Fake / Authentic user Instagram

송나현

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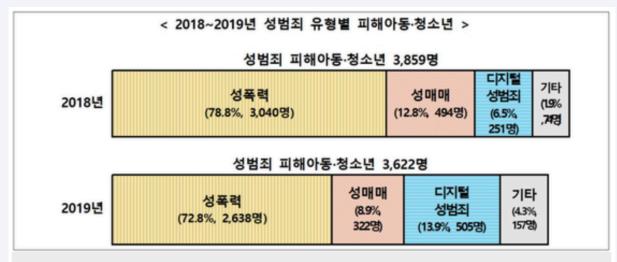
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서론

■ 서론



2018~2019년 성범죄 유형별 피해아동·청소년 〈여성가족부〉



EDA

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
post	43307	NaN	NaN	NaN	152.552	701.72	0	4	22	102	76200
follower	43307	NaN	NaN	NaN	827.477	12503.9	0	107	289	712.5	1.9e+06
following	43307	NaN	NaN	NaN	2817.93	2806.1	0	483	1400	6100	7800
biography_lengh	43307	NaN	NaN	NaN	46.2633	60.6034	0	0	13	85	555
picture	43307	NaN	NaN	NaN	0.932644	0.250641	0	1	1	1	1
link	43307	NaN	NaN	NaN	0.142448	0.349513	0	0	0	0	1
caption_length	43307	NaN	NaN	NaN	120.868	212.129	-1	2	30	133	3274
caption_zero	43307	NaN	NaN	NaN	0.291397	0.356736	0	0	0.111111	0.529412	1
non_image_percentage	43307	NaN	NaN	NaN	0.184412	0.258915	0	0	0.056	0.278	1
like_rate	43307	NaN	NaN	NaN	20.4049	146.742	0	1.95	7.85	17.99	26650
comment_rate	43307	NaN	NaN	NaN	1.11732	6.80205	0	0.05	0.32	0.95	1009.09
location_tag	43307	NaN	NaN	NaN	0.16909	0.280428	0	0	0	0.231	1
hashtag	43307	NaN	NaN	NaN	0.449444	1.201	0	0	0	0.444	30
promotional_keywords	43307	NaN	NaN	NaN	0.0440439	0.266913	0	0	0	0	20
followers_keywords	43307	NaN	NaN	NaN	0.0644748	0.624448	0	0	0	0	58
cosine_similarity	43307	NaN	NaN	NaN	0.348074	0.37686	0	0.0391645	0.166252	0.654545	1
post_interval	43307	NaN	NaN	NaN	442.006	875.626	0	9.99069	146.031	517.563	26786.1
class	43307	4	а	12054	NaN	NaN	NaN	NaN	NaN	NaN	NaN

학습 데이터

- -모두 수치형 데이터
- picture, link의 경우 인코딩 필요

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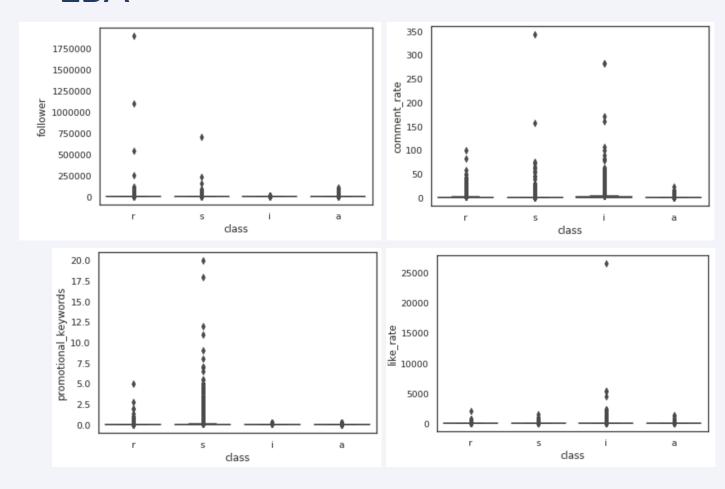
타겟 데이터

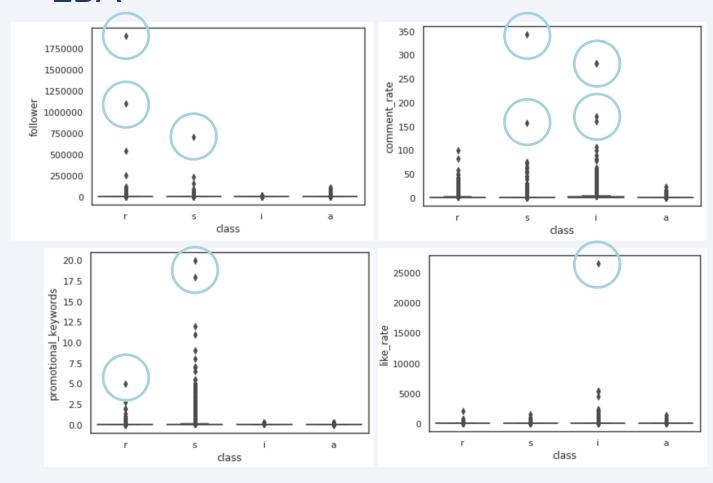
- A : 활성화 되어 있는 가짜 계정

- I : 비활성화 되어 있는 가짜 계정

- R : 진짜 계정

- S : 스팸 계정





특성 공학

■ 특성 공학

class	following>follower	like/post	comment/post
0	0	5474.920000	270.500000
0	1	15519.060000	1558.170000
0	0	13848.000000	912.000000
0	0	22484.001100	1771.000000
0	1	2099.880000	399.000000
2	1	5527.730046	4.210000
1	1	533.260006	33.279999
1	1	1298.459994	48.450002
1	1	4399.960035	199.709998
3	1	11286.000108	133.000001

특성 추가

- -following〉follower: 팔로잉이 더 많으면 1, 아니면 0
- like/post : 게시물당 좋아요 개수
- comment/post : 게시물당 댓글 개수

타겟 데이터 매핑

-r:0

-1:1

-a:2

-s:3

모델링

■ 모델링 - Baseline

```
#타켓 데이터 확인 -> 거의 valanced
y_train.value_counts(normalize=True)
2 0.286207
0 0.245188
3 0.244706
1 0.223899
Name: class, dtype: float64
#baseline model
major = y train.mode()[0]
y pred = [major] * len(y train)
from sklearn.metrics import accuracy score
accuracy score(y train, y pred)
0.2862070244409005
```

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accuracy score(y train, y pred)
0.2862070244409005
```

평가지표로 accuracy 사용

■ 모델링 - RandomForestClassifier

```
from sklearn.pipeline import make_pipeline
from category_encoders import TargetEncoder
from sklearn.ensemble import RandomForestClassifier

pipe = make_pipeline(
    TargetEncoder(),
    RandomForestClassifier(random_state=2)
)
```

			precision	recall	f1-score	support
		0 1	0.84 0.93	0.78 0.94	0.81 0.94	1702 1479
		2	0.92	0.93	0.93	1970
		3	0.93	0.97	0.95	1590
	accur	cacy			0.91	6741
	macro	avg	0.90	0.91	0.90	6741
wei	ghted	avg	0.90	0.91	0.90	6741

■ 모델링 - RandomForestClassifier

```
from sklearn.model selection import RandomizedSearchCV
from scipy.stats import randint, uniform
pipe tg = make pipeline(
    TargetEncoder(),
   RandomForestClassifier(random state=2)
dists = {
    'targetencoder min samples leaf': randint(1, 10),
    'targetencoder smoothing': [1.,10.],
    'randomforestclassifier n estimators': randint(100, 500),
    'randomforestclassifier max depth': randint(0, 20),
    'randomforestclassifier max features': uniform(0, 1),
    'randomforestclassifier min samples leaf': randint(1, 10)
}
clf tg = RandomizedSearchCV(
    pipe tq,
    param distributions=dists,
    n iter=3,
    cv=3,
    scoring='accuracy',
    verbose=1,
    n jobs=-1
clf_tg.fit(X_train, y_train)
```

모델링 - RandomForestClassifier

```
from sklearn.model selection import RandomizedSearchCV
from scipy.stats import randint, uniform
pipe tg = make pipeline(
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    'targetencoder smoothing': [1.,10.],
    'randomforestclassifier n estimators': randint(100, 500),
    'randomforestclassifier max depth': randint(0, 20),
    'randomforestclassifier max features': uniform(0, 1),
    'randomforestclassifier min samples leaf': randint(1, 10)
}
                                                                   precision
                                                                                   recall f1-score
                                                                                                           support
clf tg = RandomizedSearchCV(
   pipe tq,
                                                                          0.83
                                                                                      0.79
                                                                                                  0.81
                                                                                                              1702
   param distributions=dists,
                                                                                                  0.94
                                                                                      0.95
                                                                                                              1479
   n iter=3,
                                                                          0.94
   cv=3,
                                                                         0.92
                                                                                      0.93
                                                                                                  0.93
                                                                                                              1970
   scoring='accuracy',
                                                                          0.93
                                                                                      0.96
                                                                                                  0.94
                                                                                                              1590
   verbose=1,
   n jobs=-1
                                                                                                  0.91
                                                                                                               6741
                                                       accuracy
                                                                                      0.91
                                                                                                  0.91
                                                                                                               6741
                                                                          0.90
                                                      macro avg
                                                  weighted avg
                                                                          0.90
                                                                                      0.91
                                                                                                  0.90
                                                                                                               6741
clf_tg.fit(X_train, y_train)
```

■ 모델링 - LGBMClassifier

```
from lightgbm import LGBMClassifier
pipe lg = make pipeline(
    TargetEncoder(),
   LGBMClassifier()
dists = {
    'targetencoder min samples leaf': randint(1, 10),
    'targetencoder smoothing': [1.,10.],
    'lgbmclassifier learning rate': [0.1, 0.01],
    'lgbmclassifier num leaves': randint(1, 50),
    'lgbmclassifier max depth': randint(1, 20),
    'lgbmclassifier n estimators': randint(100, 500)
}
clf lg = RandomizedSearchCV(
    pipe lq,
    param distributions=dists,
    n iter=5,
    cv=3,
    scoring='accuracy',
    verbose=1,
    n jobs=-1
clf lg.fit(X train, y train)
```

■ 모델링 - LGBMClassifier

cv=3,

verbose=1,
n jobs=-1

scoring='accuracy',

clf lg.fit(X train, y train)

```
from lightgbm import LGBMClassifier

pipe_lg = make_pipeline(
    TargetEncoder(),
    LGBMClassifier()
)

dists = {
    'targetencoder_min_samples_leaf': randint(1, 10),
    'targetencoder_smoothing': [1.,10.],
    'lgbmclassifier_learning_rate': [0.1, 0.01],
    'lgbmclassifier_num_leaves': randint(1, 50),
    'lgbmclassifier_max_depth': randint(1, 20),
    'lgbmclassifier_nestimators': randint(100, 500)
}

clf_lg = RandomizedSearchCV(
    pipe_lg,
    param_distributions=dists,
    n iter=5,

precision
```

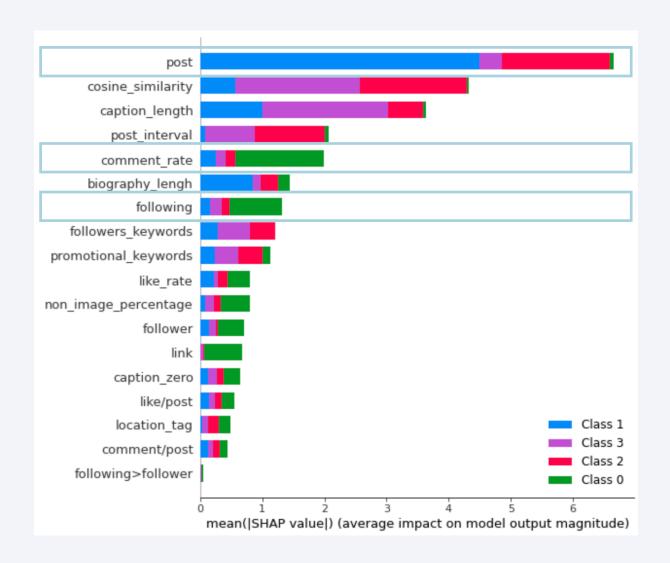
검증 데이터 사용 결과

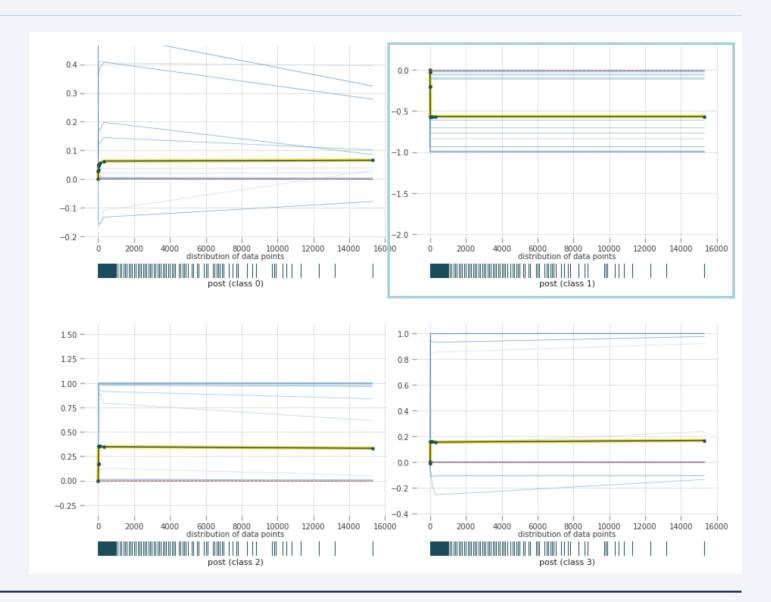
		precision	recall	f1-score	support
	0 1 2 3	0.92 0.95 0.98 0.97	0.90 0.95 0.98 0.98	0.91 0.95 0.98 0.98	1702 1479 1970 1590
vei	accuracy macro avg ghted avg	0.95 0.95	0.95 0.96	0.96 0.95 0.95	6741 6741 6741

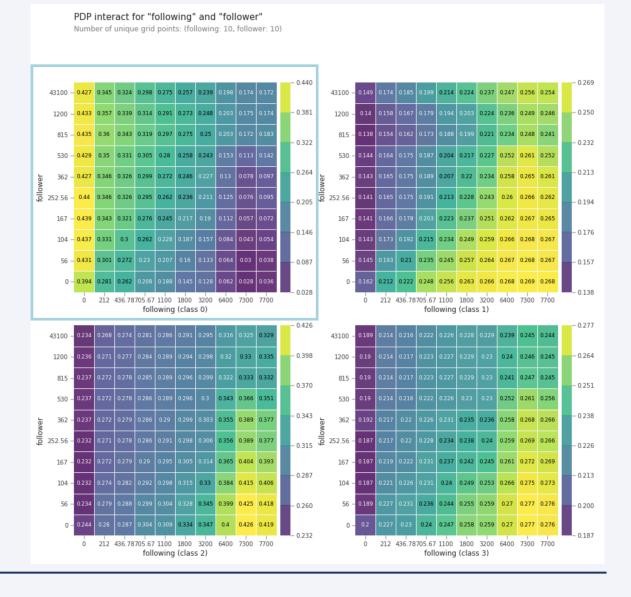
테스트 데이터 사용 결과

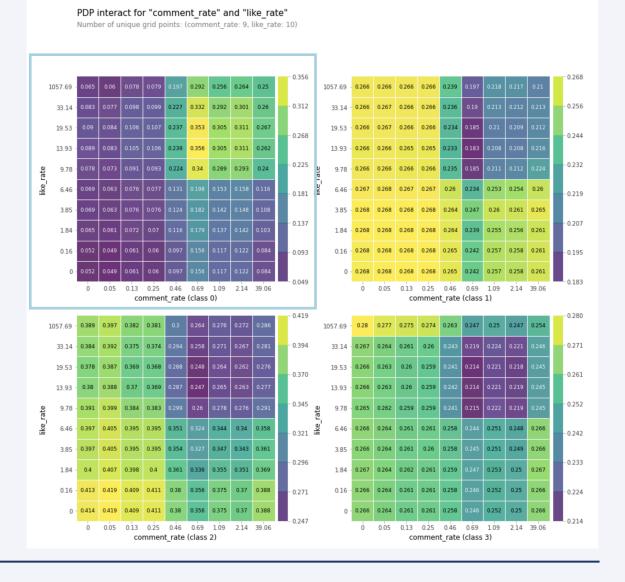
	precision	recall	f1-score	support
0	0.90	0.89	0.90	2100
1	0.96	0.95	0.95	1928
2	0.97	0.97	0.97	2358
3	0.96	0.98	0.97	2040
				1
accuracy			0.95	8426
macro avg	0.95	0.95	0.95	8426
weighted avg	0.95	0.95	0.95	8426

모델 해석









결론

■ 결론

- 타겟값은 네가지로 분류가 되나 진짜 계정을 제외한 나머지 계정들은 비슷한 분포를 보인다.

〉추후 연구에서는 진짜 계정/가짜 계정 두가지 클래스로 타겟값을 선정해야 할 것

- '낯선 사람'과 '랜선친구'를 구분하는데 도움이 될 것

감사합니다.