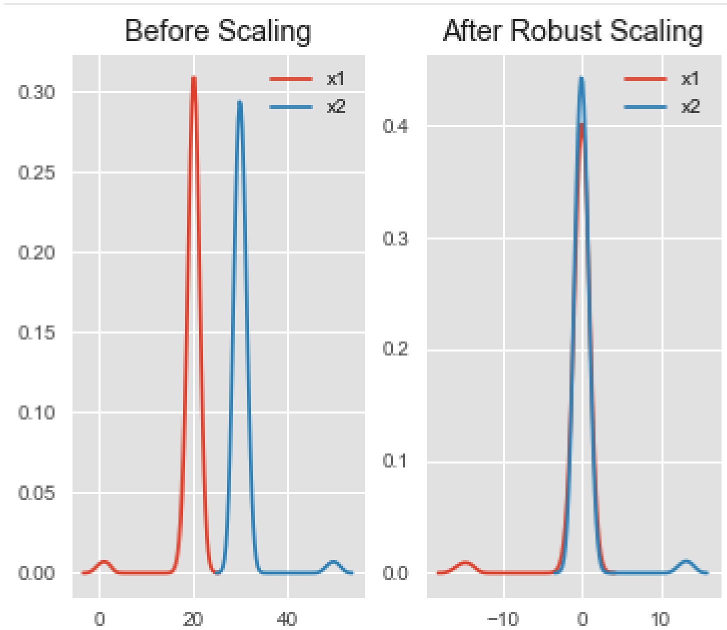
- 원 분포대로 모델링 구축하고 추후 개선시 transform 진행

단위 표준화 (Scaling)

- 모든 변수의 단위를 동일한 기준(스케일)로 통일
  - 이번 사례의 경우 tarffic(byte) 변수로 인해, 필수적인 과정
- Standard Scaler (Mean: 0, std: 1)
- MinMax Scaler (default: min=0, max=1)
- Robust Scaler (x - q1 / q3-q1)
- Source: http://benalexkeen.com/feature-scaling-with-scikit-learn/ (http://benalexkeen.com/feature-scaling-with-scikit-learn/)







In [78]:
```
df4_std_scale = df4.copy() # after removes outliers
```

In [79]:
```
df4_std_scale.head()
```

Out[79]:

	viewCount	editCount	shareCount	searchCount	add	move	rename	a
iduser								
10100018739106	12.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100037810674	23.0	0.0	0.0	1.0	13.0	0.0	0.0	(
10100036273719	4.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100027752244	6.0	0.0	1.0	0.0	0.0	0.0	0.0	(
10100006151000	33.0	0.0	0.0	0.0	16.0	0.0	0.0	(

In [80]:
```
from sklearn.preprocessing import StandardScaler
import warnings
warnings.filterwarnings('ignore')

for c in df4_std_scale:
    df4_std_scale[c] = StandardScaler().fit_transform(np.array(df4_std_s
cale[c]).reshape(-1, 1)).round(4)
```

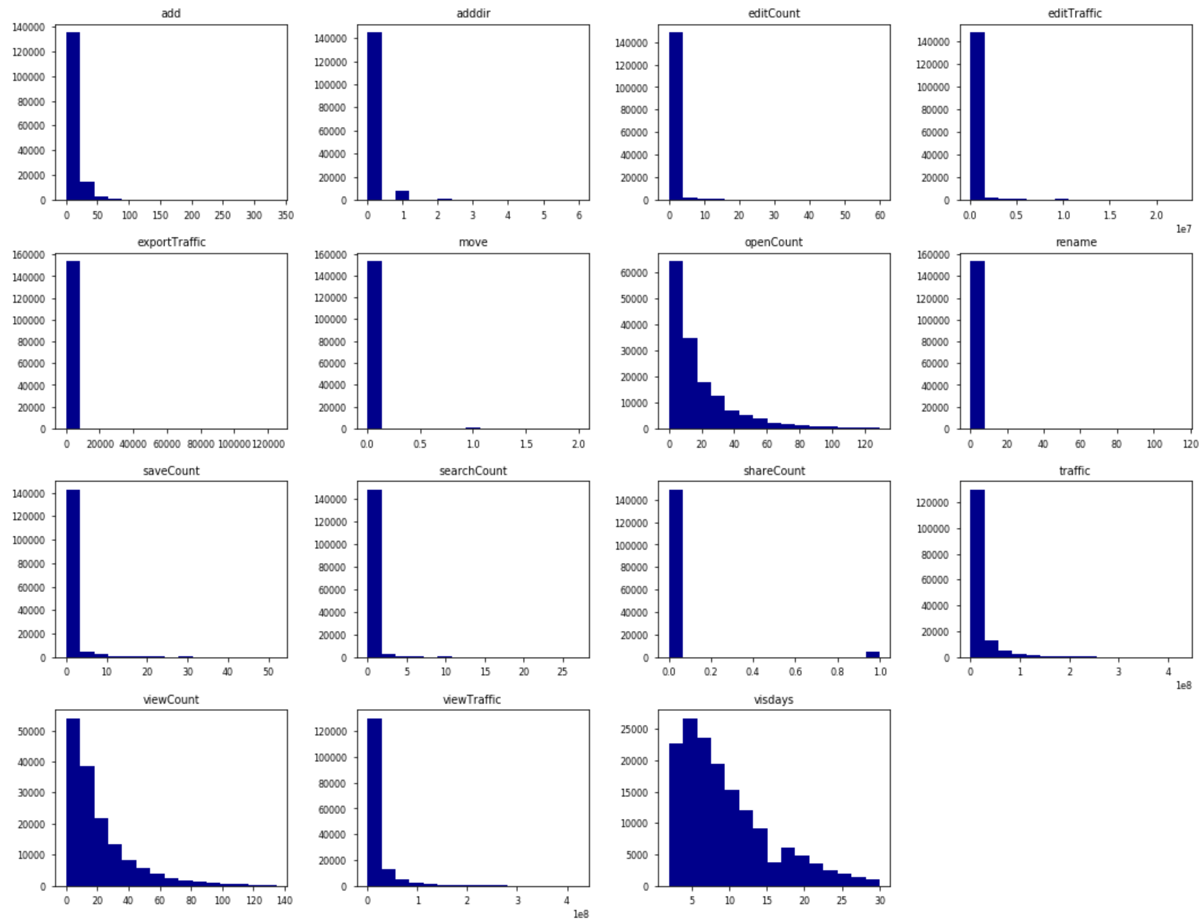
In [81]:
```
df4_std_scale.describe().round(2)
```

Out[81]:

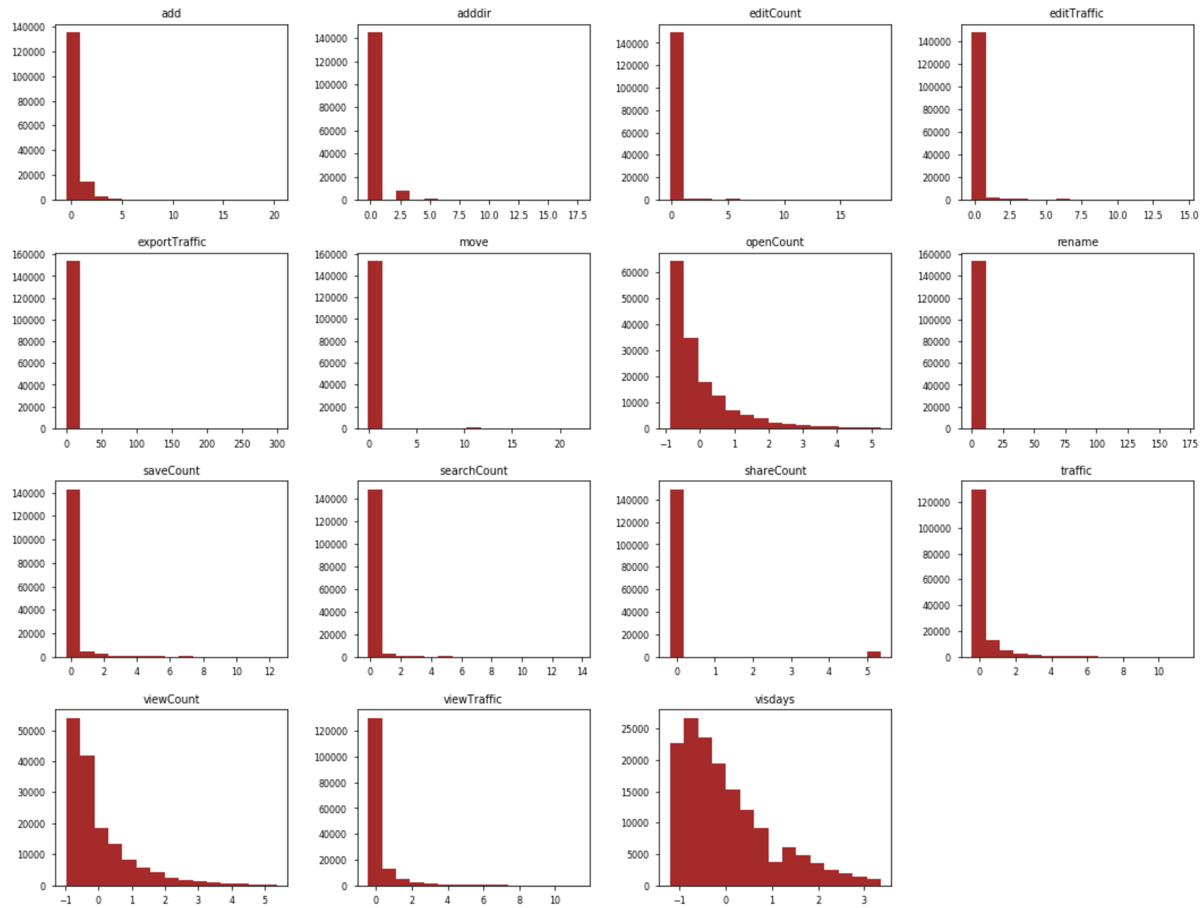
	viewCount	editCount	shareCount	searchCount	add	move	rename
count	154089.00	154089.00	154089.00	154089.00	154089.00	154089.00	154089.00
mean	-0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00
std	1.00	1.00	1.00	1.00	1.00	1.00	1.00
min	-0.97	-0.18	-0.19	-0.17	-0.52	-0.07	-0.03
25%	-0.69	-0.18	-0.19	-0.17	-0.52	-0.07	-0.03
50%	-0.36	-0.18	-0.19	-0.17	-0.52	-0.07	-0.03
75%	0.30	-0.18	-0.19	-0.17	0.35	-0.07	-0.03
max	5.37	18.61	5.37	13.79	20.33	22.00	168.91

Q) 단위 변화후 분포에는 어떠한 변화가 있을까요?

In [82]:
```
df4.hist(bins=15, color='darkblue', figsize=(18,14), grid=False);
```



In [83]:
```
df4_std_scale.hist(bins=15, color='brown', figsize=(18,14), grid=False);
```



In [84]:
```
df4_minmax_scale = df4.copy()
```

In [85]:
```
from sklearn.preprocessing import MinMaxScaler

for c in df4_minmax_scale:
    df4_minmax_scale[c] = MinMaxScaler().fit_transform(np.array(df4_minmax_scale[c]).reshape(-1,1).round(4))
```

In [86]:
```
df4_minmax_scale.describe()
```

Out[86]:

	viewCount	editCount	shareCount	searchCount	add	move
count	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000
mean	0.1528	0.0095	0.0335	0.0119	0.0251	0.0030
std	0.1577	0.0532	0.1800	0.0716	0.0480	0.0453
min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
25%	0.0444	0.0000	0.0000	0.0000	0.0000	0.0000
50%	0.0963	0.0000	0.0000	0.0000	0.0000	0.0000
75%	0.2000	0.0000	0.0000	0.0000	0.0417	0.0000
max	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

In [87]:
```
df4_robust_scale = df4.copy()
```

In [88]:
```
from sklearn.preprocessing import RobustScaler

for c in df4_robust_scale:
    df4_robust_scale[c] = RobustScaler().fit_transform(np.array(df4_robu
st_scale[c]).reshape(-1,1).round(4))
```

In [89]:
```
df4_robust_scale.describe()
```

Out[89]:

	viewCount	editCount	shareCount	searchCount	add	move
count	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000
mean	0.3630	0.5710	0.0335	0.3206	0.6026	0.0059
std	1.0140	3.1927	0.1800	1.9344	1.1509	0.0906
min	-0.6190	0.0000	0.0000	0.0000	0.0000	0.0000
25%	-0.3333	0.0000	0.0000	0.0000	0.0000	0.0000
50%	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
75%	0.6667	0.0000	0.0000	0.0000	1.0000	0.0000
max	5.8095	60.0000	1.0000	27.0000	24.0000	2.0000

In [90]:
```
# dataset after removes outliers, not transform, no scale
df4.head()
```

Out[90]:

	viewCount	editCount	shareCount	searchCount	add	move	rename	a
iduser								
10100018739106	12.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100037810674	23.0	0.0	0.0	1.0	13.0	0.0	0.0	(
10100036273719	4.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100027752244	6.0	0.0	1.0	0.0	0.0	0.0	0.0	(
10100006151000	33.0	0.0	0.0	0.0	16.0	0.0	0.0	(

In [91]:
```
df5 = df4.join(df2['group'])
```

In [92]:
```
df5.head()
```

Out[92]:

	viewCount	editCount	shareCount	searchCount	add	move	rename	a
iduser								
10100018739106	12.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100037810674	23.0	0.0	0.0	1.0	13.0	0.0	0.0	(
10100036273719	4.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100027752244	6.0	0.0	1.0	0.0	0.0	0.0	0.0	(
10100006151000	33.0	0.0	0.0	0.0	16.0	0.0	0.0	(

In [93]:
```
df5.describe()
```

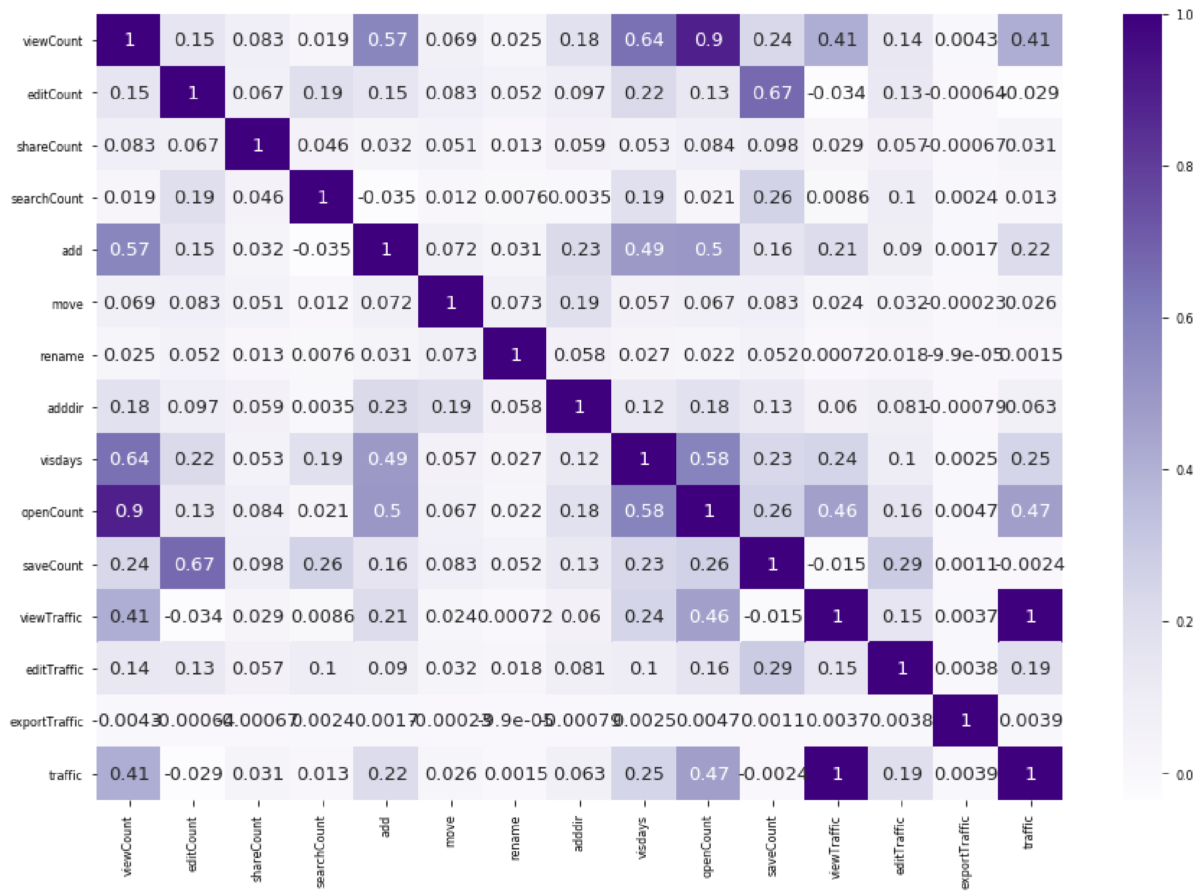
Out[93]:

	viewCount	editCount	shareCount	searchCount	add	move	
count	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000	154089.0000	1
mean	20.6225	0.5710	0.0335	0.3206	8.4366	0.0059	(
std	21.2937	3.1927	0.1800	1.9344	16.1130	0.0906	(
min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	(
25%	6.0000	0.0000	0.0000	0.0000	0.0000	0.0000	(
50%	13.0000	0.0000	0.0000	0.0000	0.0000	0.0000	(
75%	27.0000	0.0000	0.0000	0.0000	14.0000	0.0000	(
max	135.0000	60.0000	1.0000	27.0000	336.0000	2.0000	1

[**Multicollinearity (https://ko.wikipedia.org/wiki/%EB%8B%A4%EC%A4%91%EA%B3%B5%EC%84%A0%EC%84%B1)**](https://ko.wikipedia.org/wiki/%EB%8B%A4%EC%A4%91%EA%B3%B5%EC%84%A0%EC%84%B1)

- 변수 삭제 1): EX) editTraffic, exportTraffic, viewTraffic, openCount
- 변수 삭제 2): 분포가 정상이 아닌 경우 (우선 유지)
- 변수 축소 EX) PCA, Factor Analysis, etc

In [94]:
```python
fig, ax = plt.subplots(figsize=(15,10))

sns.heatmap(df5.corr(), annot=True, annot_kws={"size": 13}, cmap='Purples');
```



In [95]:
```python
# 상관관계 높은 변수 제거
drop_cols = ['editTraffic', 'exportTraffic', 'viewTraffic', 'openCount']
```

In [96]:
```python
df5.drop(drop_cols, axis=1, inplace=True)
```

KAIST Korea Advanced Institute of Science and Technology

In [97]:
```python
df5.head()
```

Out[97]:

	viewCount	editCount	shareCount	searchCount	add	move	rename	a
iduser								
10100018739106	12.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100037810674	23.0	0.0	0.0	1.0	13.0	0.0	0.0	(
10100036273719	4.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100027752244	6.0	0.0	1.0	0.0	0.0	0.0	0.0	(
10100006151000	33.0	0.0	0.0	0.0	16.0	0.0	0.0	(

Imbalance Issues

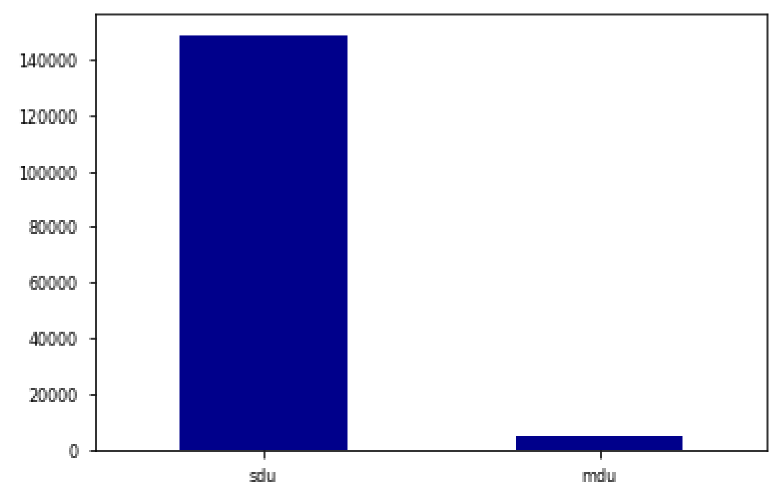
- 결제자 여부에 대한 데이터 사례가 불충분 => 모델이 sdu 로 대부분 예측하는 결과
  - SDU(0)를 SDU(0)로 예측하는 정확도(True Negative)는 높을 수있으나, MDU(1)를 MDU(1) 예측하는 TP 는 낮을 것으로 예상
- how to handle imbalance
  - https://machinelearningmastery.com/tactics-to-combat-imbalanced-classes-in-your-machine-learning-dataset/ (https://machinelearningmastery.com/tactics-to-combat-imbalanced-classes-in-your-machine-learning-dataset/)

In [98]:
```python
df5.group.value_counts().transform(lambda x: x / x.sum())
```

Out[98]:
```
sdu    0.9668
mdu    0.0332
Name: group, dtype: float64
```

In [99]:
```python
df5.group.value_counts().plot(kind='bar', color='darkblue', rot=0)
```

Out[99]: <matplotlib.axes._subplots.AxesSubplot at 0x1a3493e790>




```python
'] == 'sdu', 0, 1)
```

```
In [101]: df5.head()
```

Out[101]:

	viewCount	editCount	shareCount	searchCount	add	move	rename	a
iduser								
10100018739106	12.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100037810674	23.0	0.0	0.0	1.0	13.0	0.0	0.0	(
10100036273719	4.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100027752244	6.0	0.0	1.0	0.0	0.0	0.0	0.0	(
10100006151000	33.0	0.0	0.0	0.0	16.0	0.0	0.0	(

분류 모델 종류

- **Logistic Regression**
  - Logistic regression fits a logistic model to data and makes predictions about the probability of an event (between 0 and
- **Naive Bayes**
  - Naive Bayes uses Bayes Theorem to model the conditional relationship of each attribute to the class variable
- **k-Nearest Neighbor**
  - The k-Nearest Neighbor (kNN) method makes predictions by locating similar cases to a given data instance (using a similarity function) and returning the average or majority of the most similar data instances. The kNN algorithm can be used for classification or regression.
- **Trees-based model**
  - Classification and Regression Trees (CART) are constructed from a dataset by making splits that best separate the data for the classes or predictions being made. The CART algorithm can be used for classification or regression
- **Random Forest**
  - Random Forest is a machine learning algorithm used for classification, regression, and feature selection. It's an ensemble technique, meaning it combines the output of one weaker technique in order to get a stronger result. The weaker technique in this case is a decision tree. Decision trees work by splitting the and re-splitting the data by features. If a decision tree is split along good features, it can give a decent predictive output
- **SVM (Support Vector Machines)**
  - Support Vector Machines (SVM) are a method that uses points in a transformed problem space that best separate classes into two groups. Classification for multiple classes is supported by a one-vs-all method. SVM also supports regression by modeling the function with a minimum amount of allowable error

Cross Validation

- 모델 구축 후 성능 검증을 위해 전체 Dataset을 Train, Validation과 Test로 나눈다.
- Testset은 최적화된 파라메터로 구축된 최종 모델의 성능을 파악하기 위해 단 1회만 사용한다.
- 최적화 파라메터는 Scikit-learn에서 제공하는 grid_serach를 이용해 구한다.
- Dataset을 나눌 때 test_size 옵션으로 Train, Test의 비율을 설정할 수 있고, random_state로 seed 값을 지정할 수 있다.
- 데이터 샘플이 너무 많다면, 연상 비용이 크게 증가할 수 있어 샘플링이 필요하다.

```
# 샘플링 예시 코드 / frac에는 샘플링셋의 비율을 입력, Replace는 비복원으로 지정(False)
df_sampled = df.sample(frac=.1, replace=False)
```

In [102]:
```
from sklearn.cross_validation import train_test_split

# set ind vars and target var
X = df5.drop('group', axis=1)
y = df5.group

# split train, test
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=4
2)
```

In [103]:
```
# Scaling
scaler = MinMaxScaler()

# fit_transform
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.fit_transform(X_test)
```

In [104]:
```
# max
print(X_train_scaled.max(axis=0))
print(X_test_scaled.max(axis=0))
print(' ')
# min
print(X_train_scaled.min(axis=0))
print(X_test_scaled.min(axis=0))
```

```
[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]

[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```

In [105]:
```
print(X_train_scaled.shape)
print(y_train.shape)
print(X_test_scaled.shape)
print(y_test.shape)
```

```
(115566, 11)
(115566,)
(38523, 11)
(38523,)
```

모델 파라메터 설정

- 기본 모델: **Logistic Regression**
  - http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html (http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html)
- 주요 파라메터 (C)
  - C 값 (기본값 = 1)
  - C 값이 작으면 Penalty 강해짐 (단순 모델)
  - C 값이 크면 Penalty 약해짐 (정규화 없어짐)
  - 보통 로그스케일로 지정(10배씩) = 0.01, 0.1, 1, 10
- penalty
  - L2: Ridge, 일반적으로 사용 (default)
  - L1: LASSO, 변수가 많아서 줄여야할 때 사용, 모델의 단순화 및 해석에 용이

In [106]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

# set params
param_grid = {'C': [0.001, 0.01, 0.1, 1, 10, 100],
              'penalty': ['l1', 'l2']}

# grid search
grid_search = GridSearchCV(LogisticRegression(), param_grid, cv=5)

# fit
grid_search.fit(X_train_scaled, y_train)
```

Out[106]:
```
GridSearchCV(cv=5, error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=Fals
e, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.00
01,
          verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'penalty': ['l1', 'l2'], 'C': [0.001, 0.01, 0.1, 1,
10, 100]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

How the grid_search module works:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score

# SET default
best_score = 0

# iterataion
for r in ['l1', 'l2']:
    for C in [0.001, 0.01, 0.1, 1, 10, 100]:
        lm = LogisticRegression(penalty = r, C=C)
        scores = cross_val_score(lm, X_train, y_train, cv=5)
        score = np.mean(scores)
        if score > best_score:
            best_score = score
            best_parameters = {'C': C, 'penalty': r}
```

In [107]:
```
print(grid_search.best_params_)
print(grid_search.best_score_)
print(grid_search.best_estimator_)
```

```
{'penalty': 'l1', 'C': 0.001}
0.9661578665005278
LogisticRegression(C=0.001, class_weight=None, dual=False, fit_intercep
t=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.00
01,
          verbose=0, warm_start=False)
```

In [108]:
```
grid_search.score(X_test_scaled, y_test) # accuracy
```

Out[108]: 0.9687978610180931

In [109]:
```
grid_search.predict(X_test_scaled)
```

Out[109]: array([0, 0, 0, ..., 0, 0, 0])

In [110]:
```
print(len(grid_search.predict(X_test_scaled)))
print(len(y_test))
```

```
38523
38523
```

1차 모델 평가 (about the first model)

In [111]:
```
print('when grid searching: ', grid_search.best_score_)
print('at the trainset:, ', grid_search.score(X_test_scaled, y_test))
```

```
('when grid searching: ', 0.9661578665005278)
('at the trainset:, ', 0.9687978610180931)
```

In [112]:
```
# 실제 테스트셋의 label 분포
y_test.value_counts()
```

Out[112]:
```
0    37321
1     1202
Name: group, dtype: int64
```

In [113]:
```
# 모델 예측 결과
pd.Series(grid_search.predict(X_test_scaled)).value_counts()
```

Out[113]:
```
0    38523
dtype: int64
```

In [114]:
```
from sklearn.metrics import confusion_matrix

print(confusion_matrix(grid_search.predict(X_test), y_test))
```

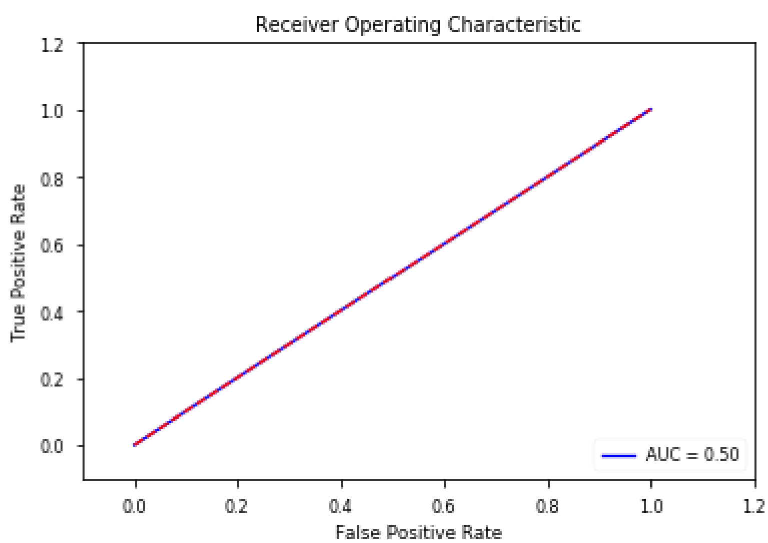
```
[[37321  1202]
 [    0     0]]
```

In [115]:
```
from sklearn.metrics import classification_report

print(classification_report(grid_search.predict(X_test), y_test))
```

```
             precision    recall  f1-score   support

          0       1.00      0.97      0.98     38523
          1       0.00      0.00      0.00         0

avg / total       1.00      0.97      0.98     38523
```

In [116]:
```
# ROC plot
from sklearn.metrics import roc_curve, auc

false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,
grid_search.predict(X_test))
roc_auc = auc(false_positive_rate, true_positive_rate)

fig = plt.figure(figsize=(6,4))
plt.title('Receiver Operating Characteristic')
plt.plot(false_positive_rate, true_positive_rate, 'b', label='AUC = %0.2
f'% roc_auc)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([-0.1,1.2])
plt.ylim([-0.1,1.2])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
```

Out[116]:
```
Text(0.5,0,'False Positive Rate')
```



Upsampling & Downsampling for imbalanced data

1. Collect More Data (if possible)
2. Resampling the Dataset
   - oversampling
     - no information loss, perform better than undersampling
     - overfitting issues (because of duplicates)
   - undersampling
     - help improve run time and storage problems
     - information loss, biased dataset
3. Generate Synthetic Samples

In [117]:
```
# orginal dataset
df5.group.value_counts()
```

Out[117]:
```
0    148976
1      5113
Name: group, dtype: int64
```

In [118]:
```
df5.group.value_counts().transform(lambda x: x / x.sum())
```

Out[118]:
```
0    0.9668
1    0.0332
Name: group, dtype: float64
```

In [119]:
```
def oversampling(df):

    df_pay_only = df.query("group == 1")
    df_pay_only_over = pd.concat([df_pay_only, df_pay_only, df_pay_only
], axis=0)
    df_over = pd.concat([df, df_pay_only_over], axis=0)

    return df_over
```

In [120]:
```
df5_over = oversampling(df5)
```

In [121]:
```
df5_over.group.value_counts().transform(lambda x: x / x.sum())
```

Out[121]:
```
0    0.8793
1    0.1207
Name: group, dtype: float64
```

In [122]:
```
X = df5_over.drop("group", axis=1)
y = df5_over.group

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=4
2)

# Scaling
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.fit_transform(X_test)
```

In [123]:
```
print(X_train_scaled.shape)
print(y_train.shape)
print(X_test_scaled.shape)
print(y_test.shape)
```

```
(127071, 11)
(127071,)
(42357, 11)
(42357,)
```

In [124]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

# set params
param_grid = {'C': [0.001, 0.01, 0.1, 1, 10, 100],
              'penalty': ['l1', 'l2']}

# grid search
grid_search = GridSearchCV(LogisticRegression(), param_grid, cv=5)

# fit
grid_search.fit(X_train_scaled, y_train)
```

Out[124]:
```
GridSearchCV(cv=5, error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=Fals
e, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.00
01,
          verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'penalty': ['l1', 'l2'], 'C': [0.001, 0.01, 0.1, 1,
10, 100]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

In [125]:
```
print(grid_search.best_params_)
print(grid_search.best_score_)
print(grid_search.best_estimator_)
```

```
{'penalty': 'l1', 'C': 100}
0.9193993908917062
LogisticRegression(C=100, class_weight=None, dual=False, fit_intercept=
True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.00
01,
          verbose=0, warm_start=False)
```

In [126]:
```
print(grid_search.score(X_test_scaled, y_test))
```

```
0.9208159218074935
```

In [127]:
```
from sklearn.metrics import confusion_matrix

print(confusion_matrix(grid_search.predict(X_test_scaled), y_test))
```

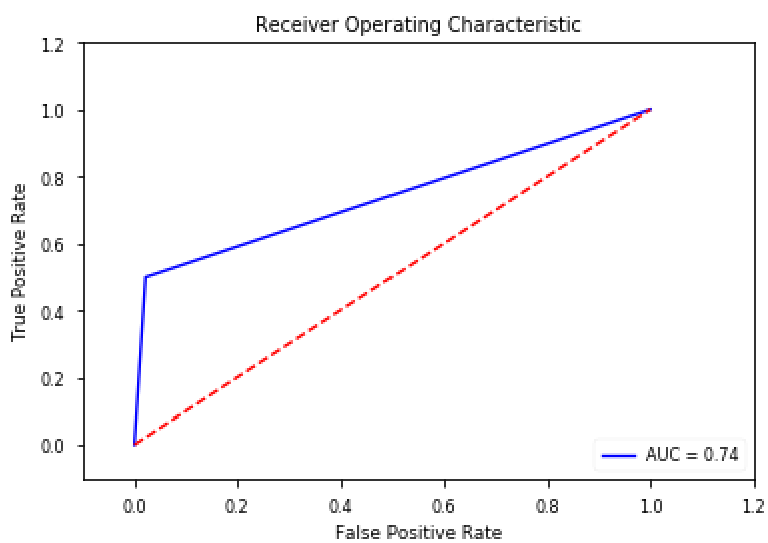
```
[[36469  2545]
 [  809  2534]]
```

In [128]:
```
from sklearn.metrics import classification_report

print(classification_report(grid_search.predict(X_test_scaled), y_test))
```

```
             precision    recall  f1-score   support

          0       0.98      0.93      0.96     39014
          1       0.50      0.76      0.60      3343

avg / total       0.94      0.92      0.93     42357
```

In [129]:
```
# ROC plot
from sklearn.metrics import roc_curve, auc

false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,
grid_search.predict(X_test_scaled))
roc_auc = auc(false_positive_rate, true_positive_rate)

fig = plt.figure(figsize=(6,4))
plt.title('Receiver Operating Characteristic')
plt.plot(false_positive_rate, true_positive_rate, 'b', label='AUC = %0.2
f'% roc_auc)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([-0.1,1.2])
plt.ylim([-0.1,1.2])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
```

Out[129]: Text(0.5,0,'False Positive Rate')



The model performance of the first application

- process
  - oversampling
  - dataset split
  - minmax scale
  - logistic regression, grid search, k-fold(5)
  - evaluation
  - Baseline score: **Precision: 0.5, Recall: 0.76, AUC: 0.74**
- How to improve
  - **There seems no overfitting issues**
    - how to avoid overfitting: collect more data
      - regularization
      - feature deduction
      - collect more samples
  - **Feature Engineering**
    - Other Scaling and Transformation
    - Feature selection or creation
      - Polynomial / Interactions
      - new features
    - Transformation
      - log, exp, sqrt (if not tree-based model)
      - Numeric to Categorical
  - **Model, Parameter Tuning**
    - KNN
    - NB
    - SVM
    - RF
    - NN .. any classification models

How to Improve

- scale
- distribution transformation
- apply other models

Change Scale to z-score & pipeline

In [130]:
```
df5_over.head() # after removes outliers
```

Out[130]:

iduser	viewCount	editCount	shareCount	searchCount	add	move	rename	a
10100018739106	12.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100037810674	23.0	0.0	0.0	1.0	13.0	0.0	0.0	(
10100036273719	4.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100027752244	6.0	0.0	1.0	0.0	0.0	0.0	0.0	(
10100006151000	33.0	0.0	0.0	0.0	16.0	0.0	0.0	(

In [131]:
```
X_train.head()
```

Out[131]:

iduser	viewCount	editCount	shareCount	searchCount	add	move	rename	a
10100008873531	17.0	0.0	0.0	5.0	0.0	0.0	0.0	(
10100002534050	28.0	0.0	0.0	16.0	0.0	0.0	0.0	(
10100036517560	36.0	0.0	0.0	0.0	80.0	0.0	0.0	(
10100013746186	4.0	0.0	0.0	0.0	0.0	0.0	0.0	(
10100000598189	8.0	0.0	0.0	0.0	0.0	0.0	0.0	(

In [132]:
```
y_train.head()
```

Out[132]:
```
iduser
10100008873531    1
10100002534050    1
10100036517560    0
10100013746186    0
10100000598189    0
Name: group, dtype: int64
```

In [133]:
```
from sklearn.pipeline import Pipeline

def pipeline_logit(X_train, y_train):

    scaler = StandardScaler()
    logit_model = LogisticRegression()

    pipe = Pipeline([('scaler', scaler), ('model', logit_model)])

    param_grid = [{'model__C': [0.001, 0.01, 0.1, 1, 10, 100],
                   'model__penalty': ['l1', 'l2']}]

    grid_search = GridSearchCV(pipe, param_grid, cv=5)
    grid_search.fit(X_train, y_train)

    return grid_search
```

In [134]:
```
grid_search = pipeline_logit(X_train, y_train)
```

In [135]:
```
print("best score: ", grid_search.best_score_)
print("best score: ", grid_search.best_params_)
```

```
('best score: ', 0.9193993908917062)
('best score: ', {'model__C': 1, 'model__penalty': 'l1'})
```

In [136]:
```
print(classification_report(grid_search.predict(X_test), y_test))
```

```
             precision    recall  f1-score   support

          0       0.98      0.94      0.96     39001
          1       0.50      0.76      0.60      3356

avg / total       0.94      0.92      0.93     42357
```

In [137]:
```
fpr, tpr, thresholds = roc_curve(y_test, grid_search.predict(X_test))
roc_auc = auc(fpr, tpr)

print(roc_auc)
```

```
0.7397755729868845
```

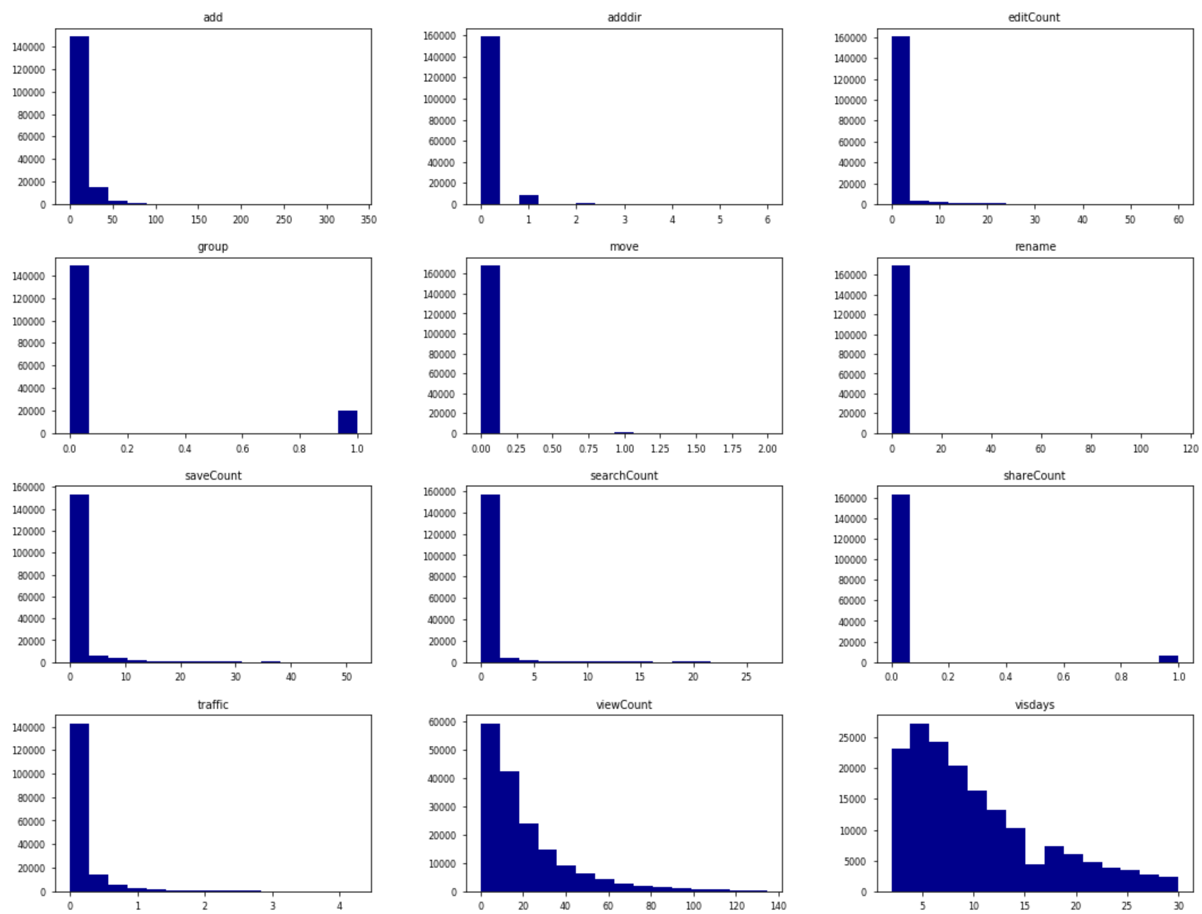
Transfrom Distribution

```
In [138]: df5_over.describe()
```

Out[138]:

	viewCount	editCount	shareCount	searchCount	add	move
count	169428.0000	169428.0000	169428.0000	169428.0000	169428.0000	169428.0000
mean	20.5642	0.8513	0.0385	0.6130	8.4348	0.0077
std	21.1871	4.0678	0.1924	2.7108	16.6001	0.1045
min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
25%	6.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50%	13.0000	0.0000	0.0000	0.0000	0.0000	0.0000
75%	27.0000	0.0000	0.0000	0.0000	13.0000	0.0000
max	135.0000	60.0000	1.0000	27.0000	336.0000	2.0000

```
In [139]: df5_over.hist(bins=15, color='darkblue', figsize=(18,14), grid=False);
```



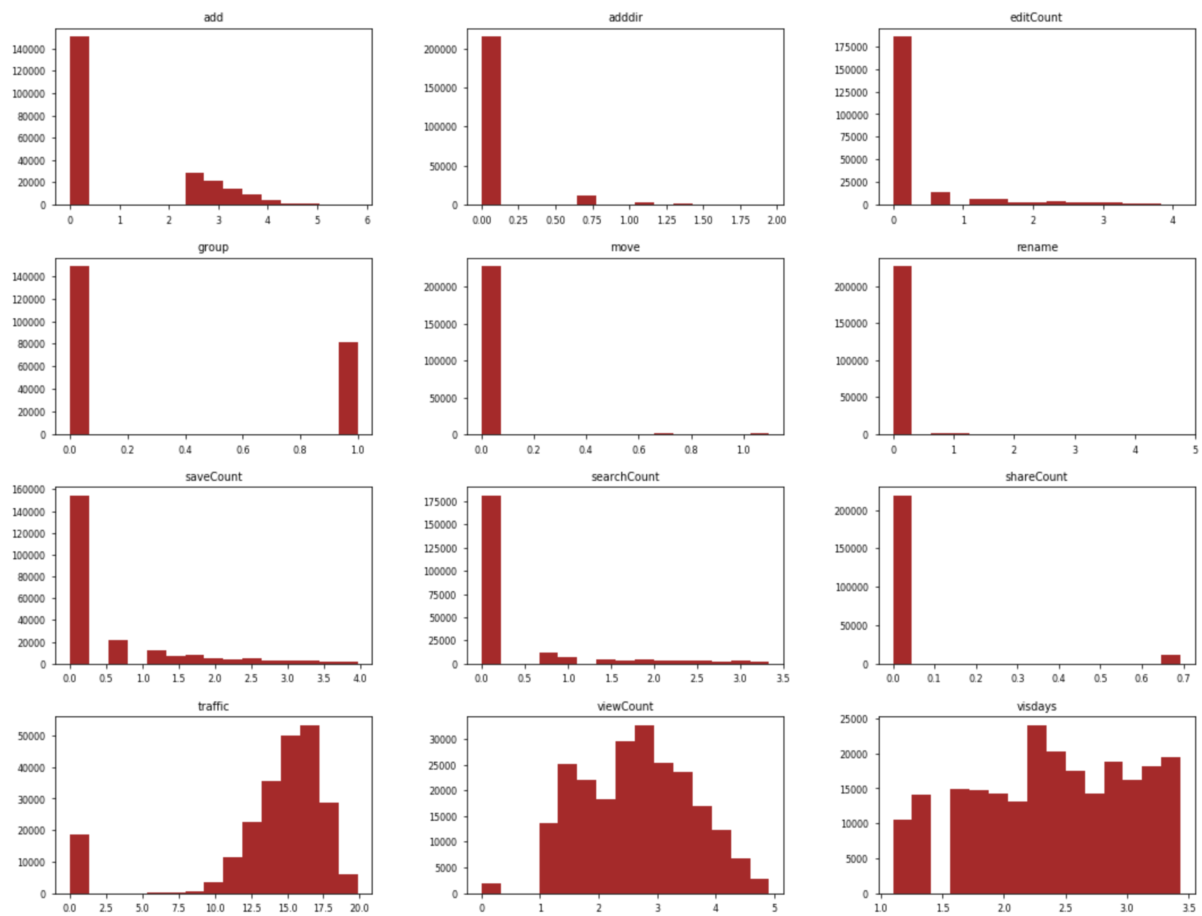

```
In [140]: df5_over_log = df5_over.loc[:,:'traffic'].apply(lambda x: np.log(x + 1))
.join(df5_over['group'])
```

In [141]:
```
df5_over_log.describe()
```

Out[141]:

	viewCount	editCount	shareCount	searchCount	add	move
count	230784.0000	230784.0000	230784.0000	230784.0000	230784.0000	230784.0000
mean	2.6496	0.3324	0.0359	0.3608	1.0529	0.0079
std	0.9317	0.8004	0.1537	0.7840	1.4823	0.0818
min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
25%	1.9459	0.0000	0.0000	0.0000	0.0000	0.0000
50%	2.6391	0.0000	0.0000	0.0000	0.0000	0.0000
75%	3.3322	0.0000	0.0000	0.0000	2.6391	0.0000
max	4.9127	4.1109	0.6931	3.3322	5.8201	1.0986

In [142]:
```
df5_over_log.hist(bins=15, color='brown', figsize=(18,14), grid=False);
```



In [143]:
```
X = df5_over_log.drop("group", axis=1)
y = df5_over_log.group

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=4
2)
```

In [144]:
```
grid_search = pipeline_logit(X_train, y_train)
```

In [145]:
```
def evaluation(grid, X_test, y_test):

    print(classification_report(grid.predict(X_test), y_test))

    print("best score: ", grid.best_score_)
    print("best params: ", grid.best_params_)

    fpr, tpr, thresholds = roc_curve(y_test, grid.predict(X_test))
    roc_auc = auc(fpr, tpr)

    return roc_auc
```

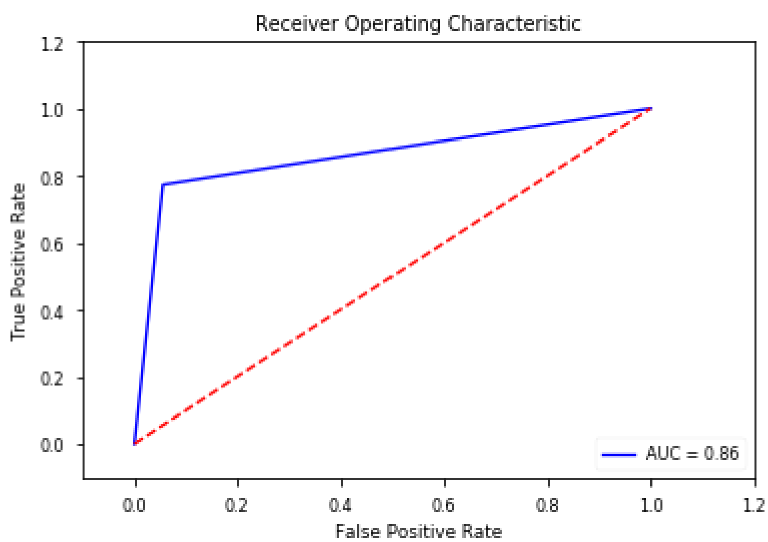
In [146]:
```
evaluation(grid_search, X_test, y_test)
```

```
             precision    recall  f1-score   support

          0       0.94      0.88      0.91     39879
          1       0.77      0.88      0.83     17817

avg / total       0.89      0.88      0.89     57696

('best score: ', 0.8856708726197079)
('best params: ', {'model__C': 0.01, 'model__penalty': 'l1'})
```

Out[146]:
```
0.8590521282995897
```

In [147]:
```
# ROC plot
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, grid_search.predict(X_test))
roc_auc = auc(false_positive_rate, true_positive_rate)

fig = plt.figure(figsize=(6,4))
plt.title('Receiver Operating Characteristic')
plt.plot(false_positive_rate, true_positive_rate, 'b', label='AUC = %0.2f'% roc_auc)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([-0.1,1.2])
plt.ylim([-0.1,1.2])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
```

Out[147]:
```
Text(0.5,0,'False Positive Rate')
```



The current score: Precision: 0.77, Recall: 0.88, AUC: 0.86

[Feature Selection (https://machinelearningmastery.com/feature-selection-machine-learning-python/)](https://machinelearningmastery.com/feature-selection-machine-learning-python/)

- Efficiency
- [Multicollinearity (https://ko.wikipedia.org/wiki/%EB%8B%A4%EC%A4%91%EA%B3%B5%EC%84%A0%EC%84%B1)](https://ko.wikipedia.org/wiki/%EB%8B%A4%EC%A4%91%EA%B3%B5%EC%84%A0%EC%84%B1)
- How to select
  - Univariate Selection: T-test, ANOVA, Coefficient
  - Feature Importance (Tree-based model)
  - RFE

In [148]:
```
print(len(X_train.columns))
print(len(X_test.columns))
```

```
11
11
```

Univariate Selection

- F value (http://scikit-learn.org/stable/modules/classes.html#module-sklearn.feature_selection)
- http://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.SelectKBest.html#sklearn.feature_selection.Se (http://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.SelectKBest.html#sklearn.feature_selection.Se
- 그룹내 분산이 작고, 그룹간 분산이 클 경우 F value가 커짐 (F value가 크다는 의미는 그룹간 통계적 차이가 크다는 것을 의미)

In [149]:
```
from sklearn.feature_selection import SelectKBest, f_classif

def pipeline_logit_kbest(X_train, y_train):

    select = SelectKBest(score_func=f_classif) # if regression problem,
 score_func=f_regression

    scaler = StandardScaler()
    logit_model = LogisticRegression()

    pipe = Pipeline([('scaler', scaler), ('feature_selection', select),
('model', logit_model)])

    param_grid = [{'feature_selection__k': [3,5,7],
                  'model__C': [0.001, 0.01, 0.1, 1, 10, 100],
                  'model__penalty': ['l1', 'l2']
                  }]

    grid_search = GridSearchCV(pipe, param_grid, cv=5)
    grid_search.fit(X_train, y_train)

    return grid_search
```

In [150]:
```
grid_search_kbest = pipeline_logit_kbest(X_train, y_train)
```

In [151]:
```
evaluation(grid_search_kbest, X_test, y_test)
```

```
             precision    recall  f1-score   support

          0       0.93      0.84      0.88     41386
          1       0.67      0.84      0.74     16310

avg / total       0.86      0.84      0.84     57696

('best score: ', 0.841444814198558)
('best params: ', {'model__C': 0.001, 'feature_selection__k': 7, 'model
__penalty': 'l1'})
```

Out[151]: 0.7996079647801195

In [152]:
```
mask = grid_search_kbest.best_estimator_.named_steps['feature_selection'
].get_support()
features_list = list(X_train.columns.values)

selected_features = []
for bool, features in zip(mask, features_list):
    if bool:
        selected_features.append(features)

print(selected_features)
```

```
['editCount', 'shareCount', 'searchCount', 'rename', 'visdays', 'saveCo
unt', 'traffic']
```

Feature Importance of ExtraTreesClassifier

In [153]:
```
from sklearn.ensemble import ExtraTreesClassifier

def pipeline_tree_kbest(X_train, y_train):

    select = SelectKBest() # if regression problem, score_func=f_regress
ion

#    scaler = StandardScaler()
    extra_tree_model = ExtraTreesClassifier()

    pipe = Pipeline([('feature_selection', select), ('model', extra_tree
_model)])

    param_grid = [{'feature_selection__k': [5,7],
                   'model__max_depth': [4, 6], # max_depth: The maximum
 depth of the tree.
                   'model__n_estimators': [10, 50], # n_estimators: The
 number of trees in the forest.
                   'model__min_samples_split': [50, 100]}]

    grid_search = GridSearchCV(pipe, param_grid, cv=3)
    grid_search.fit(X_train, y_train)

    return grid_search
```

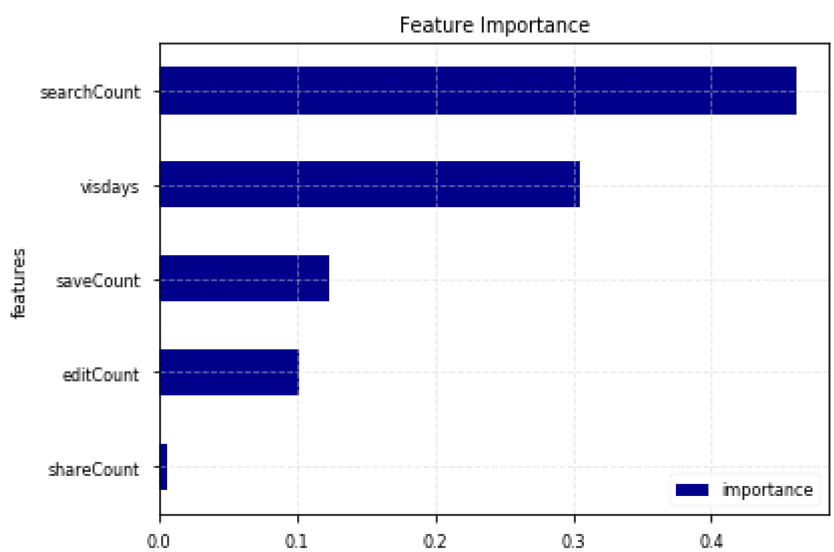
In [154]:
```
grid_search_tree = pipeline_tree_kbest(X_train, y_train)
```

In [155]:
```
evaluation(grid_search_tree, X_test, y_test)
```

```
             precision    recall  f1-score   support

          0       0.93      0.83      0.88     41873
          1       0.66      0.84      0.74     15823

avg / total       0.86      0.84      0.84     57696

('best score: ', 0.8464884914032169)
('best params: ', {'feature_selection__k': 5, 'model__max_depth': 6, 'm
odel__min_samples_split': 50, 'model__n_estimators': 50})
```

Out[155]:
```
0.794933338222801
```

In [156]:
```
mask = grid_search_tree.best_estimator_.named_steps['feature_selection']
.get_support()
feature_importance = grid_search_tree.best_estimator_.named_steps['mode
l'].feature_importances_

features_list = list(X_train.columns.values)

selected_features = []
for bool, features in zip(mask, features_list):
    if bool:
        selected_features.append(features)

# create a df
feature_importance_pd = pd.DataFrame(list(zip(selected_features, feature
_importance)),\
                                    columns=['features', 'importance'])\
                          .set_index("features").sort_values("importanc
e")

# visiual
feature_importance_pd.plot(kind='barh', color='darkblue')

plt.title("Feature Importance")
plt.grid(color='lightgrey', alpha=0.5, linestyle='--')
plt.tight_layout()
```



Q) RFE (recursive feature elimination)

- Backward 방식중 하나로 모든 변수를 다 포함시키고 반복해서 학습을 하면서 중요하지 않은 변수를 하나씩 제거하는 방식
    - [API DOC (http://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.RFE.html#sklearn.feature_selection.RFE)](http://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.RFE.html#sklearn.feature_selection.RFE)
- 위 방식을 이용해서 원하는 모델을 이용해 Feature Selection(elimination)을 해보세요.

In [157]:
```
## RFE (Recursive Feature Elimination)
# short ver.
from sklearn.svm import LinearSVC
from sklearn.feature_selection import RFE

svm = LinearSVC()
rfe = RFE(svm, 1)
rfe = rfe.fit(X_train, y_train)

print(X.columns.tolist())
print(rfe.support_)
print(rfe.ranking_)
```

```
['viewCount', 'editCount', 'shareCount', 'searchCount', 'add', 'move',
'rename', 'adddir', 'visdays', 'saveCount', 'traffic']
[False False False False False False False False  True False False]
[ 6  8  4  2 10  3  5  9  1  7 11]
```

In [158]:
```
# pipeline ver.
def pipeline_lm_rfe(X_train, y_train):

    scaler = StandardScaler()
    lm = LogisticRegression()
    select = RFE(lm, 1)

    pipe = Pipeline([('feature_selection', select), ('scaler', scaler),
('model', lm)])

    param_grid = [{'model__C': [0.01, 1],
                  'model__penalty': ['l1', 'l2']
                  }]

    grid_search = GridSearchCV(pipe, param_grid, cv=2)
    grid_search.fit(X_train, y_train)

    return grid_search
```

In [159]:
```
grid_search_rfe = pipeline_lm_rfe(X_train, y_train)
```

In [160]:
```
evaluation(grid_search_rfe, X_test, y_test)
```

```
             precision    recall  f1-score   support

          0       0.85      0.80      0.83     39562
          1       0.62      0.69      0.65     18134

avg / total       0.78      0.77      0.77     57696

('best score: ', 0.7702671473470142)
('best params: ', {'model__C': 0.001, 'model__penalty': 'l1'})
```

Out[160]: 0.734118603380132

In [161]:
```
print(X_train.columns.tolist())
print(grid_search_rfe.best_estimator_.named_steps['feature_selection'].s
upport_)
print(grid_search_rfe.best_estimator_.named_steps['feature_selection'].r
anking_)
```

```
['viewCount', 'editCount', 'shareCount', 'searchCount', 'add', 'move',
'rename', 'adddir', 'visdays', 'saveCount', 'traffic']
[False False False False False False False False  True False False]
[ 6 10  4  2  9  3  5  8  1  7 11]
```

Q) Random Forest, SVM이나 NB, Neural Network 등 다른 모델도 파이프라인에 사용해보세요.

```
# KNN
from sklearn.neighbors import KNeighborsClassifier

params_grid = [{'n_neighbors': [3, 5, 10], # default: 5
                'metric': ['euclidean', 'manhattan']
                # cityblock’, ‘cosine’, ‘euclidean’, ‘l1’, ‘l2’, ‘manhattan’
               }]

# SVC
from sklearn.svm import SVC

params_grid = [{'C': [1, 10], # Penalty parameter C of the error term
                'gamma': [1, 10] # Higher the value of gamma, will try to ex
act fit
                'kernel': ['linear', 'rbf']
               }]

# neural_network
from sklearn.neural_network import MLPClassifier

params_grid = [{'solver': [1, 10],
                'hidden_layer_sizes': [(5,2), (3,3)]
               }]
```

In [164]:
```
from sklearn.neural_network import MLPClassifier

def pipeline_nn(X_train, y_train):

    select = SelectKBest(score_func=f_classif) # if regression problem,
 score_func=f_regression
    scaler = MinMaxScaler()
    mlp = MLPClassifier()

    pipe = Pipeline([('scaler', scaler), ('feature_selection', select),
('model', mlp)])

    param_grid = [{'feature_selection__k': [5,7],
                  'model__solver': ['sgd', 'adam'],
                  'model__hidden_layer_sizes': [(5,2), (3,3)]
                  }]

    grid_search = GridSearchCV(pipe, param_grid, cv=2)
    grid_search.fit(X_train, y_train)

    return grid_search
```

In [165]:
```
grid_search_nn = pipeline_nn(X_train, y_train)
```

In [166]:
```
evaluation(grid_search_nn, X_test, y_test)
```

```
             precision    recall  f1-score   support

          0       0.92      0.87      0.89     39168
          1       0.76      0.83      0.79     18528

avg / total       0.87      0.86      0.86     57696

('best score: ', 0.8605911443889813)
('best params: ', {'model__hidden_layer_sizes': (3, 3), 'feature_select
ion__k': 7, 'model__solver': 'adam'})
```

Out[166]: 0.8370449122468682