American Express-Default Prediction

Predict if a customer will default in the future

Intro >> **Introducing Our Team**

team_ amazon

Introducing Our Team

정주희	손희경	최유림
Team Leader	**Team Member_1**	**Team Member_2**
• XGBoost, LightGBM Modeling	• Random Forest Modeling	• CatBoost Modeling
• PPT	• EDA	• EDA
• Announcement	• Organize Data	• Organize Data

>> Table of contents

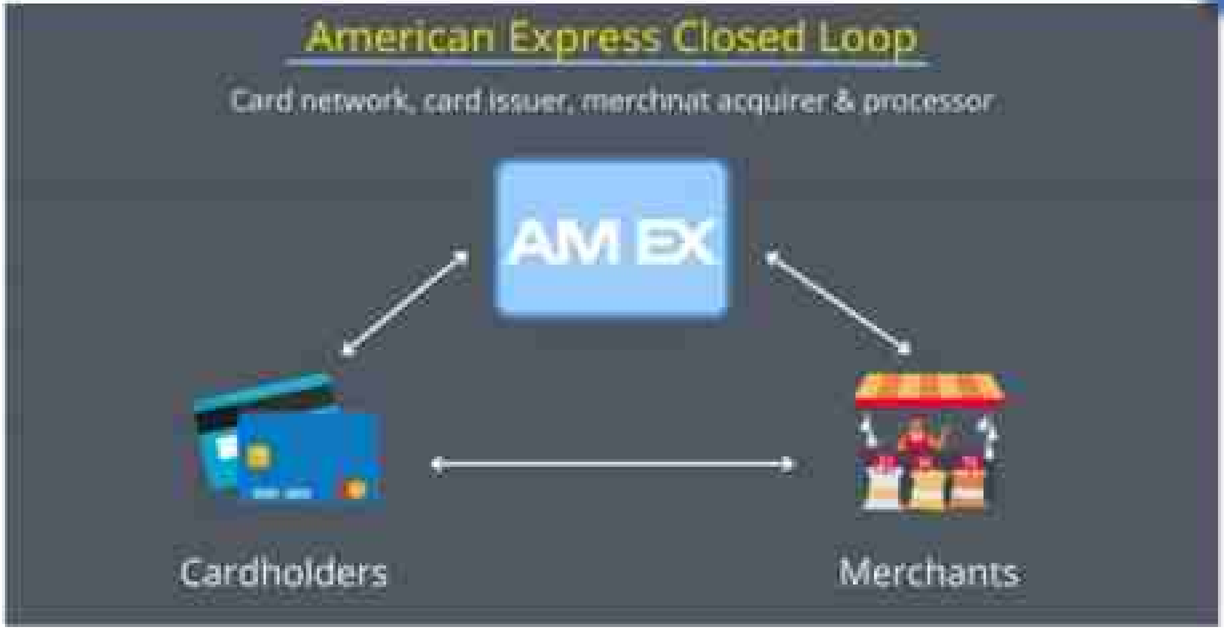
1

Competition Description

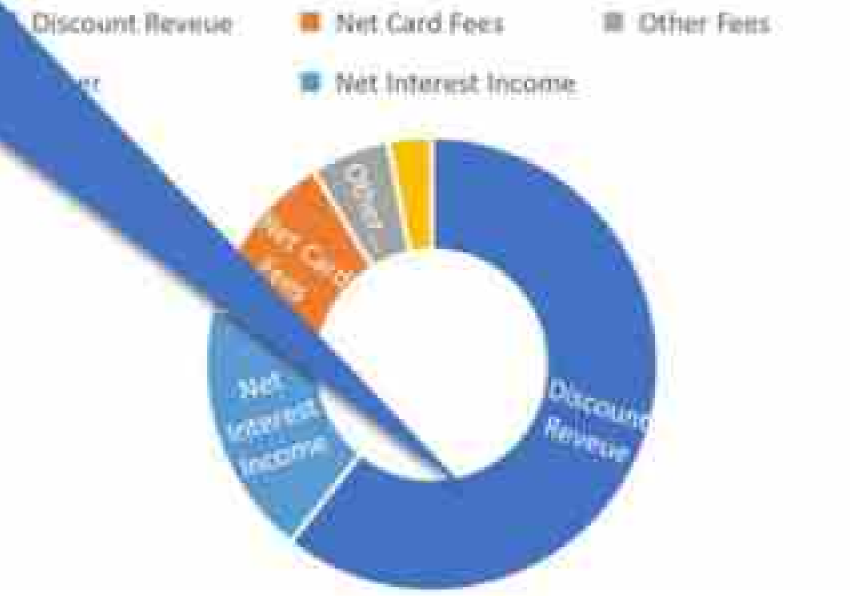
Discount Revenue(60%)

:카드 결제 수수료

American Express Business Model



revenues



“

Whether out at a restaurant or buying tickets to a concert, modern life counts on the convenience of a credit card to make daily purchases. It saves us from carrying large amounts of cash and also can advance a full purchase that can be paid over time. How do card issuers know we'll pay back what we charge? That's a complex problem with many existing solutions—and even more potential improvements, to be explored in this competition.

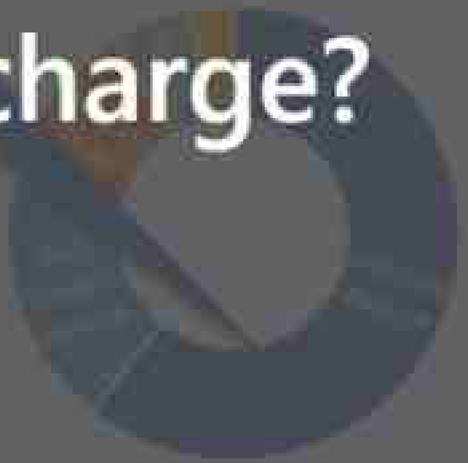
”

Part I >>

Discount Revenue(60%)

American Express Business Model

revenues



"How do card issuers know
we'll pay back what we charge?"

Competition Description_ Variables

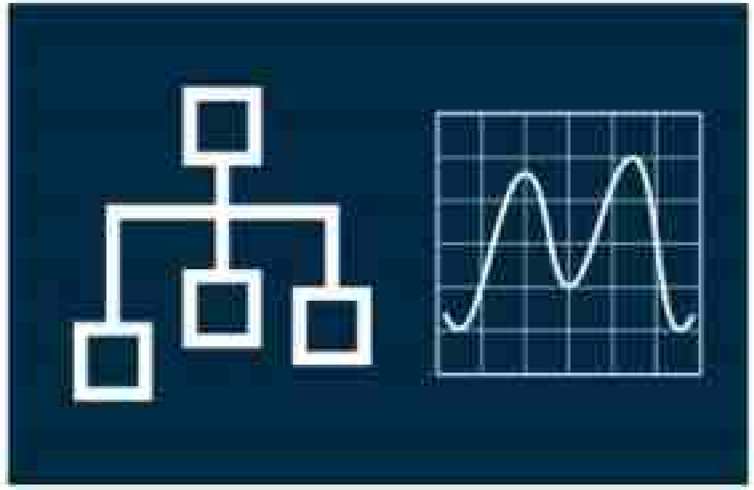
anonymous

anonymized customer
profile information

time-series data

The target binary variable is calculated
by observing 18 months performance window
after the latest credit card statement

target=1 : does not pay due amount in 120 days
after their latest statement date

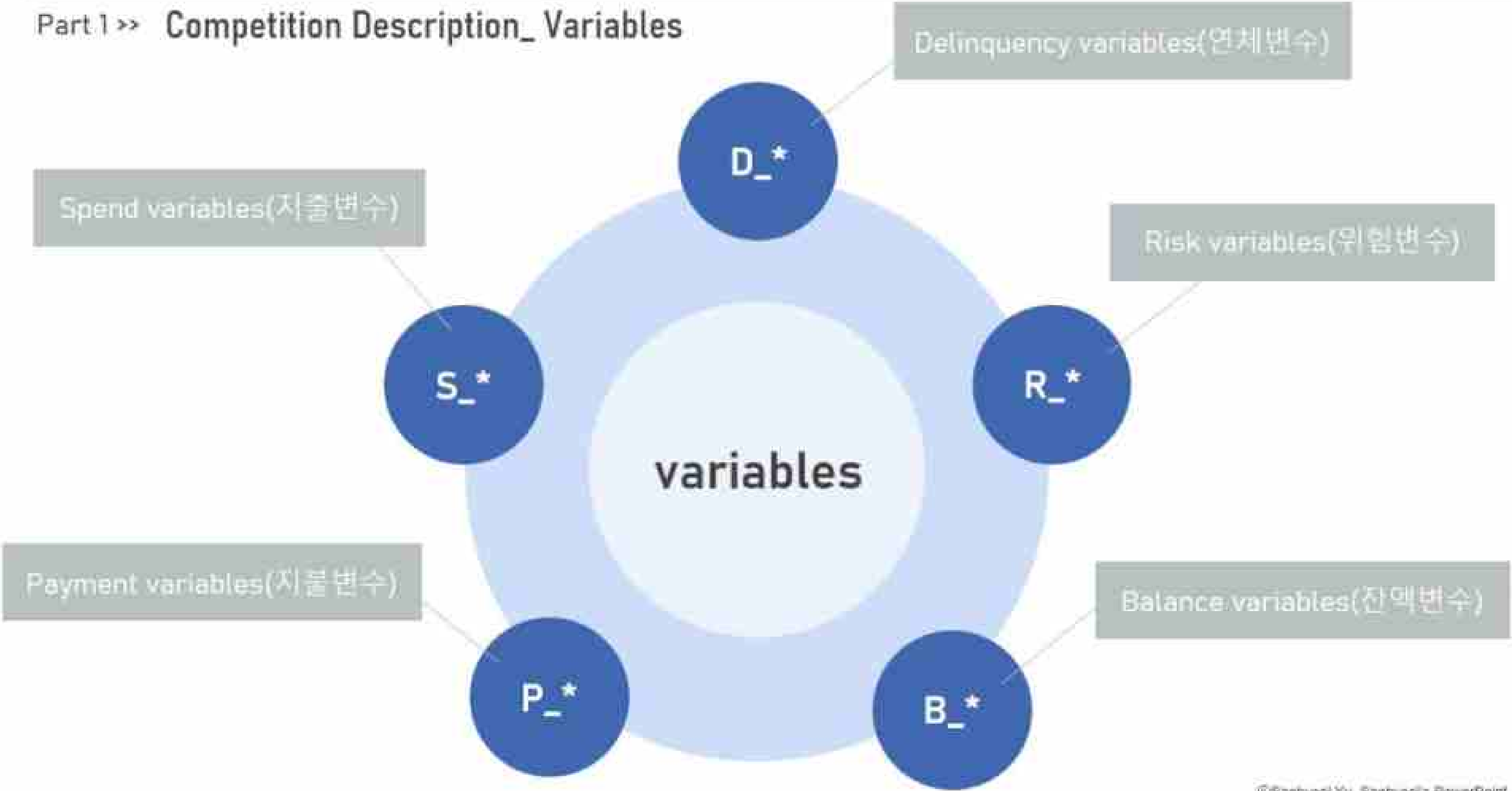


categorical/numerical

C : 'B_30', 'B_38', 'D_114', 'D_116', 'D_117', 'D_120',
'D_126', 'D_63', 'D_64', 'D_66', 'D_68'

predict 'target = 1' for each customer_ID

Competition Description_ Variables



Understand Customer Data_ Unique Customer

In [7]:

```
unique_customer_count = len(train.groupby("customer_ID")['customer_ID'].count())
print("unique customer data in training data -->", unique_customer_count)
unique_customer_count_test = len(test.groupby("customer_ID")['customer_ID'].count())
print("unique customer data in test data -->", unique_customer_count_test)
```

```
unique customer data in training data --> 458913
unique customer data in test data --> 924621
```

2

Data Preprocessing and EDA

Exploratory Data Analysis

train_data.csv(16.39 GB),
test_data.csv(33.82 GB)

industrial scale data set
(50.31 GB)

Reduce data size

EDA
Exploratory Data Analysis

- Change Data types
- File format : csv → parquet
- save → Multiple Files or Not

Exploratory Data Analysis_ How to reduce Data size?

File Format

- 압축률과 저장순서, dtype 기억 여부 고려
- csv : 행별 저장
  parquet : 열별 저장
- feather, parquet, pickle : 데이터를 압축
- csv : dtype기억×
  parquet : dtype기억o

>>

Reduce dtypes

- column 'customer_ID'
- column 'S_2'
  : pd.to_datetime()
  : 10 → 4byte
- categorical column (11)
  : int8로 변환 (8 → 1byte)
- numerical column (177)
  : float64 → float32

>>

File Saving type

Multiple Files
or
Not

>>

Remove Noise

Features
- integers
- random noise injected

↓

- float32(4byte)
  → int8(1byte)

Exploratory Data Analysis_ Methods of data reduction(1) : File Format

- 행 기반 압축 → 데이터 압축률 우수
- 특정 column의 데이터만 읽고 처리 가능
  → 데이터 처리에 들어가는 자원 절약됨
- column에 동일한 dtype이 저장
  → column별로 적합한(데이터형에 유리한) 인코딩 사용가능
- 특정 column을 선택해서 가져오는 형식
  → 선택하지 않은 column 데이터는 I/O가 발생하지 않음
  → 시간, 메모리 사용량 줄일 수 있음
- 파일 형식이 dtype을 기억
  → int64에서 int8로 downcast하면 다음에도 파일을 int8로 불러옴

Exploratory Data Analysis_ Methods of data reduction(2) : Reduce dtypes

Customer_ID

S_2

문자열 [64byte] → int64 [8byte]

문자열 [10byte] → pd.to_datetime() [4byte]

Categorical variables

최대 8개의 값 가짐

→ int8로 변경

[8byte → 1byte]

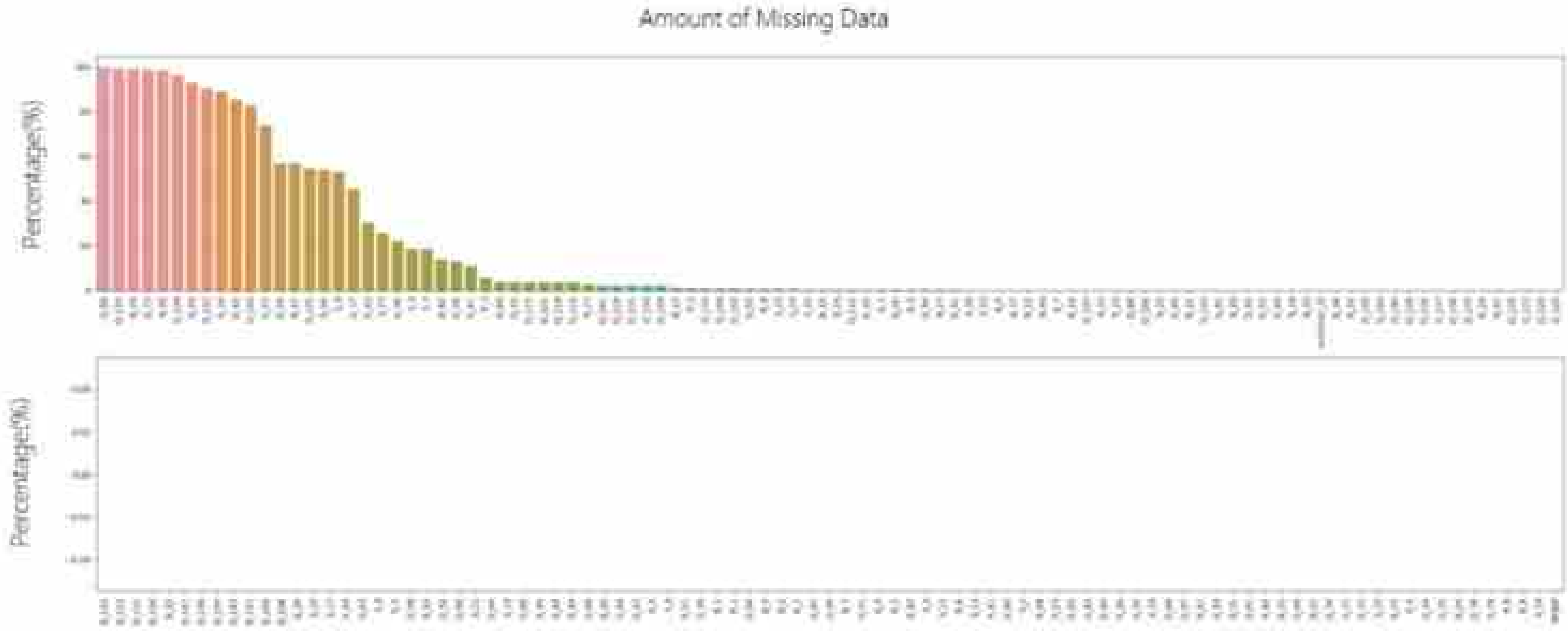
Numerical variable

float64 → float32로 변경

[8byte → 4byte]

Exploratory Data Analysis_ Missing Value

Verification_ Missing Value



Verification_ Missing Value

“

결측치가 매우 많음. 처리 필요

→결측치 비율 80%를 넘는 feature: 23개, 이들 제거함

”

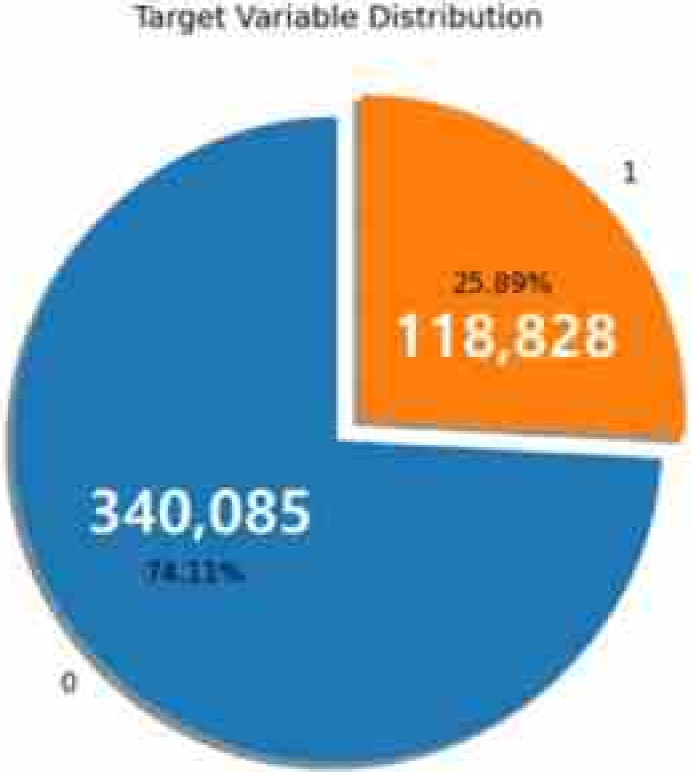
Verification_Missing Value

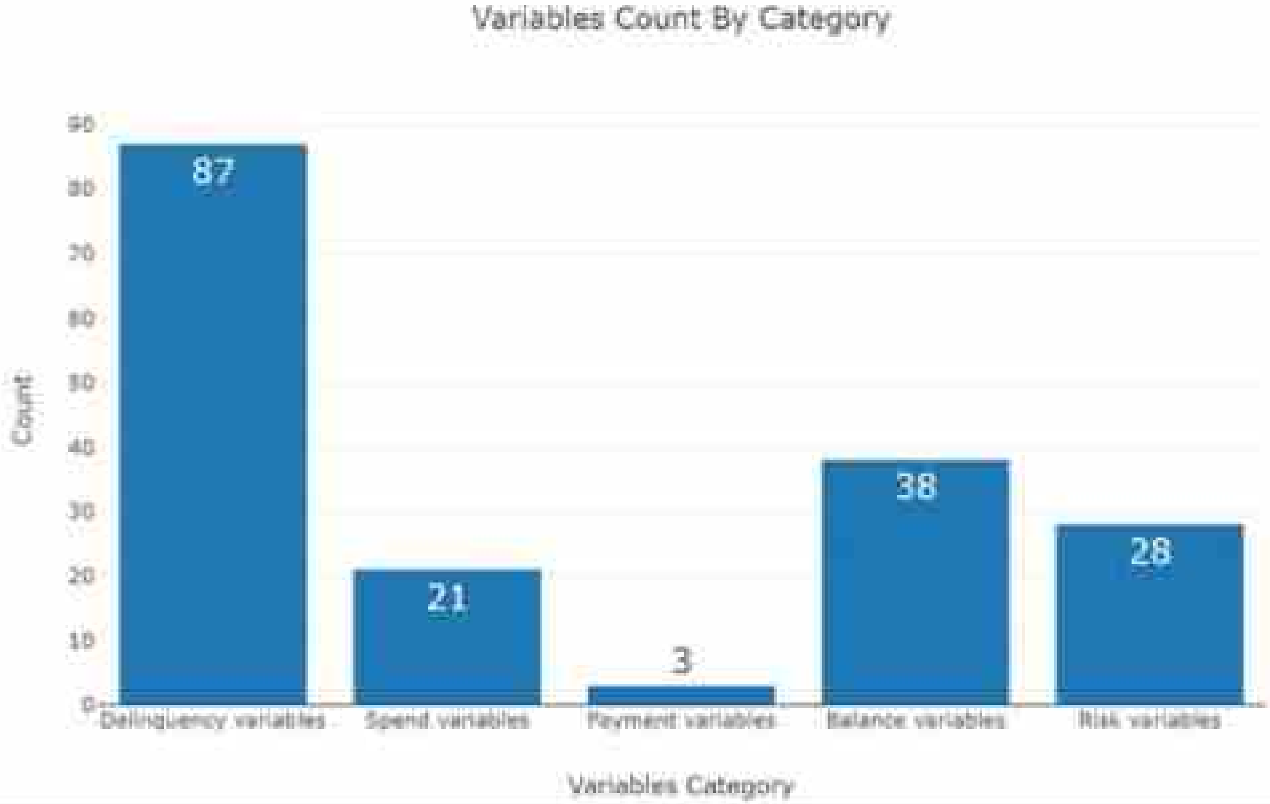
```
# Removing Columns With NaNs Rate Higher Than Threshold
nan_pct_threshold = 80
to_remove_cols = list(nan_values_pct[nan_values_pct > nan_pct_threshold].index)
print(f"Columns With NaN Values Rate > {nan_pct_threshold}%: {len(to_remove_cols)} Columns")
train_data = train_data.drop(columns=to_remove_cols).reset_index(drop=True)
```

```
Columns With NaN Values Rate > 80%: 23 Columns
```

Part 2 >> Exploratory Data Analysis_ Missing Value

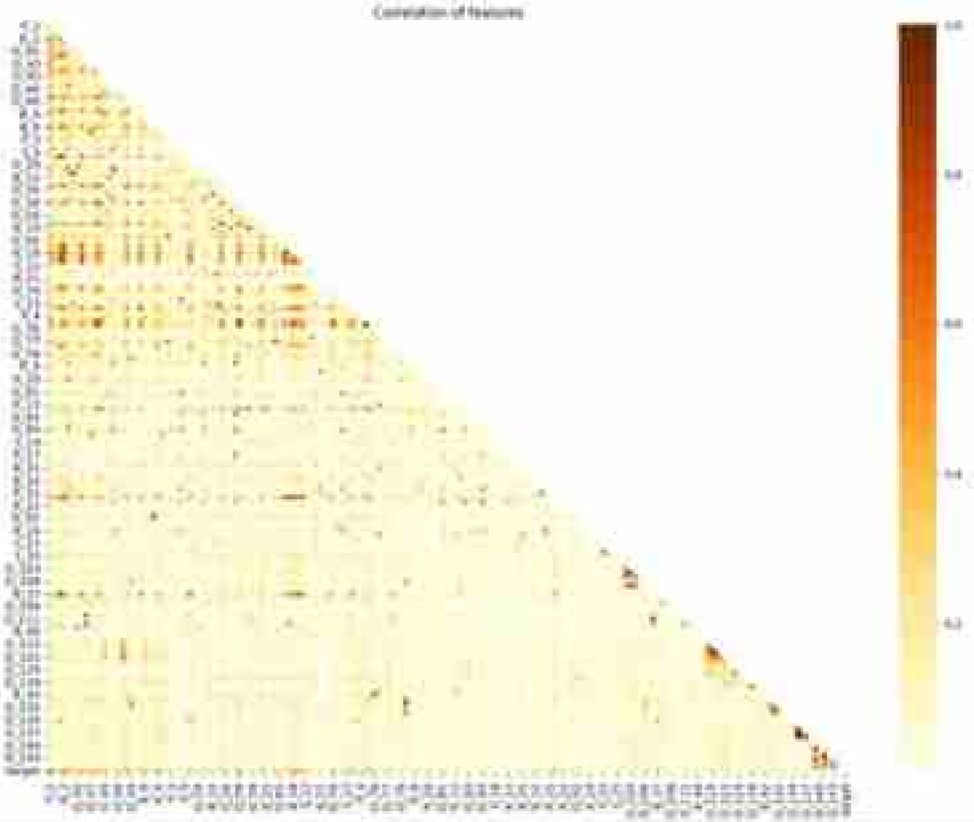
Verification_ After Missing Value Processing





Part 2 >> Exploratory Data Analysis_ Correlation

Verification_ Correlation between variables(heatmap)



insight

Feature 상관관계 파악필요
→ Heatmap이용해 시각화

상관관계가 뚜렷하지 않음

일부 색이 진한 점들은 다시
결과값 unstack해야 함

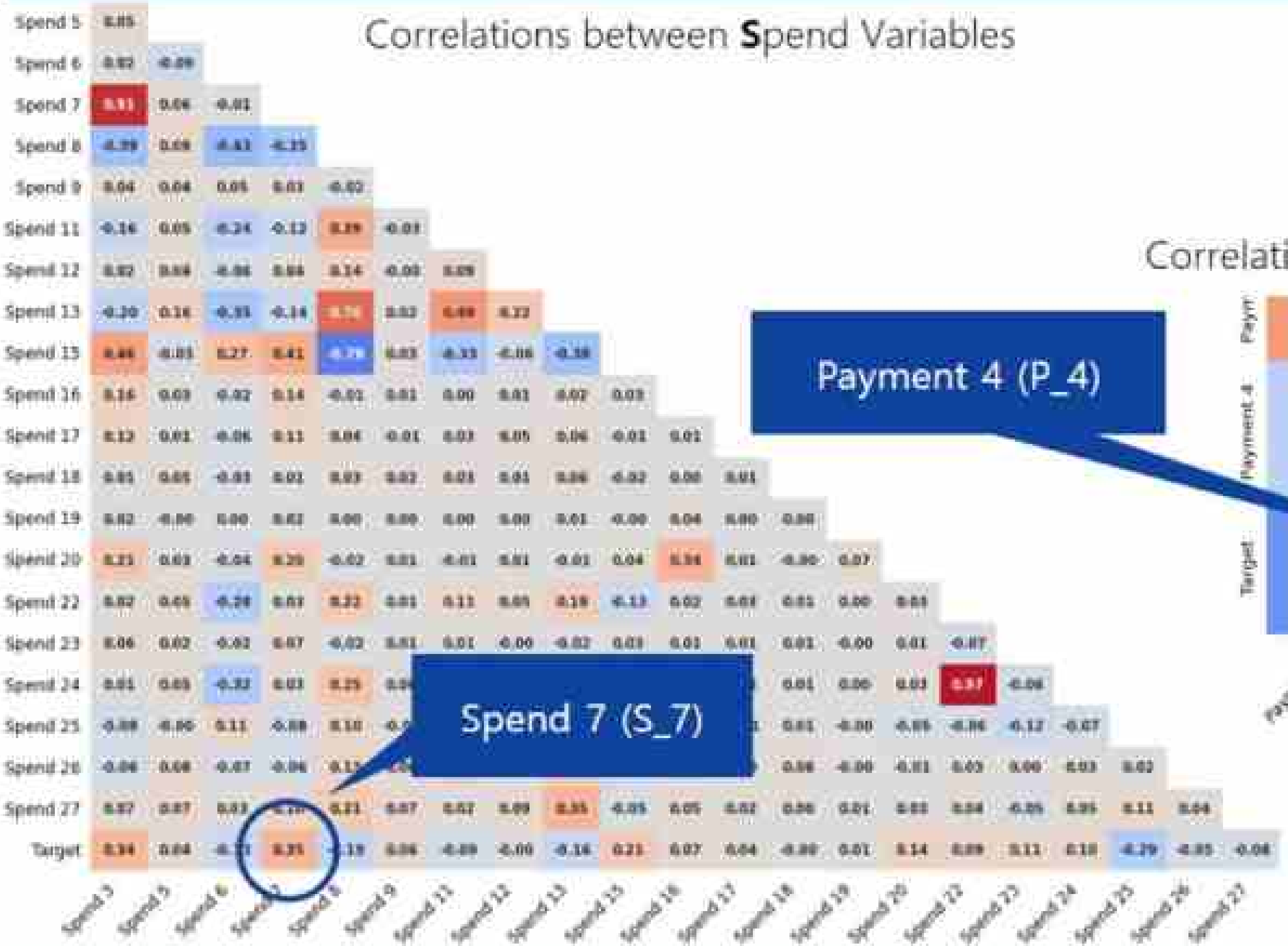
Verification_ Correlation between Unstacked Variables

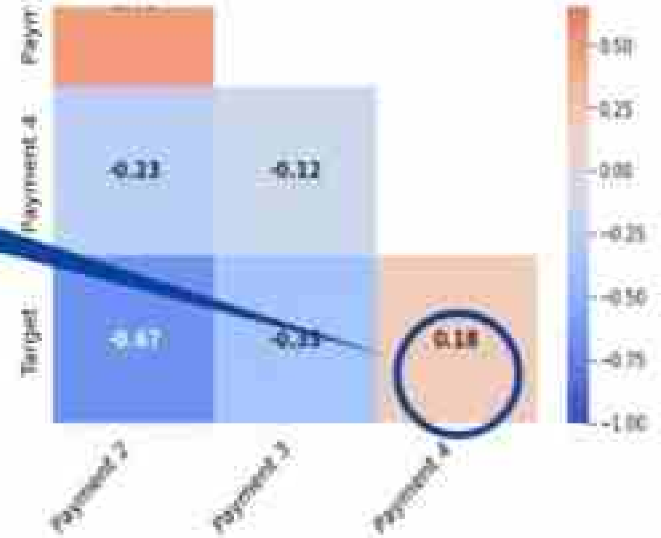
In [30]:

```python
unstacked = correlations.unstack()
unstacked = unstacked.sort_values(ascending=False, kind="quicksort").drop_duplicates().head(25)
unstacked
```

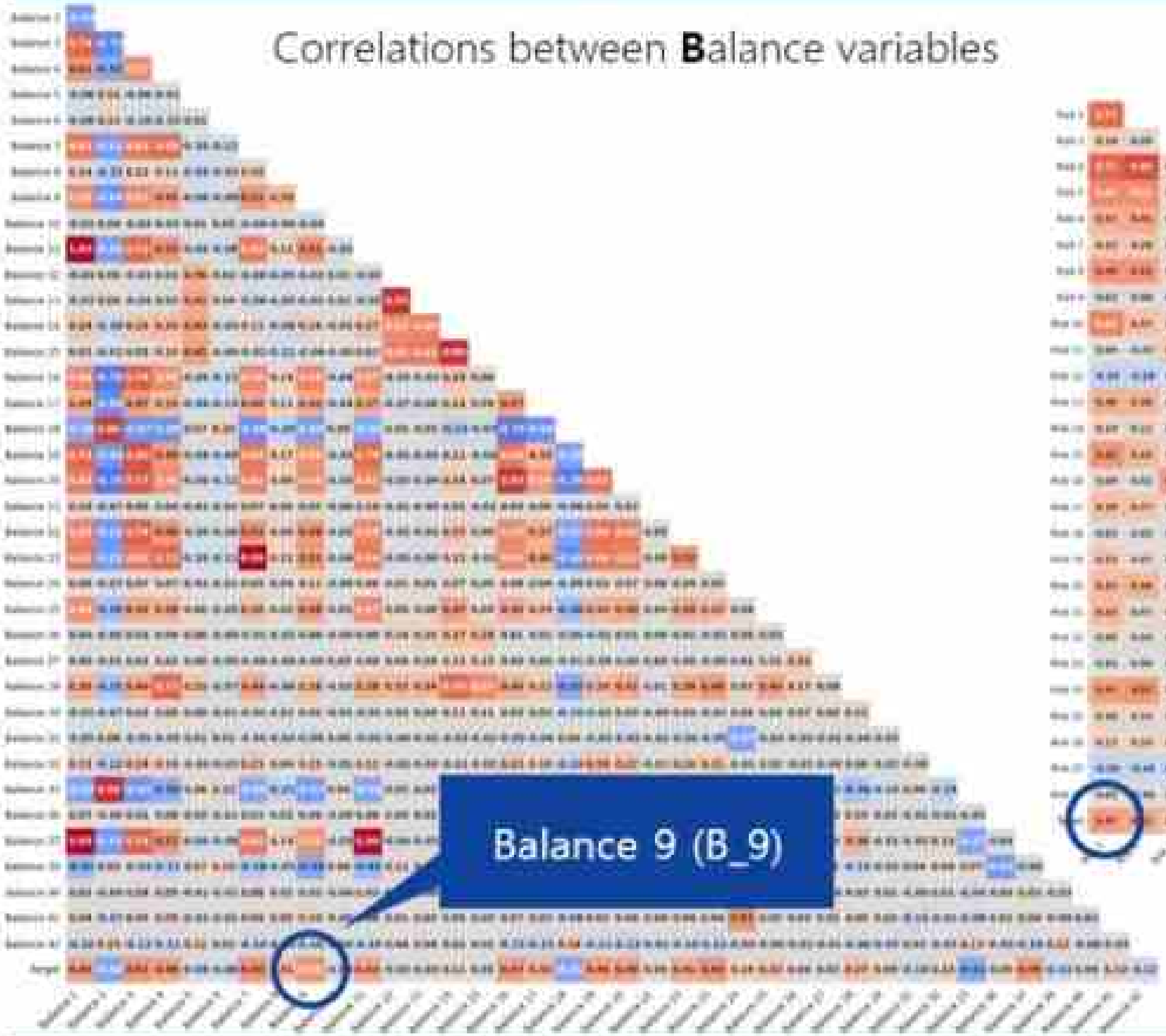
```
[illegible]
dtype: float64
```

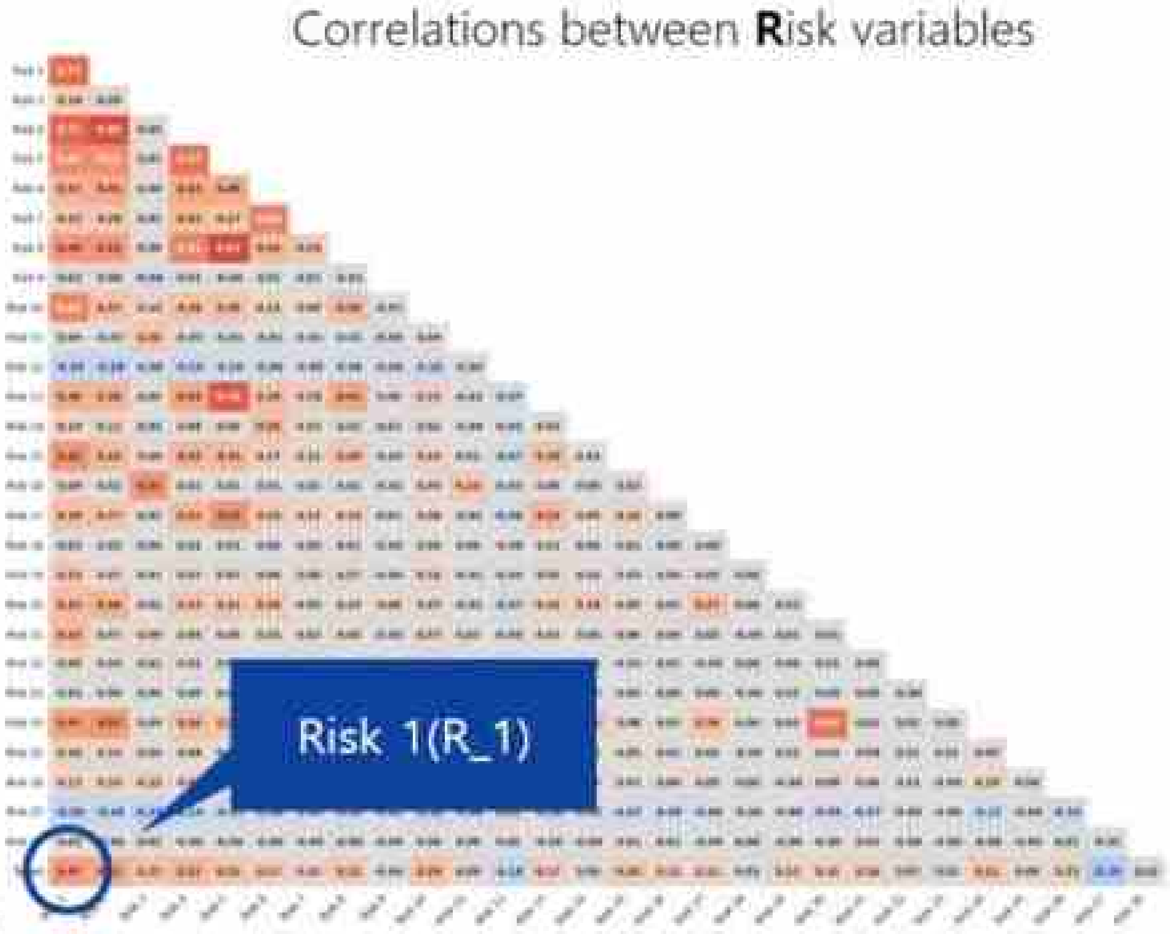
Part 2 >> Exploratory Data Analysis_ Statistical Values





Part 2 >> Exploratory Data Analysis_ Statistical Values





Exploratory Data Analysis_ Statistical Values

Verification_ Statistical value (count,mean,std,min,max,Quantiles)_target '0'

```
ex_customer_data[ex_customer_data["target"] == 0][b_cols[:10]].describe()
```

	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8
count	9032.000000	9032.000000	9032.000000	9032.000000	9032.000000	9032.000000	9032.000000	8.989000e+03
mean	0.081276	0.719796	0.081671	0.130928	0.097953	0.161655	0.133657	3.310980e-01
std	0.156970	0.355266	0.181874	0.182206	0.331847	0.319970	0.192023	4.688353e-01
min	-0.141469	0.000184	0.000003	0.000017	0.000007	-0.000552	-0.096913	2.764867e-07
25%	0.007554	0.620152	0.004455	0.019144	0.007463	0.037204	0.024911	3.603379e-03
50%	0.021453	0.817121	0.008435	0.055663	0.017671	0.140455	0.045870	7.330273e-03
75%	0.061725	1.003689	0.041836	0.161089	0.072235	0.199933	0.156390	1.002241e+00
max	1.320823	1.009999	1.171260	1.283849	12.974426	20.331217	1.252293	1.010181e+00

Exploratory Data Analysis_ Statistical Values

Verification_ Statistical value (count,mean,std,min,max,Quantiles)_target '1'

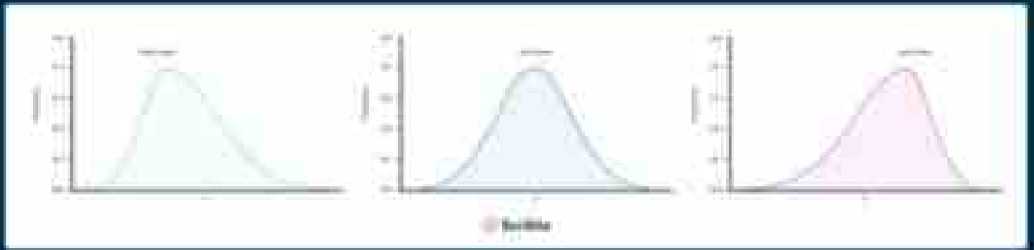
```
ex_customer_data[ex_customer_data["target"] == 1][b_cols[:10]].describe()
```

	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8
count	3030.000000	3030.000000	3030.000000	3030.000000	3030.000000	3030.000000	3030.000000	3022.000000
mean	0.257518	0.299894	0.298945	0.328520	0.031458	0.043737	0.355820	0.734537
std	0.279484	0.375638	0.300259	0.296676	0.084002	0.085808	0.252973	0.444182
min	-0.046790	0.000034	0.000085	0.000082	0.000006	-0.002122	0.000510	0.000006
25%	0.054462	0.028687	0.036761	0.120258	0.007023	0.009662	0.159904	0.009335
50%	0.136546	0.066485	0.220646	0.251262	0.011993	0.017531	0.309124	1.003016
75%	0.378923	0.810611	0.455126	0.450153	0.023515	0.038585	0.510301	1.006530
max	1.323411	1.009960	1.258546	2.187350	2.188328	1.926984	1.252394	1.010065

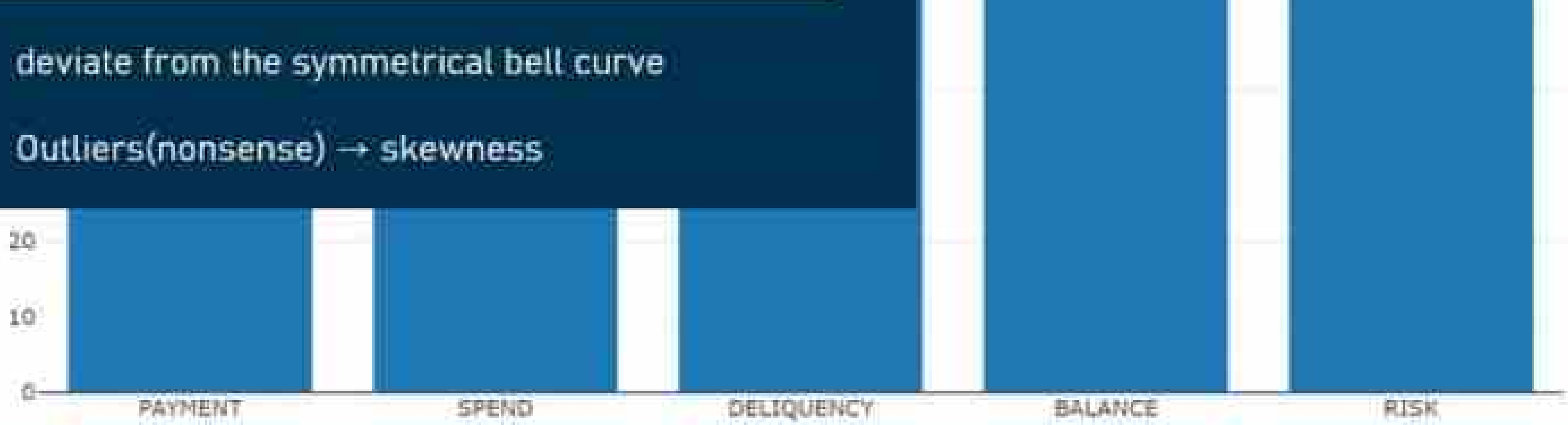
Part 2 >>

Exploratory Data Analysis_ Outlier detection for skewed data

Verification_ Skewness R Rate for each Variable Category

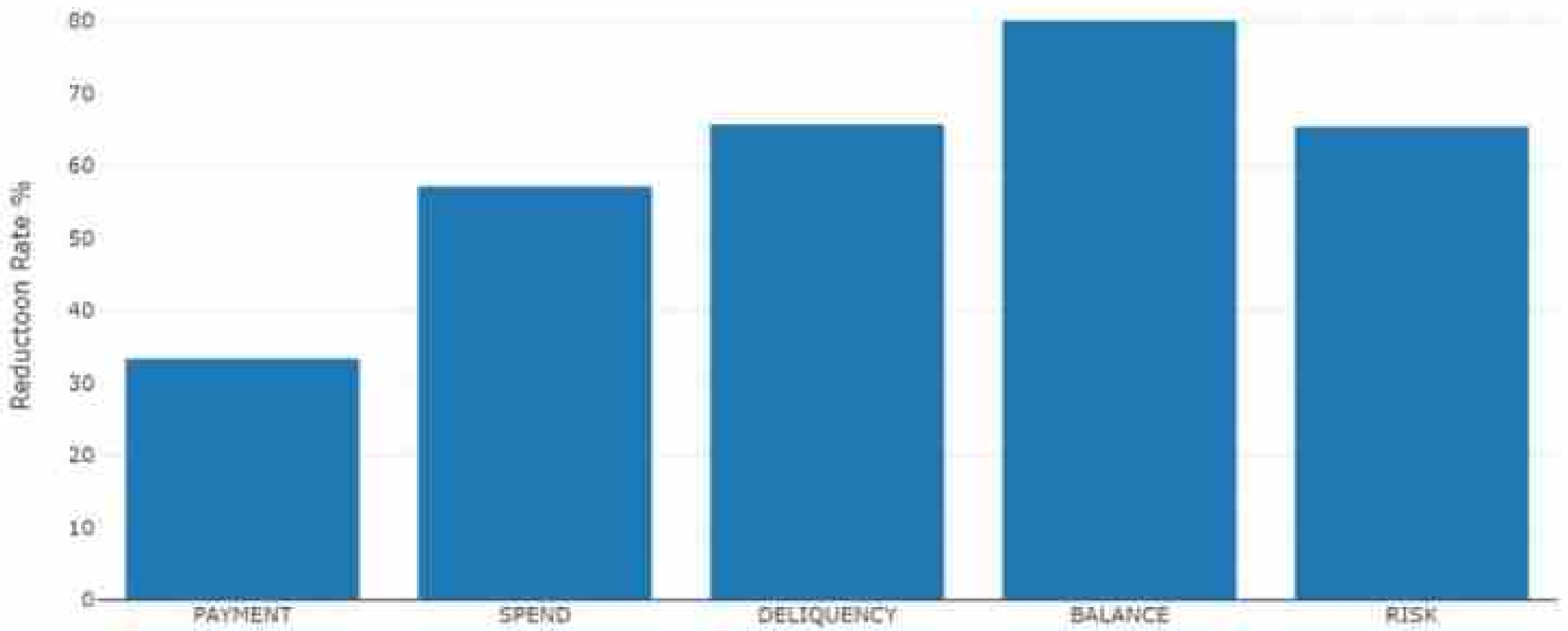


- deviate from the symmetrical bell curve
- Outliers(nonsense) → skewness

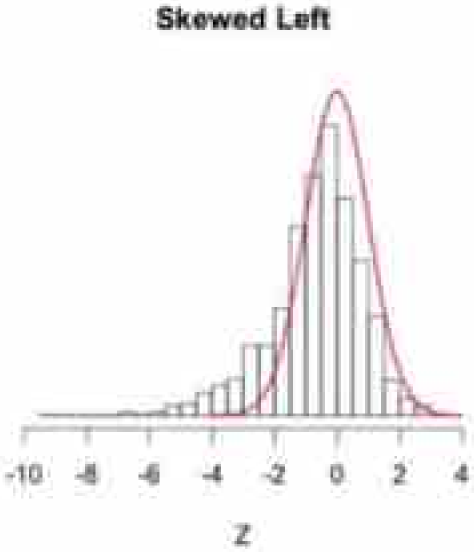


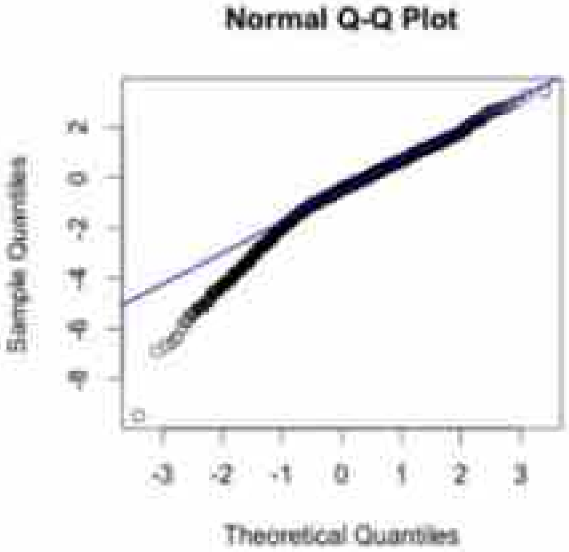
Exploratory Data Analysis_ Outlier detection for skewed data

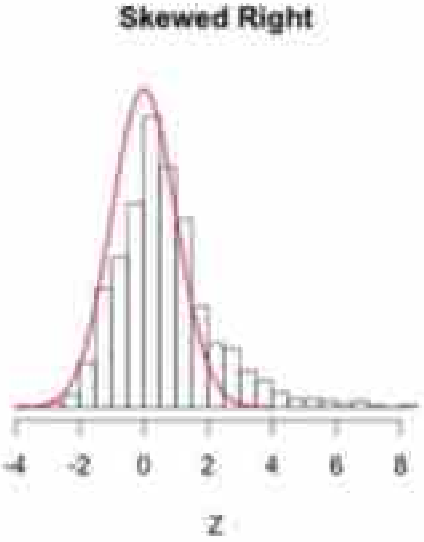
Verification_ Skewness Reduction Rate for each Variable Category

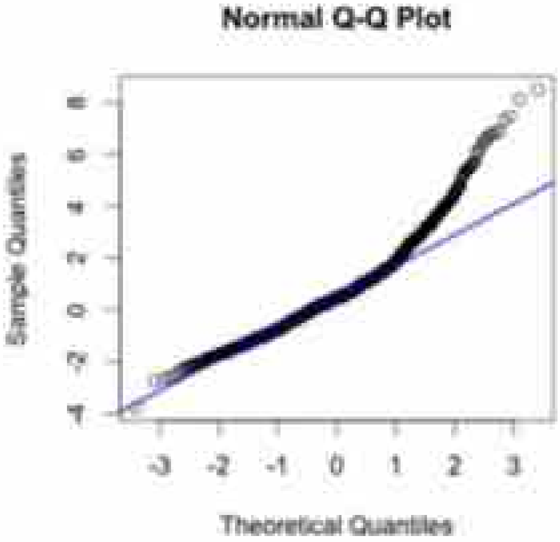


Verification_ Quantile-Quantile plot

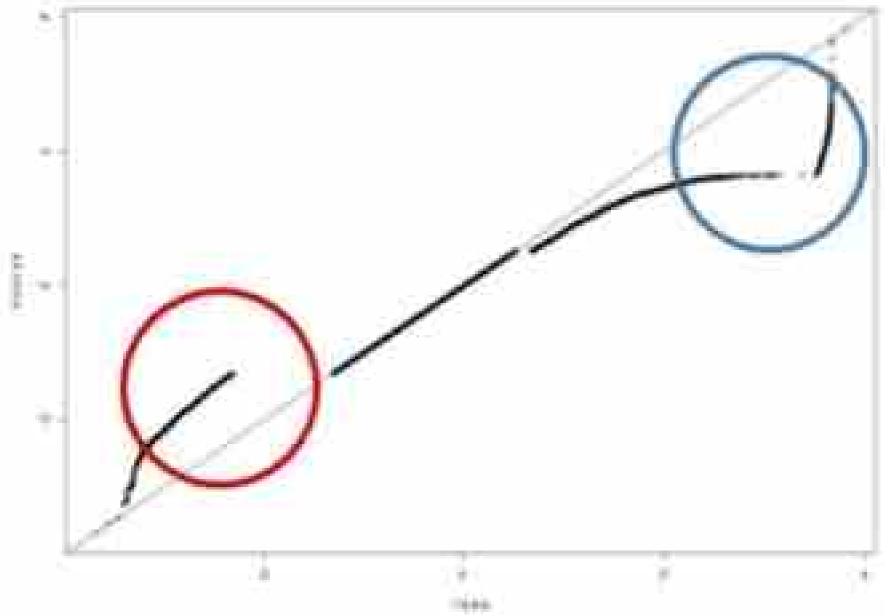


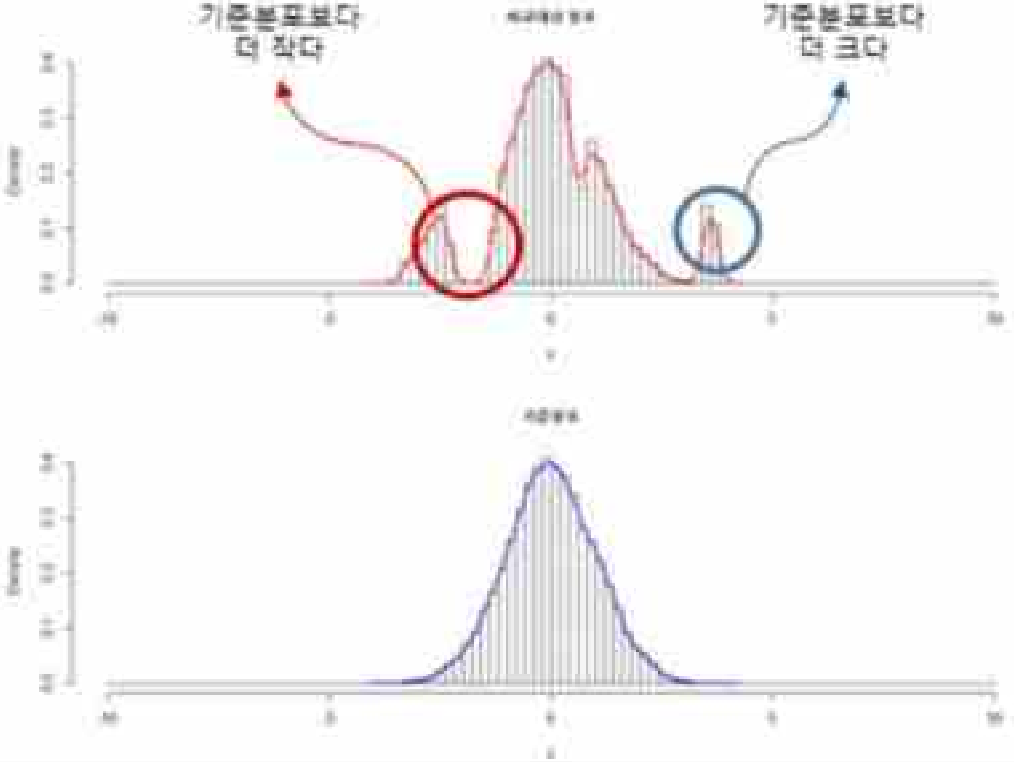






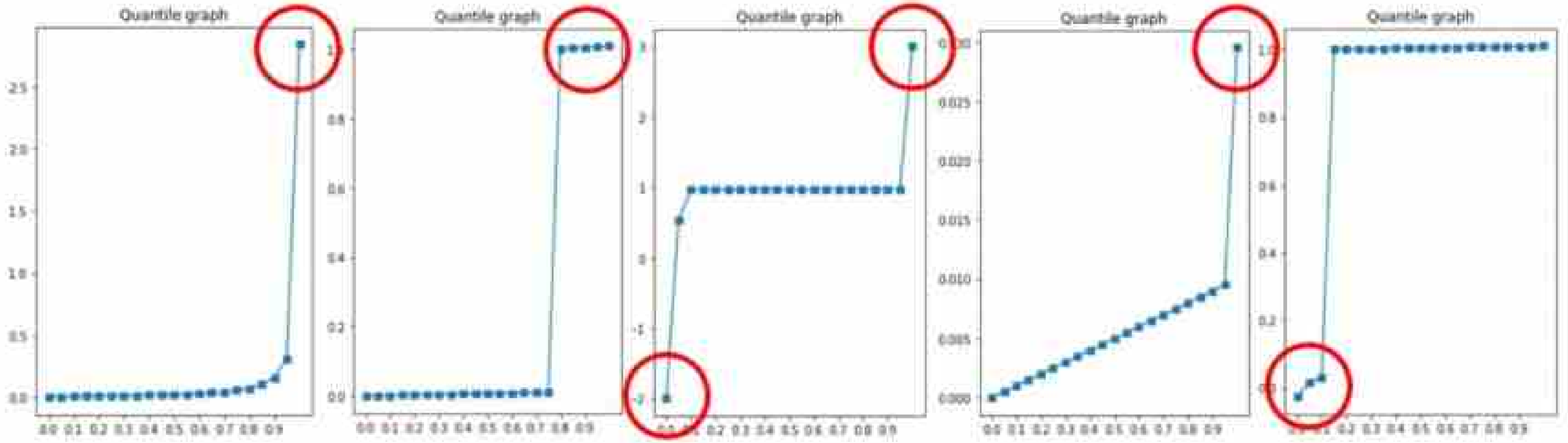
Verification_ Quantile-Quantile plot





Exploratory Data Analysis_ Understanding Features with Quantiles

Verification_ Quantile graph for Outlier detection

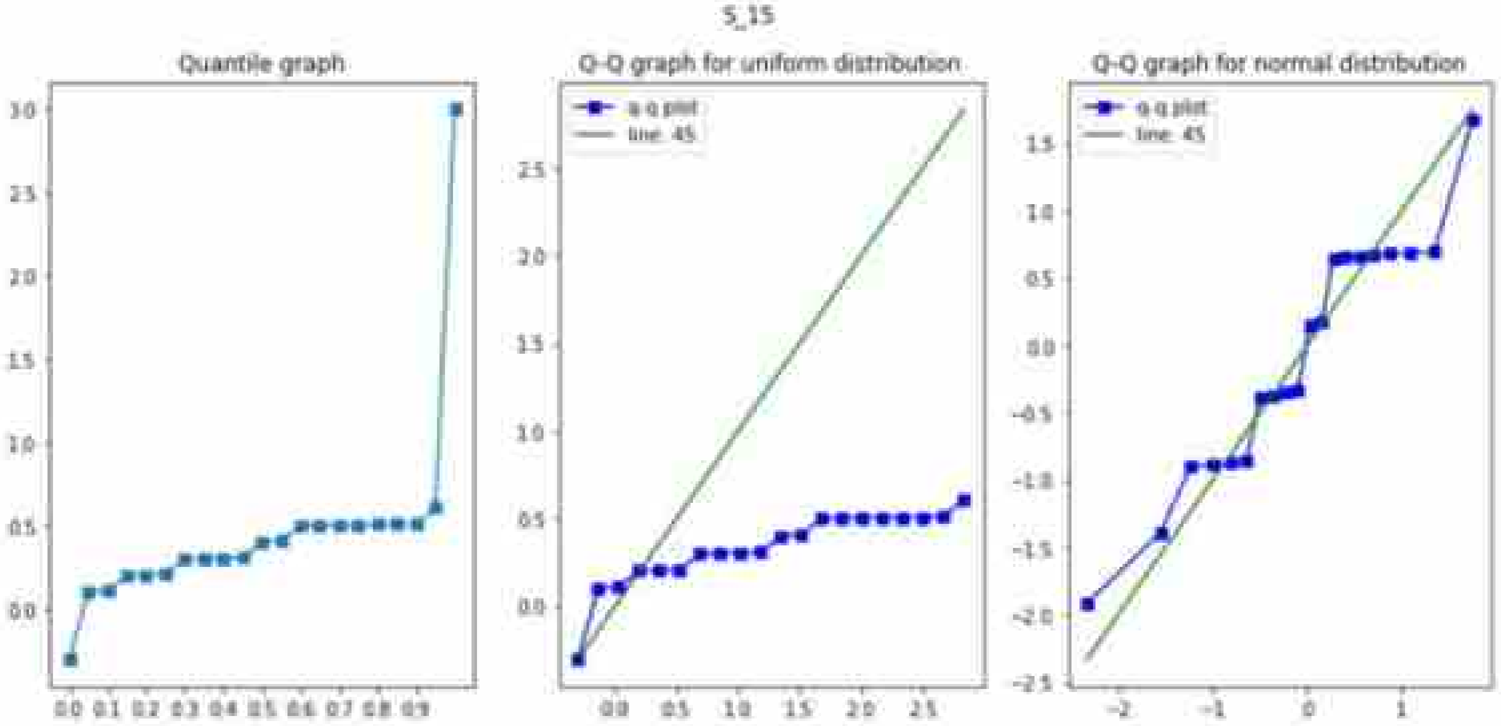


Verification_ Quantile graph for Outlier detection

“ Outlier(이상치) 갖는 feature 많음 ”

Exploratory Data Analysis_ Understanding Features with Quantiles

Verification_ Highly discrete values

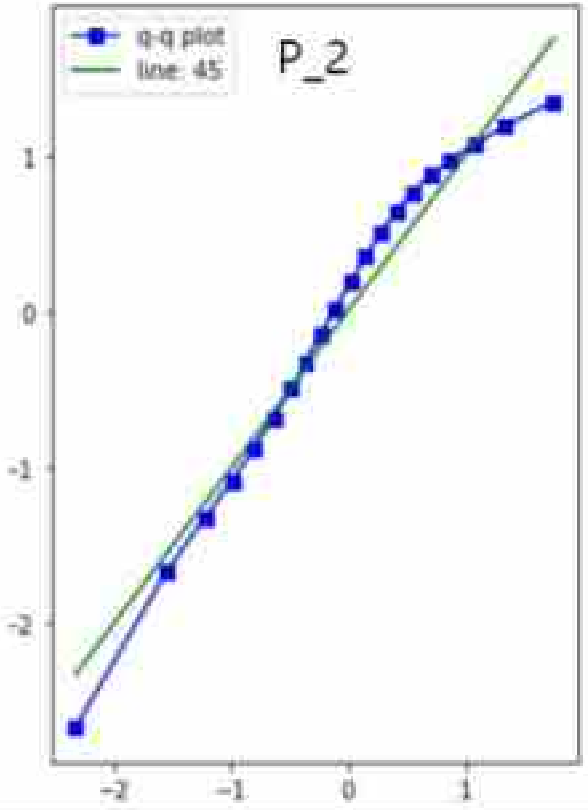


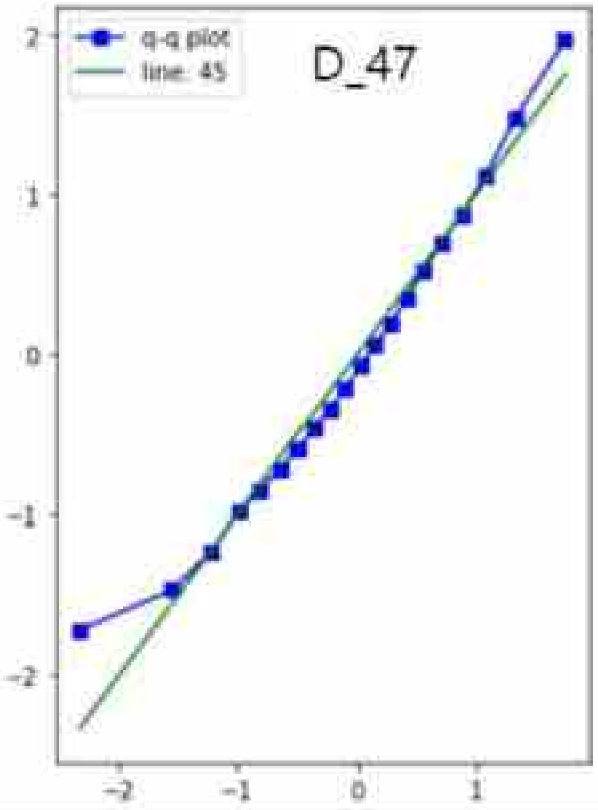
insight

S15는 최소 7개의 이산 값을 가지는 것으로 보임

 Exploratory Data Analysis_ Understanding Features with Quantiles

Verification_ Q-Q graph for Normal Distribution



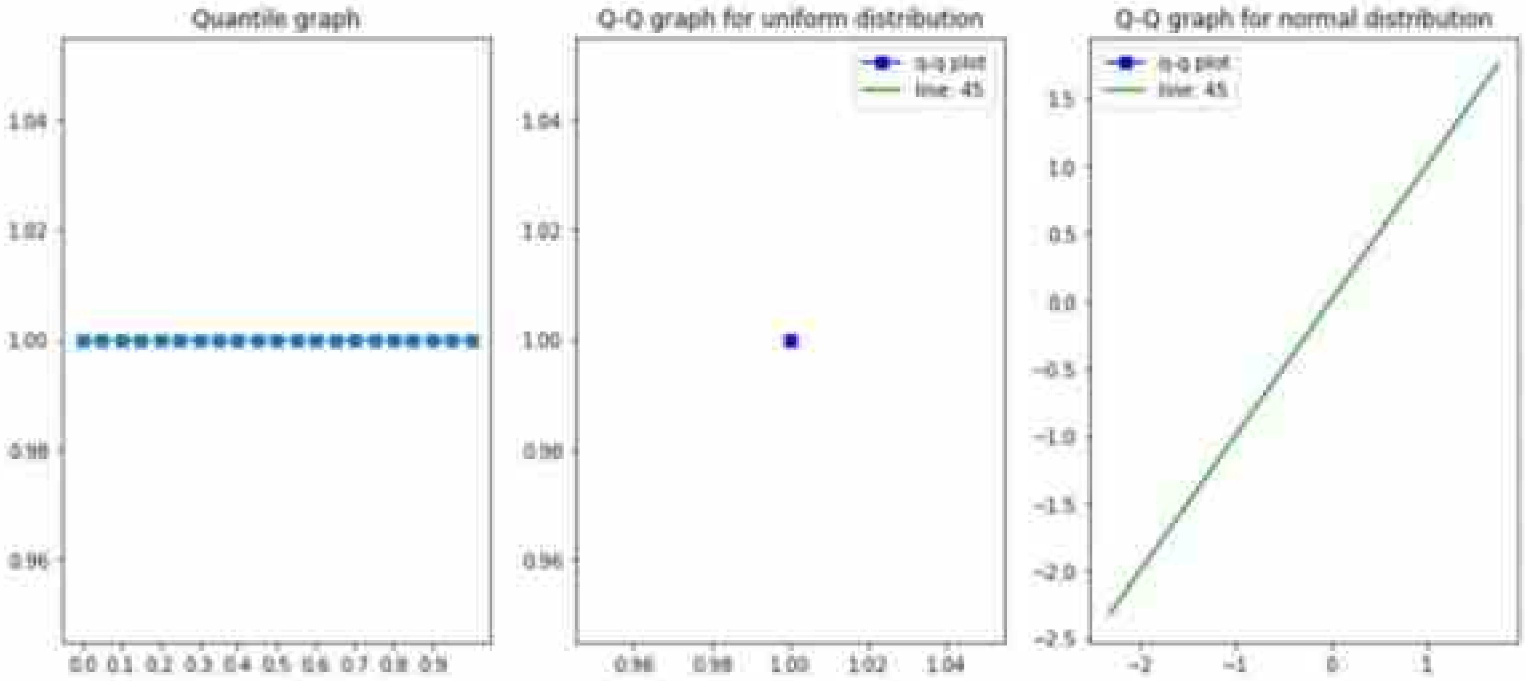


insight

P_2, D_47은
가우시안분포(=정규분포)
따르는 것으로 판단됨

Verification_ Q-Q graph for some Features

B_31

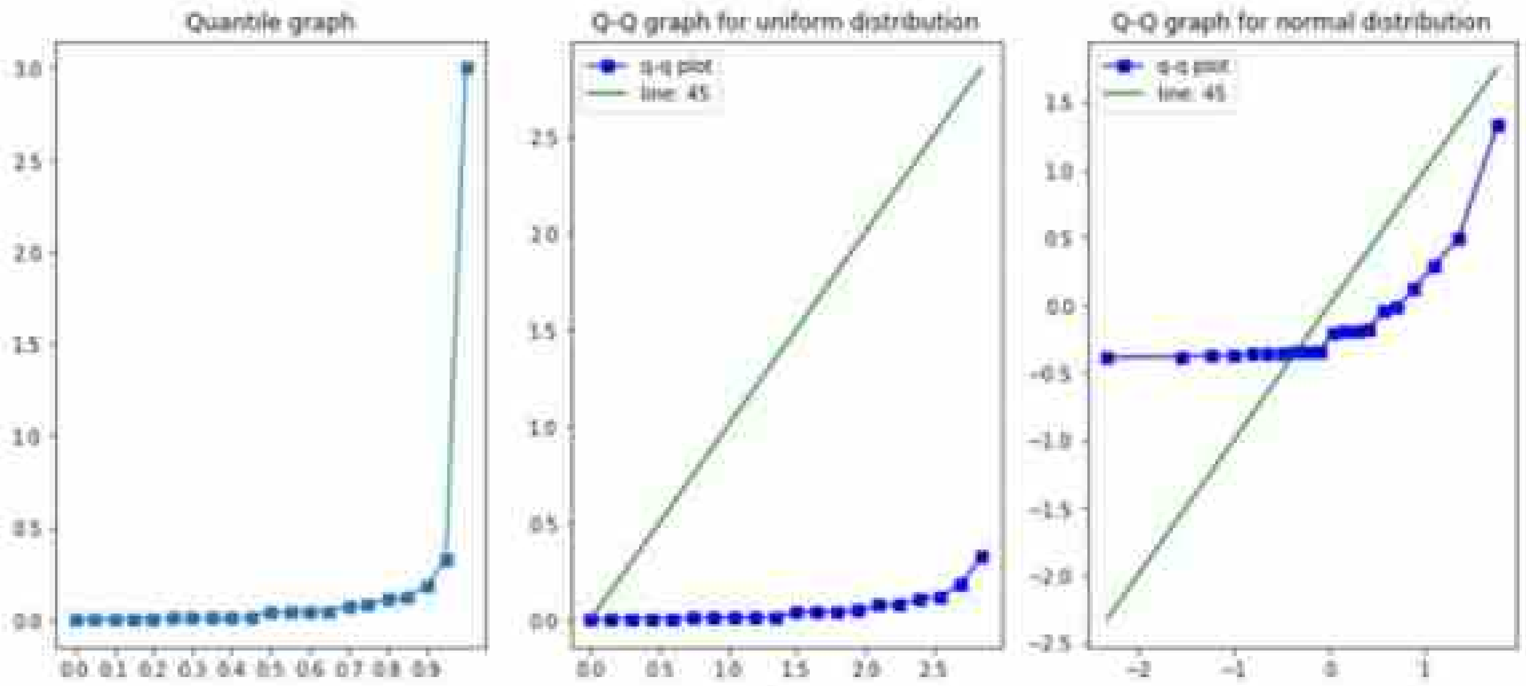


insight

B_31는 모든 분위 수에서
단일 값을 가진다고 판단됨

Verification_ Q-Q graph for some Features

R_26

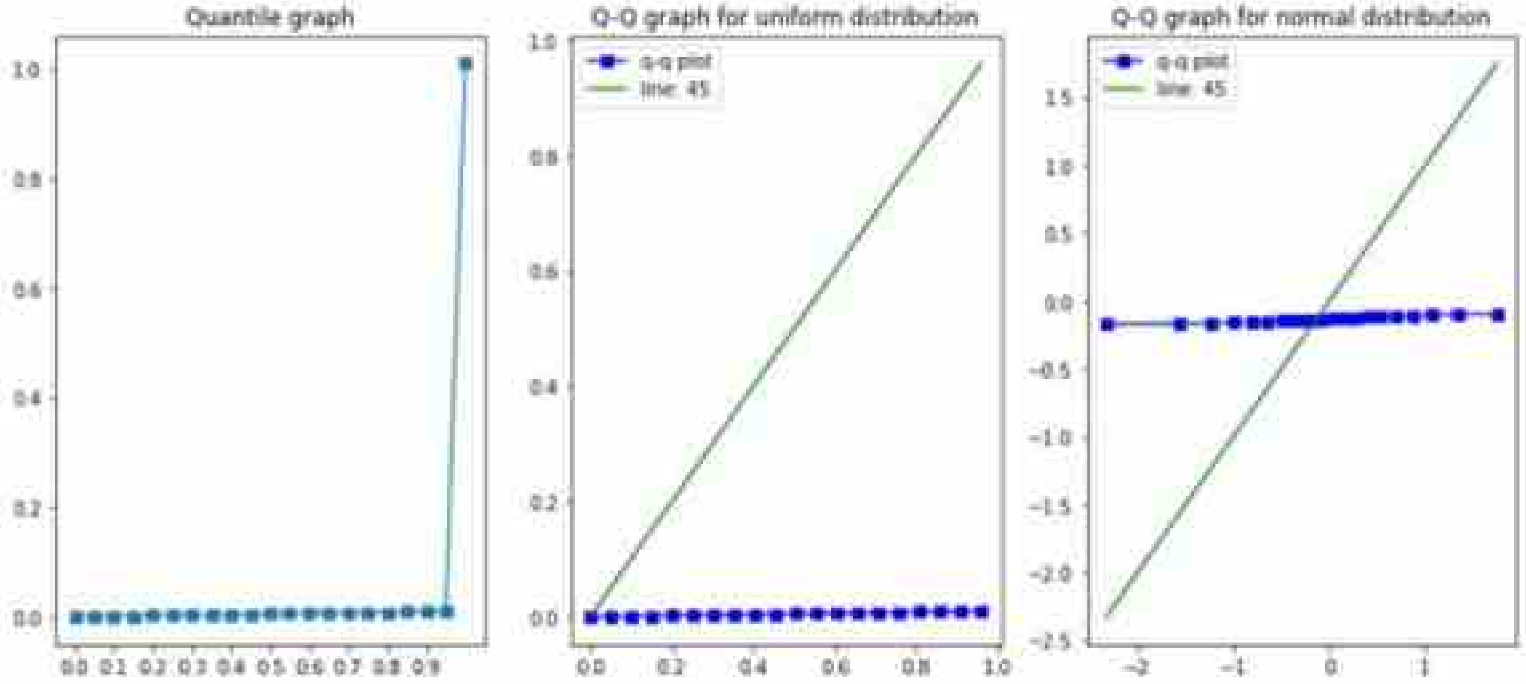


insight

R_26 는 확대 시 6개의 discrete value가 있는 것으로 판단됨

Verification_ Q-Q graph for some Features

D_94



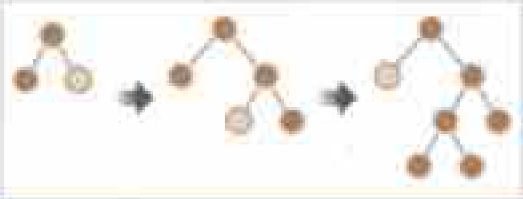
insight

D_94, S_26 기울기 거의 0
→ 이상치 값이 매우 크다고 판단됨

3

Insight about Machine Learning Model

Generate Machine Learning Model



1 Random Forest

ensemble⊃bagging⊃RF

- subsample에 대해 다수의 결정 트리 classifier를 최적화
- 여러 추론 결과 평균 → 예측 정확도를 개선 → 과적합방지
- hyperparameter xgbm보다 적음

2 XGBoost

Ensemble ⊃ boosting ⊃ GBM ⊃ XGBoost, LightGBM

- 트리기반 앙상블 균형트리분할방식
- 병렬학습이 가능 → GBM의 단점인 오랜 수행시간을 극복
- 예측 성능 우수
- 가지치기 기능 존재 조기중단 기능 존재

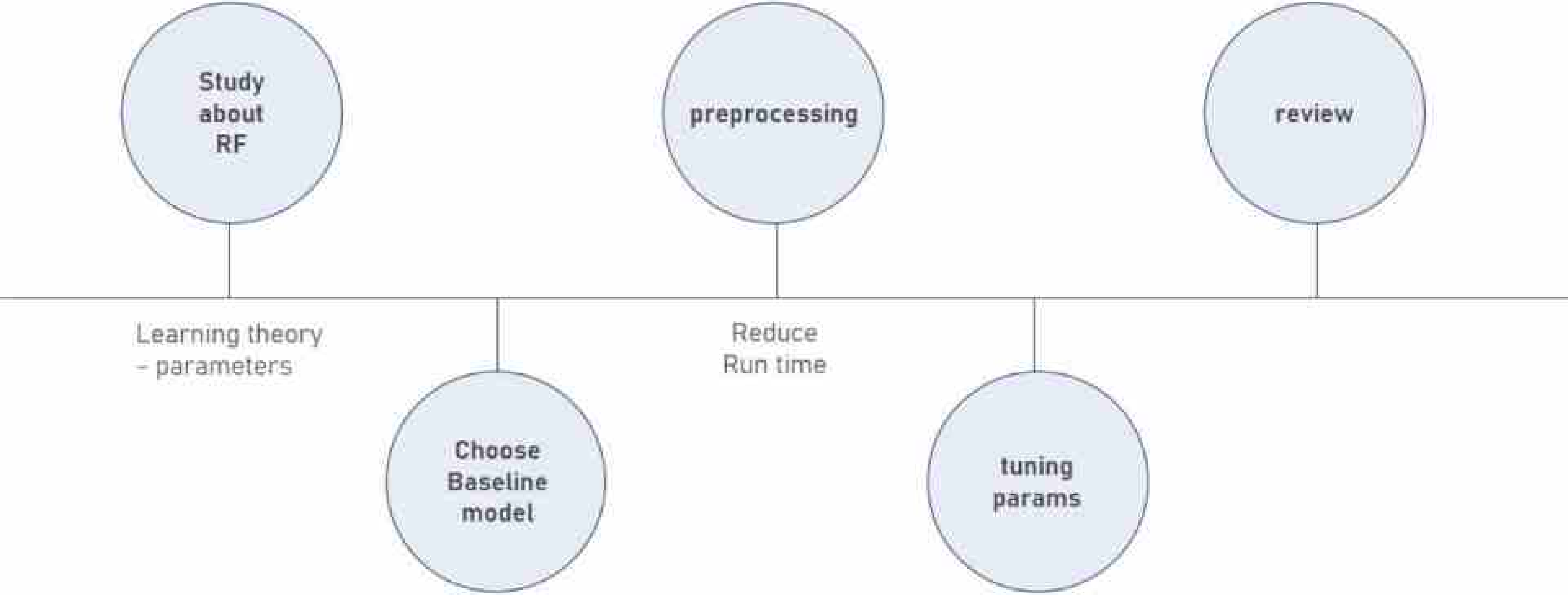
3 LightGBM

- 트리기반 앙상블 리프중심트리분할방식
- XGBoost보다 더 빠르고 메모리 사용량 적음
- 예측 성능 우수
- 10000건 이하의 dataset 처리시 과적합 가능성↑

4 CatBoost

- Categorical Boosting 범주형 feature 처리중점
- Gradient Boosting 기반 XGB, LGBM보다 우수
- Feature 자동 타깃인코딩
- 망각 결정 트리 사용 (oblivious decision tree)

Generate Machine Learning Model



Generate Machine Learning Model_ Random Forest

Missing Value Processing_ Remove Columns

In [12]:

```
#Lets remove columns if there are >90% of missing values.
#Given that there are many columns with large number of missing values, it is impractical to go throu
gh every single one of them to determine whether it is useful.
#Furthermore, we do not have information on the feature (e.g. actual name of the feature) except the
type of variable
#Brute force is thus a practical option to weed out columns with too many missing values.
#Since about 33.1% of the data are defaults(66.9% non-defaults), it is safe to say that columns with
>90% missing data are not useful.
train=train_data.dropna(axis=1, thresh=int(0.90*len(train_data)))

#Checking the shape of new train data
train.shape
## We are now left with 152 columns
```

Out[12]:

```
(5531451, 152)
```

191 columns → 152 columns

Part 3 >> Generate Machine Learning Model_ Random Forest

Missing Value Processing_ Fill Missing Values, Drop S_2, groupby

In [13]:

```
# There are multiple transactions. Lets take only the latest transaction from each customer.
# Latest transaction may have missing values, we will perform forward fill for those missing values.
# We perform forward fill as the last known value is likely to be brought forward to the next transac
tion.
# We then do a backfill if the first row happens to be NA.
train=train.set_index(['customer_ID'])
train=train.ffill().bfill()
train=train.reset_index()
train=train.groupby('customer_ID').tail(1)
train=train.set_index(['customer_ID'])

#Drop date column since it is no longer relevant
train.drop(['S_2'],axis=1,inplace=True)
#Check for number of rows
train.shape
# We now have 458913 rows, which corresponds to the number of unique customers.
```

Out[13]:

```
(458913, 150)
```

Rows : 5531451 → 458913

Columns : 152 → 150

Generate Machine Learning Model_ Random Forest

one-hot Encoding for D_63 and D_64

- 문자열인 범주형 변수를 원핫인코딩

```
train_D63 = pd.get_dummies(train[['D_63']])
train = pd.concat([train, train_D63], axis=1)
train = train.drop(['D_63'], axis=1)

train_D64 = pd.get_dummies(train[['D_64']])
train = pd.concat([train, train_D64], axis=1)
train = train.drop(['D_64'], axis=1)
```

Remove Highly Correlated Features

- 상관관계 높은 feature 제거
- absolute correlation >= 90% 이상인 열 drop

```
train_without_target=train.drop(['target'],axis=1)
cor_matrix = train_without_target.corr().abs()
upper_tri = cor_matrix.where(np.triu(np.ones(cor_matrix.shape),k=1).astype(np.bool))
#Drop out columns with absolute correlation of more than 90%
to_drop = [column for column in upper_tri.columns if any(upper_tri[column] > 0.90)]
train_drop_highcorr=train.drop(to_drop,axis=1)
train_drop_highcorr.shape
#We are now left with 145 columns, which is still significant
```

```
(458913, 145)
```

Columns : 150 → 145

Remove Columns with Low Variance = 0.1

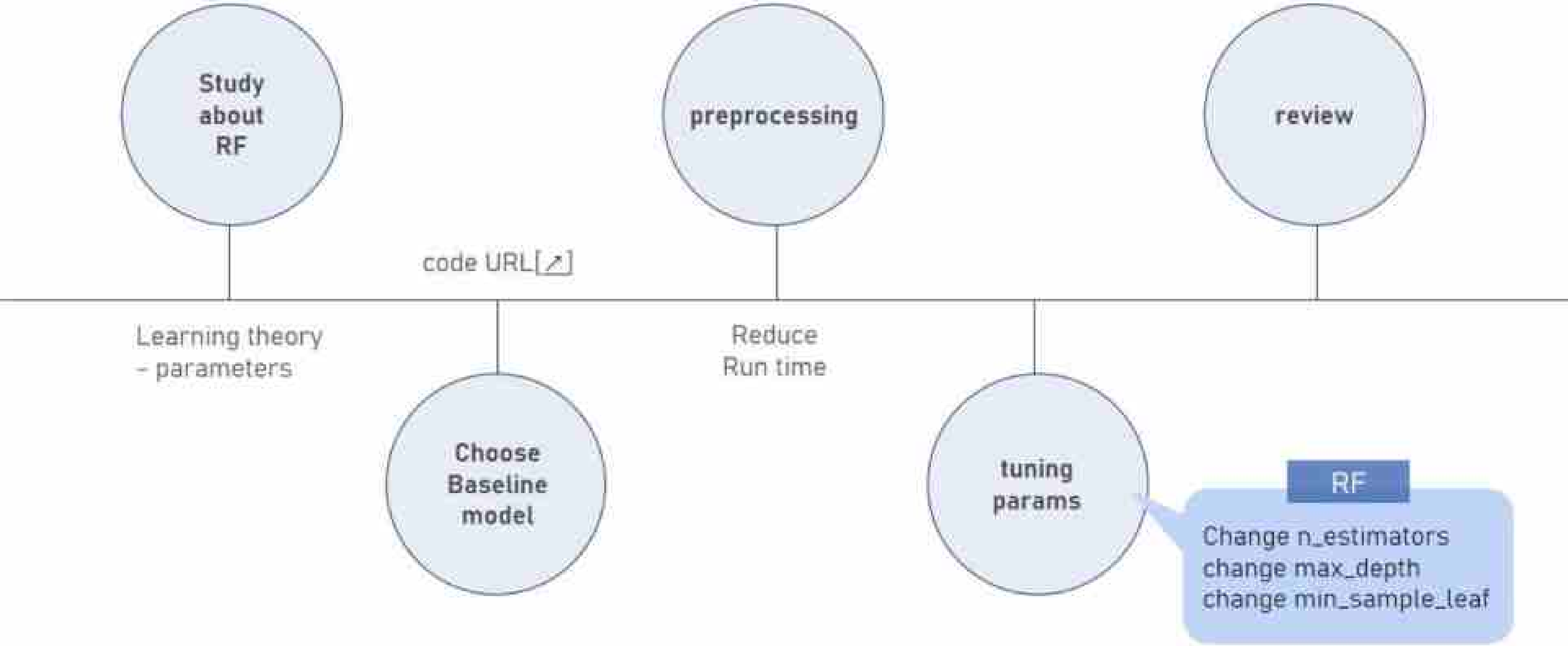
```
from sklearn.feature_selection import VarianceThreshold
from itertools import compress
def fs_variance(df, threshold:float=0.1):
    features = list(df.columns)

    # Initialize and fit the method
    vt = VarianceThreshold(threshold = threshold)
    _ = vt.fit(df)

    # Get which column names which pass the threshold
    feat_select = list(compress(features, vt.get_support()))

    return feat_select
columns_to_keep=fs_variance(train_drop_highcorr)
# We are left with 54 columns (excluding target), which passed the threshold.
train_final=train[columns_to_keep]
len(columns_to_keep)
```

55

54 columns left (except target)

Part 3 >>

Generate Machine Learning Model_ Random Forest

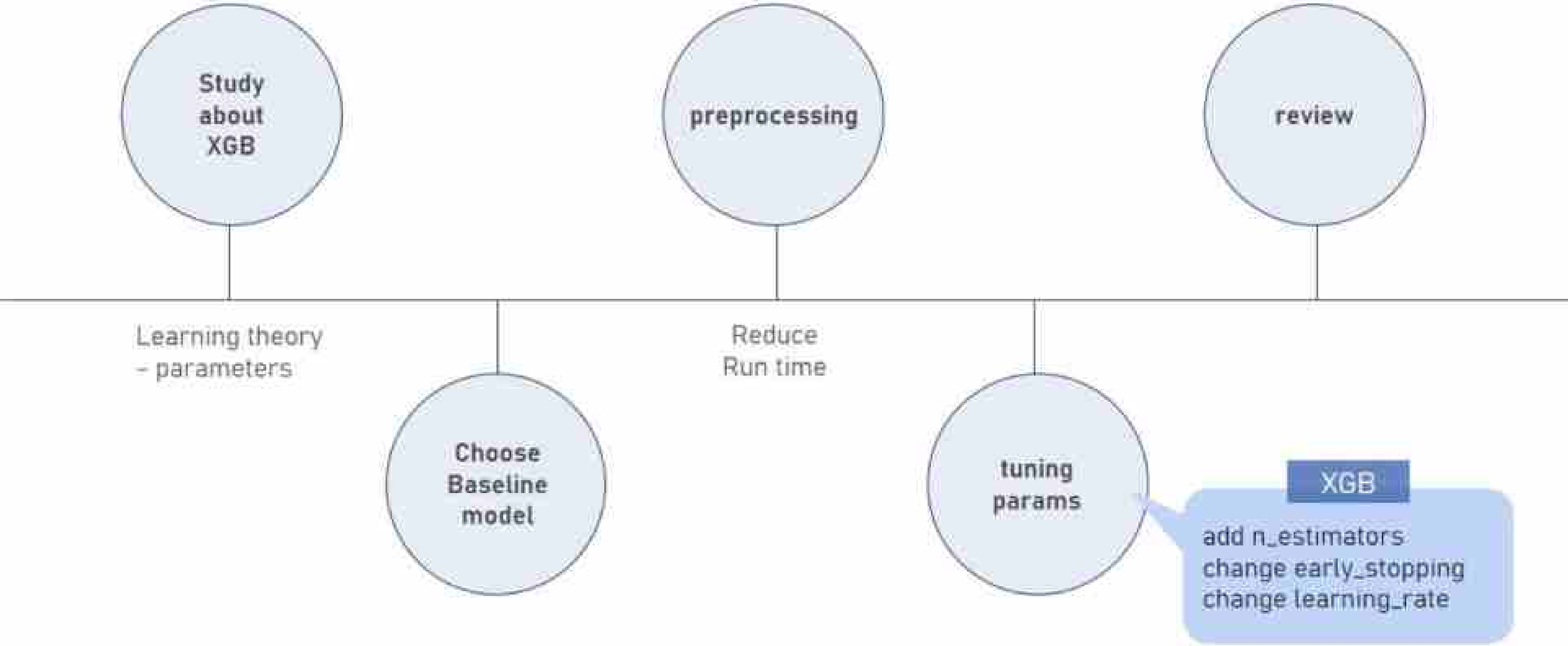


Generate Machine Learning Model_ Random Forest

No.	내용요약	소요시간	parameters	scores
1	Base RandomForest model	1058.8s - GPU	n_estimators=400, max_features='sqrt', bootstrap=True(default), max_depth=30, min_samples_leaf=1(default), min_samples_split=5, n_jobs=-1	score: 0.729
2		477.1s - CPU		
3	change n_estimators (v1)	290.8s - CPU	n_estimators → 200	score: 0.727 / ↓
4		437.6s - CPU	n_estimators → 500	score: 0.729 / -
5	change max_depth (v2)	547.8s - CPU	max_depth → 100	score: 0.728 / ↓
6		538.3s - CPU	max_depth → 40	score: 0.729 / -
7		535.3s - CPU	max_depth → 50	score: 0.729 / -
8		244.6s - CPU	max_depth → 10	score: 0.720 / ↓
9		303.5s - CPU	max_depth → 20	score: 0.742 / ↑
10	add random_state (v3)	383.9s - CPU	random_state = 77	score: 0.730 / ↑
11	change min_samples_leaf (v4)	349.5s - CPU	min_samples_leaf → 2	score: 0.744 / ↑

Part 3 >>

Generate Machine Learning Model_ XGBoost



Part 3 >> Generate Machine Learning Model_ XGBoost

No.	내용요약	소요시간	parameters	scores
1	basic XGB model	190.8s(GPU)	(n_estimators : default 100, early_stopping_rounds=100, learning_rate=0.05)	변동없음
2	add n_estimators	186.6s(GPU)	n_estimators=110	
3		176.8s(GPU)	n_estimators=120	
4		190.4s(GPU)	n_estimators=130	
5		191.8s(GPU)	n_estimators=140	
6		196.2s(GPU)	n_estimators=150	
7		183.4s - GPU	n_estimators=200	
8	change early_stopping option	192.0s - GPU	n_estimators=200, early_stopping_rounds=150	
9	change n_estimators	201.1s - GPU	n_estimators=300, early_stopping_rounds=150	
10	change learning_rate option	179.0s - GPU	n_estimators=200, learning_rate=0.1, early_stopping_rounds=100	
11		246.3s - GPU	n_estimators=200, learning_rate=0.2, early_stopping_rounds=100	

Find out the Best Parameters_ Define Parameter Range

In [13]:

```
#define parameter range
learning_rate=np.linspace(0.01,0.1,10)
max_depth=np.arange(2, 10, 2)
colsample_bylevel=np.arange(0.3, 0.8, 0.1)
iterations=np.arange(50, 1000, 50)
l2_leaf_reg=np.arange(0,10)
bagging_temperature=np.arange(0,100,10)
n_estimators=np.arange(50,500,50)
```

Generate Machine Learning Model_ XGBoost_Parameters

Define Parameter Space, Fit Condition, and Ross Function

```
xgb_cat_params = {
    'learning_rate':    hp.choice('learning_rate',    learning_rate),
    'max_depth':        hp.choice('max_depth',        max_depth),
    'colsample_bytree': hp.choice('colsample_bytree', colsample_bylevel),
    'n_estimators':     hp.choice('n_estimators',     n_estimators),
    'loss_function':        'logloss',
    'nan_mode':'Min',
    'task_type':'GPU'
}
xgb_fit_params = {
    'eval_metric': 'logloss',
    'early_stopping_rounds': 10,
    'verbose': False
}
xgb_para = dict()
xgb_para['cls_params'] = xgb_cat_params
xgb_para['fit_params'] = xgb_fit_params
xgb_para['loss_func' ] = lambda y, pred: np.sqrt(mean_squared_error(y, pred))
```

Generate Machine Learning Model_ XGBoost_Parameters

Define Parameter Space, Fit Condition, and Ross Function

```
#calling the XGBoost function by passing XGB parameter space
xgb_opt = obj.process(fn_name='xgb_cls', space=xgb_para, trials=Trials(), algo=tpe.suggest, max_evals=2)
```

In [24]:
```
#Save best parameters in a dictionary
best_param_xgb={}
best_param_xgb['learning_rate']=learning_rate[xgb_opt['learning_rate']]
best_param_xgb['colsample_bytree']=colsample_bylevel[xgb_opt['colsample_bytree']]
best_param_xgb['max_depth']=max_depth[xgb_opt['max_depth']]
best_param_xgb['n_estimators']=n_estimators[xgb_opt['n_estimators']]
```

In [25]:
```
best_param_xgb
```

Out[25]:
```
{'learning_rate': 0.05000000000000001,
 'colsample_bytree': 0.6000000000000001,
 'max_depth': 8,
 'n_estimators': 400}
```

Part 3 >> Generate Machine Learning Model_ XGBoost

F1-score of XGBoost : 0.81

Study about XGB

Learning theory
- parameters

Choose Baseline model

preprocessing

Reduce
Run time

tuning params

XGB

n_estimators = 400
colsample_bytree = 0.6
max_depth = 8
learning_rate = 0.05

review

Part 3 >> Generate Machine Learning Model_ LightGBM

F1-score of LGBM : 0.81

Study about LGBM

Learning theory
- parameters

Choose Baseline model

preprocessing

Reduce
Run time

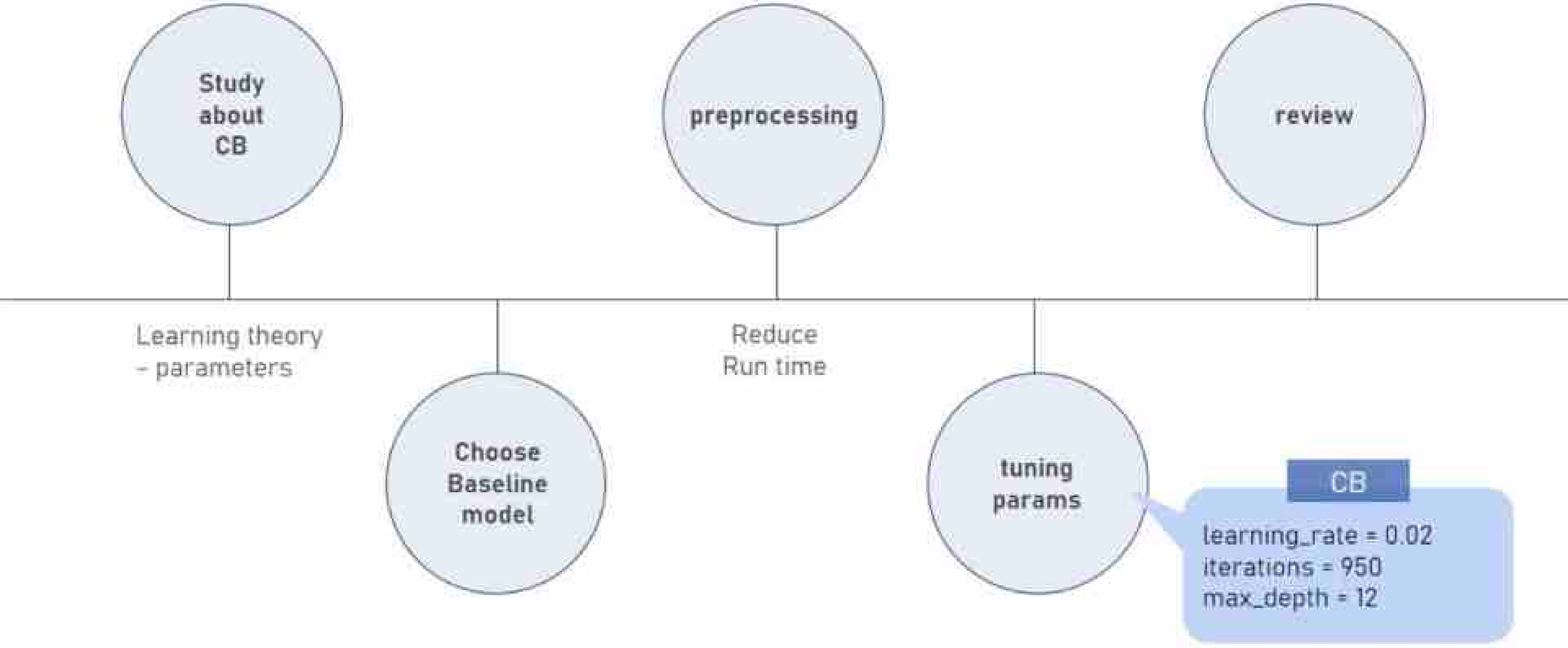
tuning params

LGBM
n_estimators = 400
colsample_bytree = 0.6
max_depth = 14
learning_rate = 0.04

review

Generate Machine Learning Model_ CatBoost

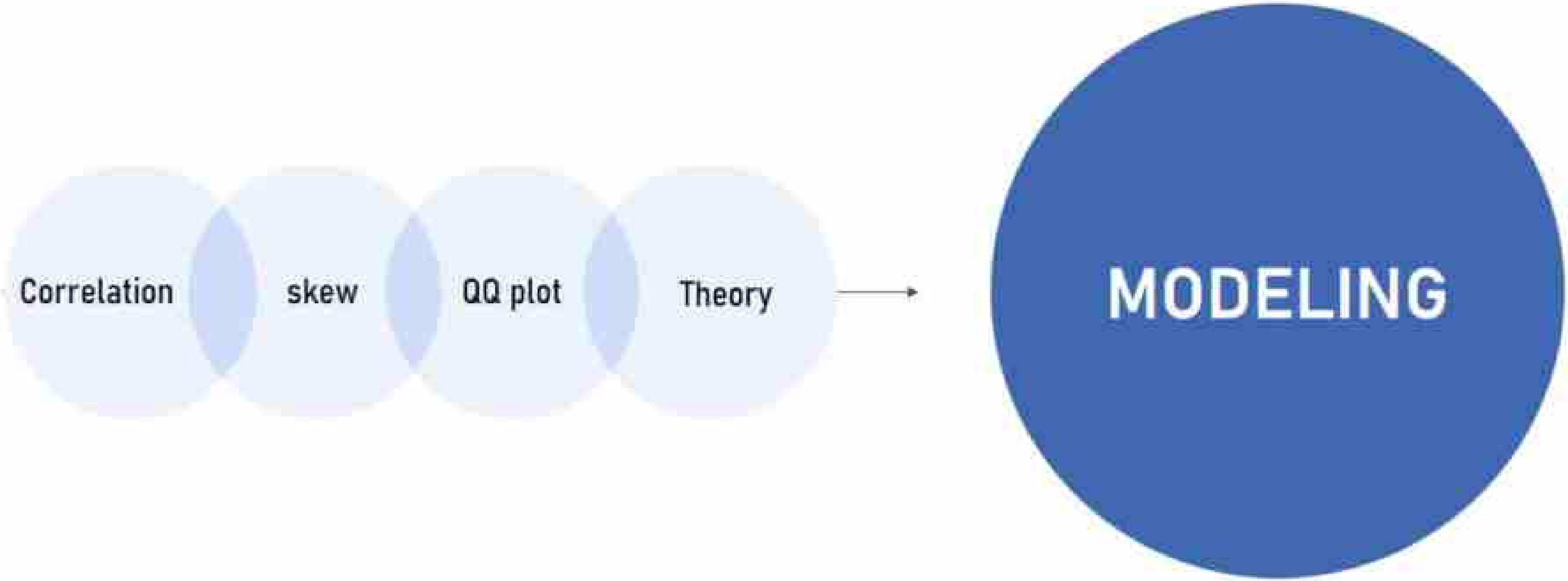
F1-score of Catboost: 0.80



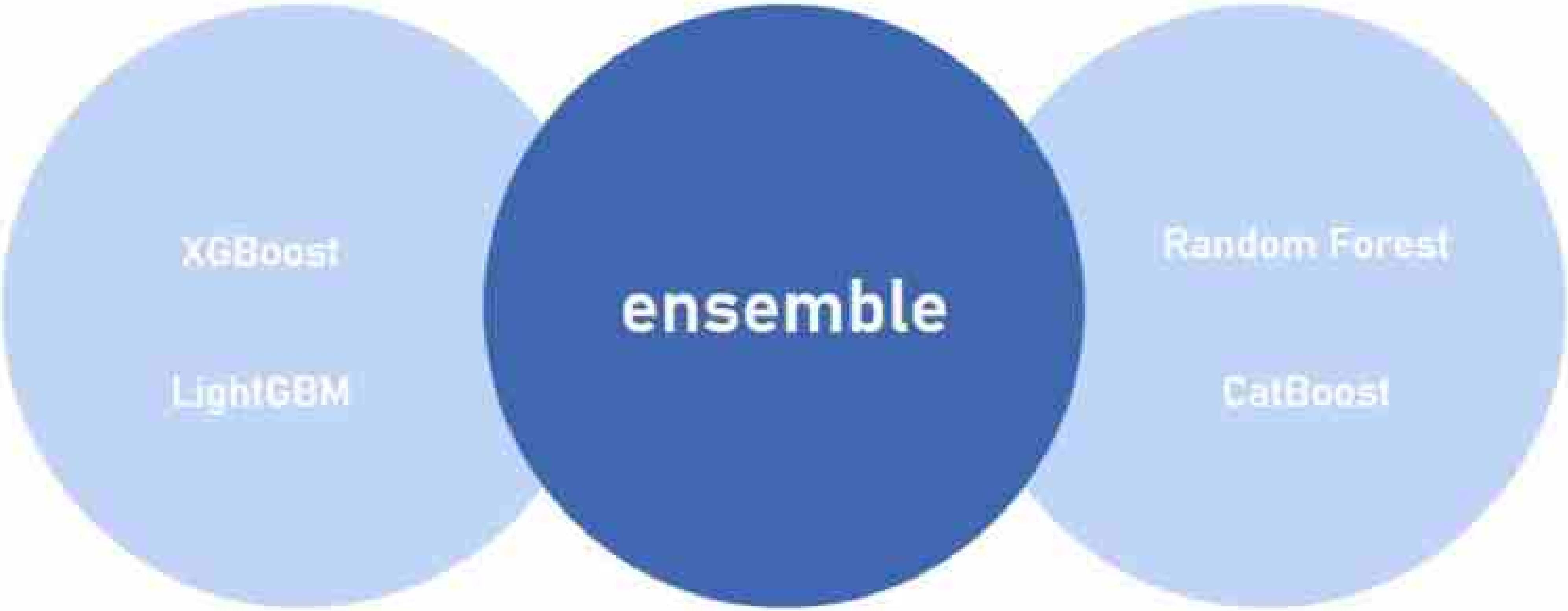
4

Conclusion

Part 4 >> **Conclusion**



Part 4 >> **Conclusion**




Q&A