American Express-Default Prediction

Predict if a customer will default in the future

Q.

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

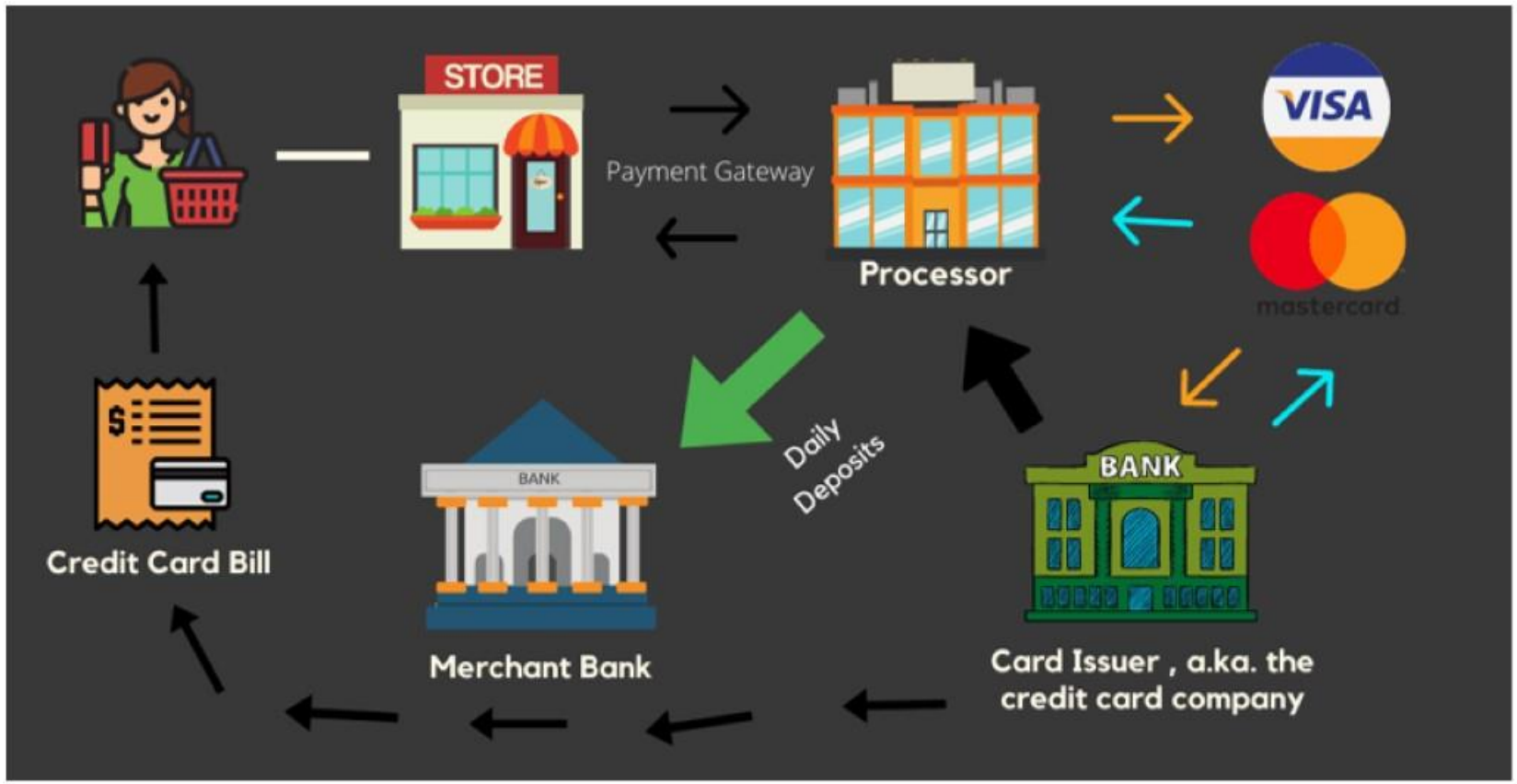
>> Table of contents

1

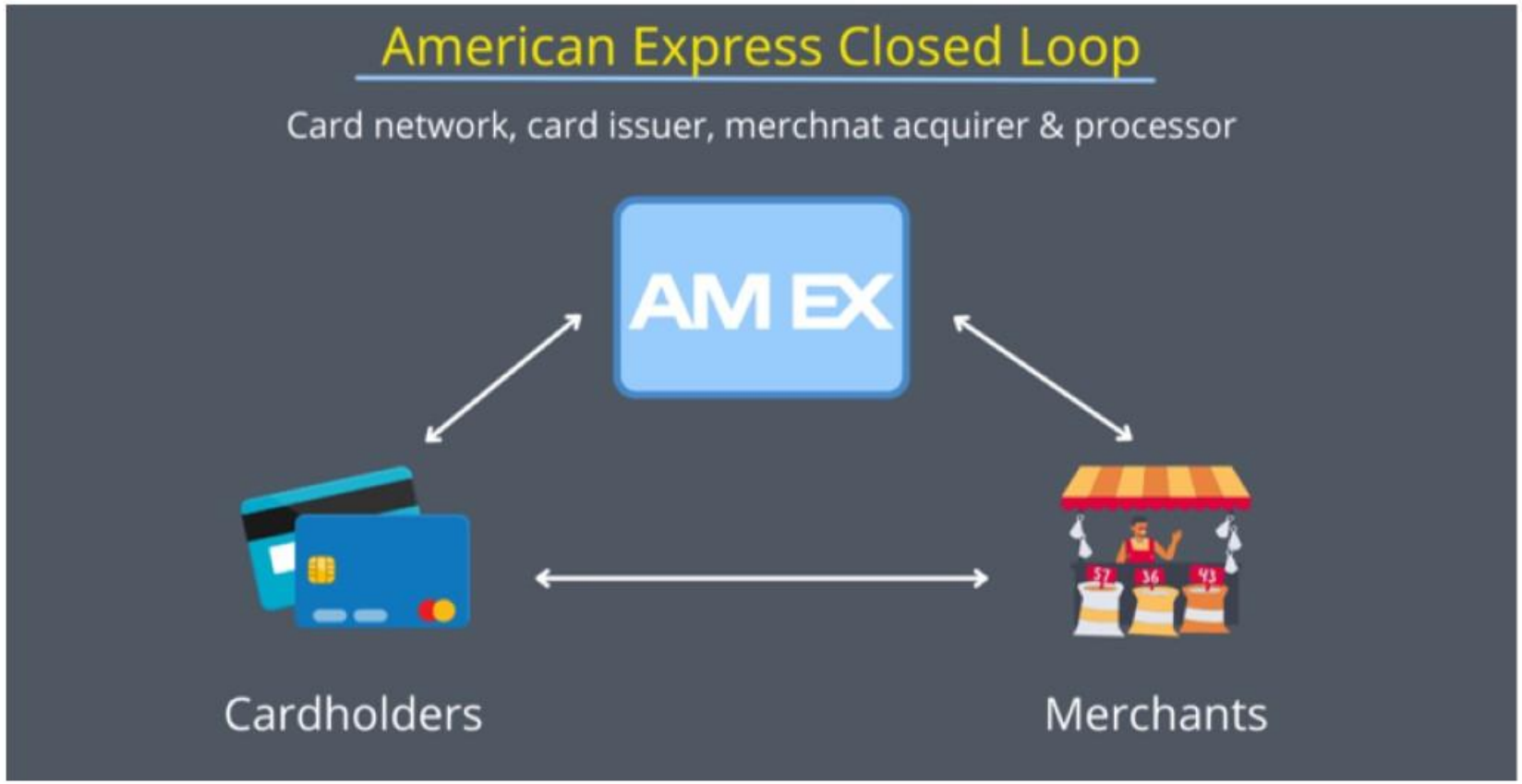
Competition Description

Part 1 >> # Competition Description_Revenue Stream

Visa, Master Card Business Model

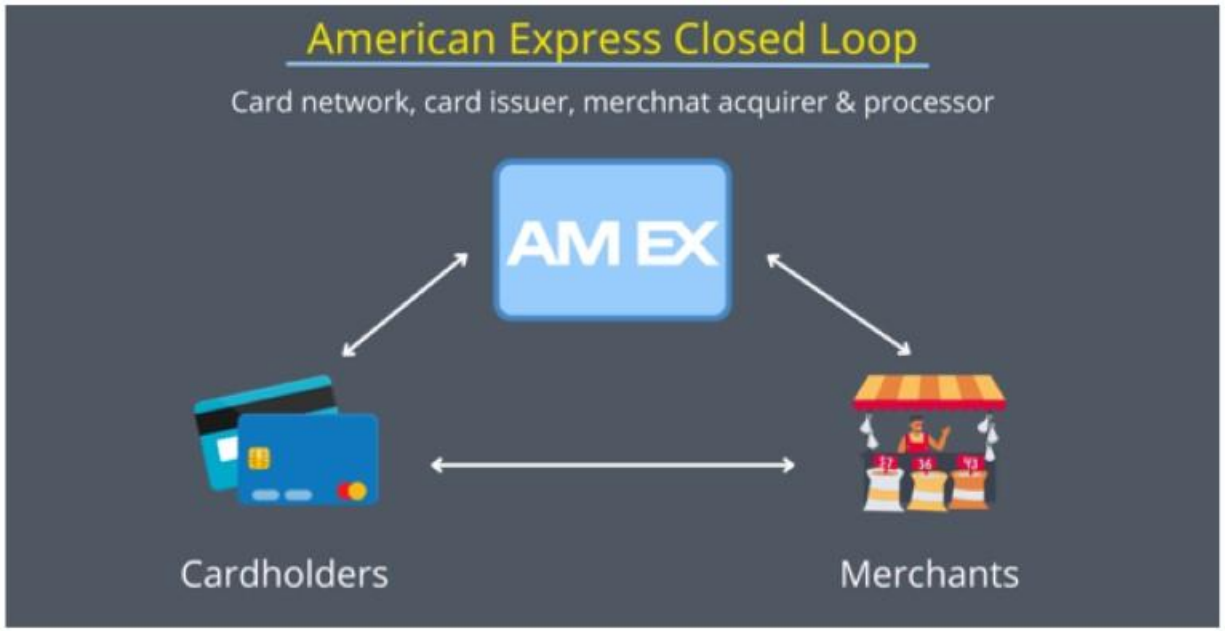


American Express Business Model

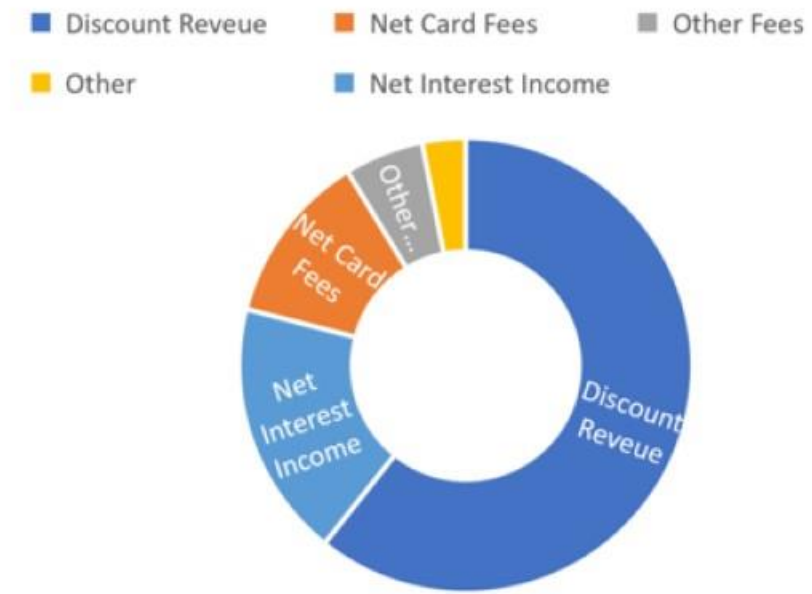


Part 1 >> Competition Description_Revenue Stream

American Express Business Model



revenues

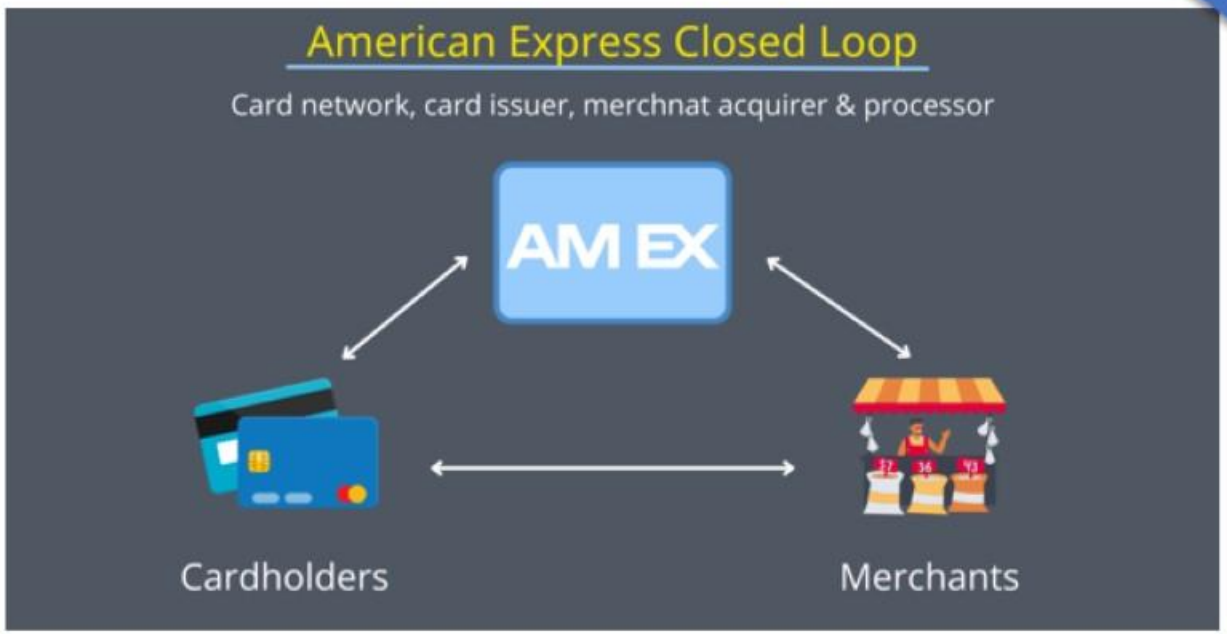


Part 1 >>

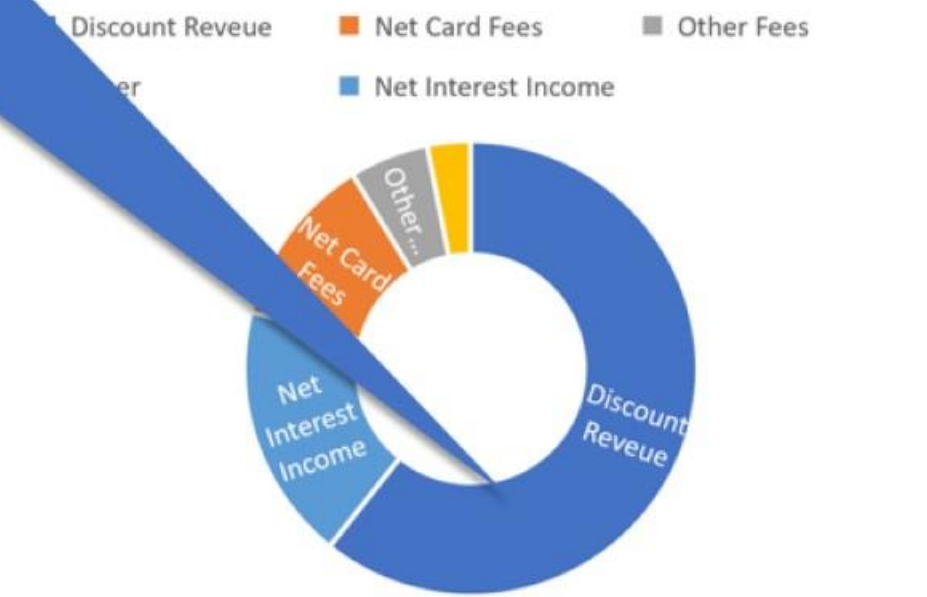
Discount Revenue(60%)

: 카드 결제 수수료

American Express Business Model



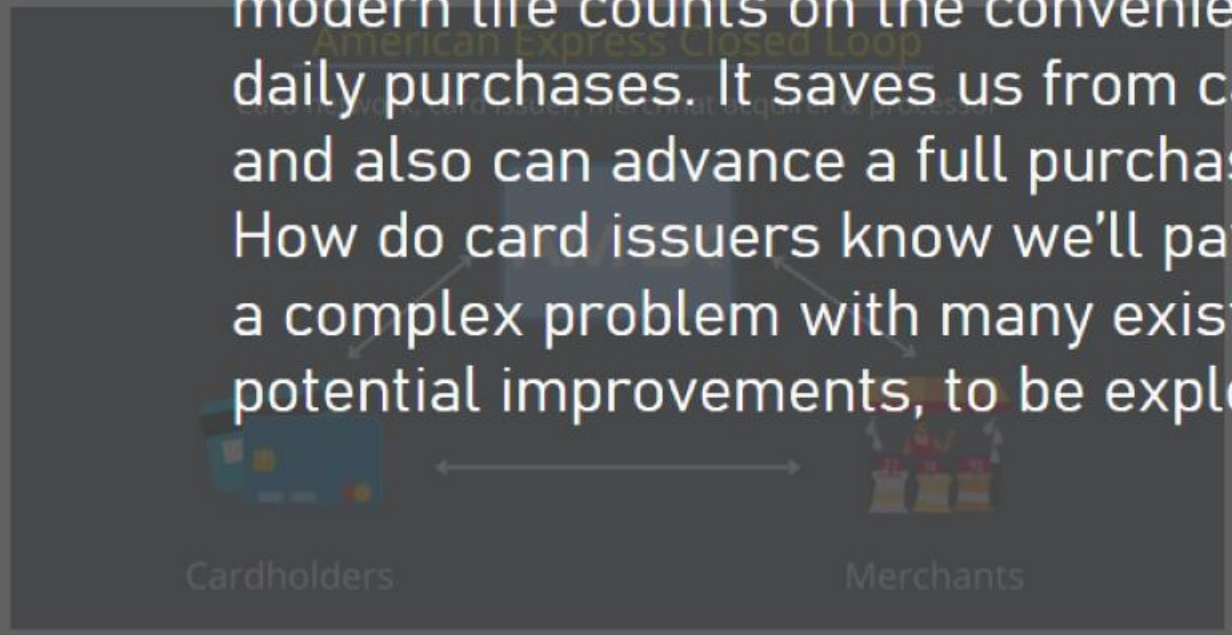
revenues

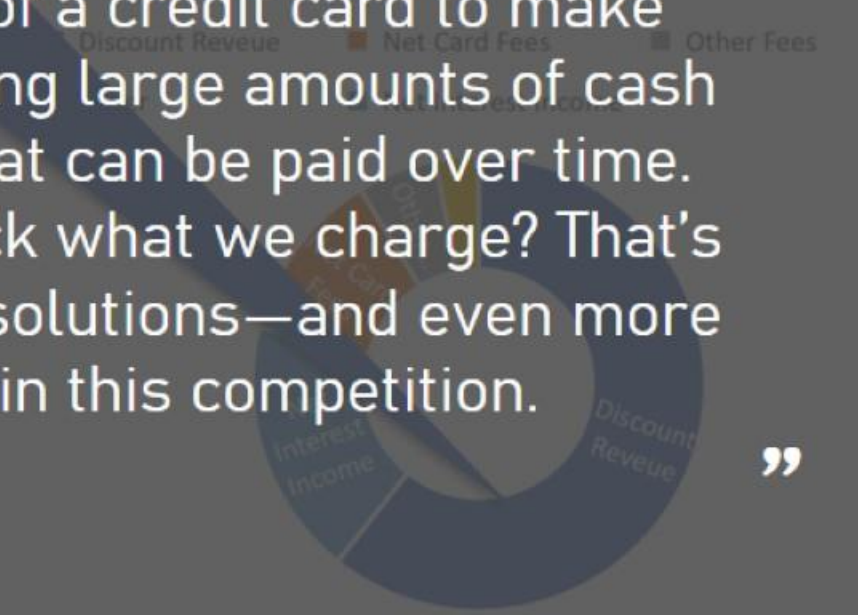


Discount Revenue(60%)

: 카드 결제 수수료

“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.”





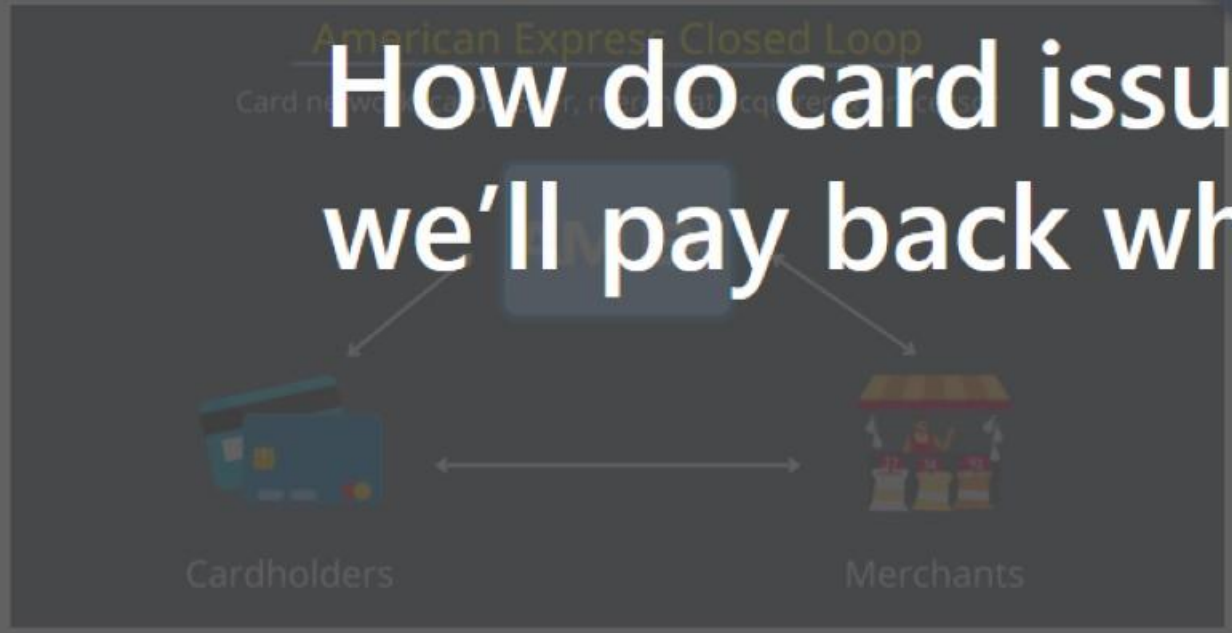
Part 1 >>

Discount Revenue(60%)

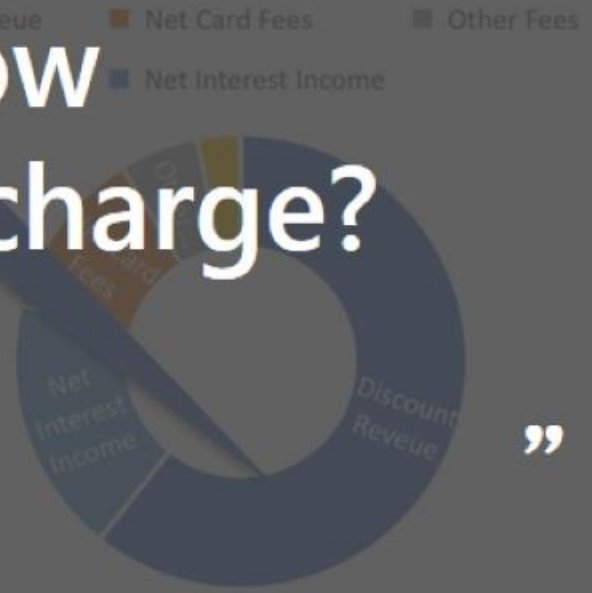
: 카드 결제 수수료

“

American Express Business Model



revenues



”

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

Part 1 >> Competition Description_Variables

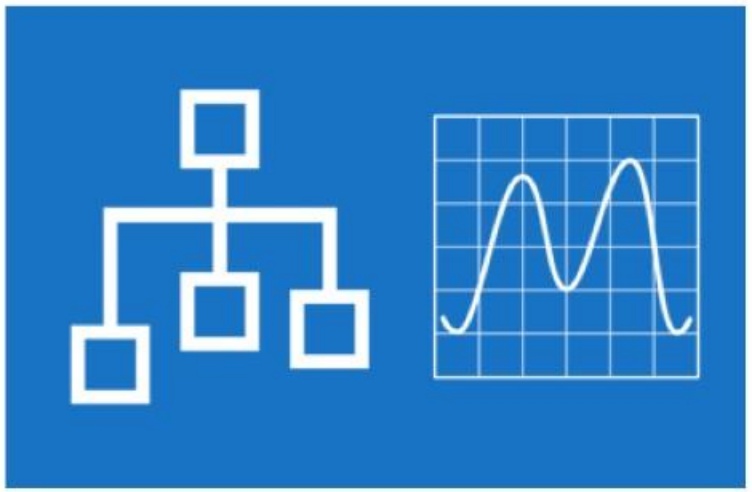
anonymous

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

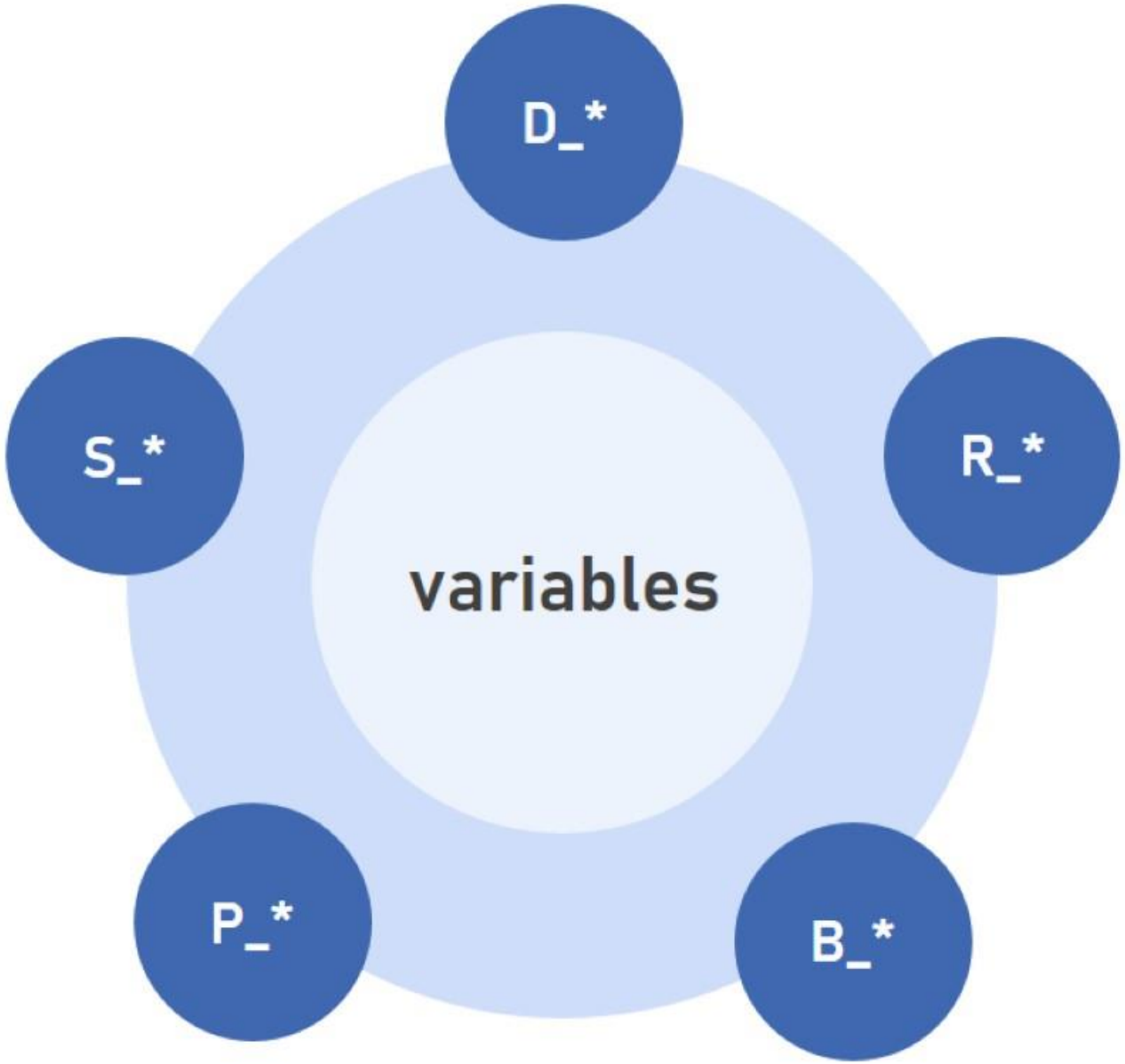


categorical/numerical

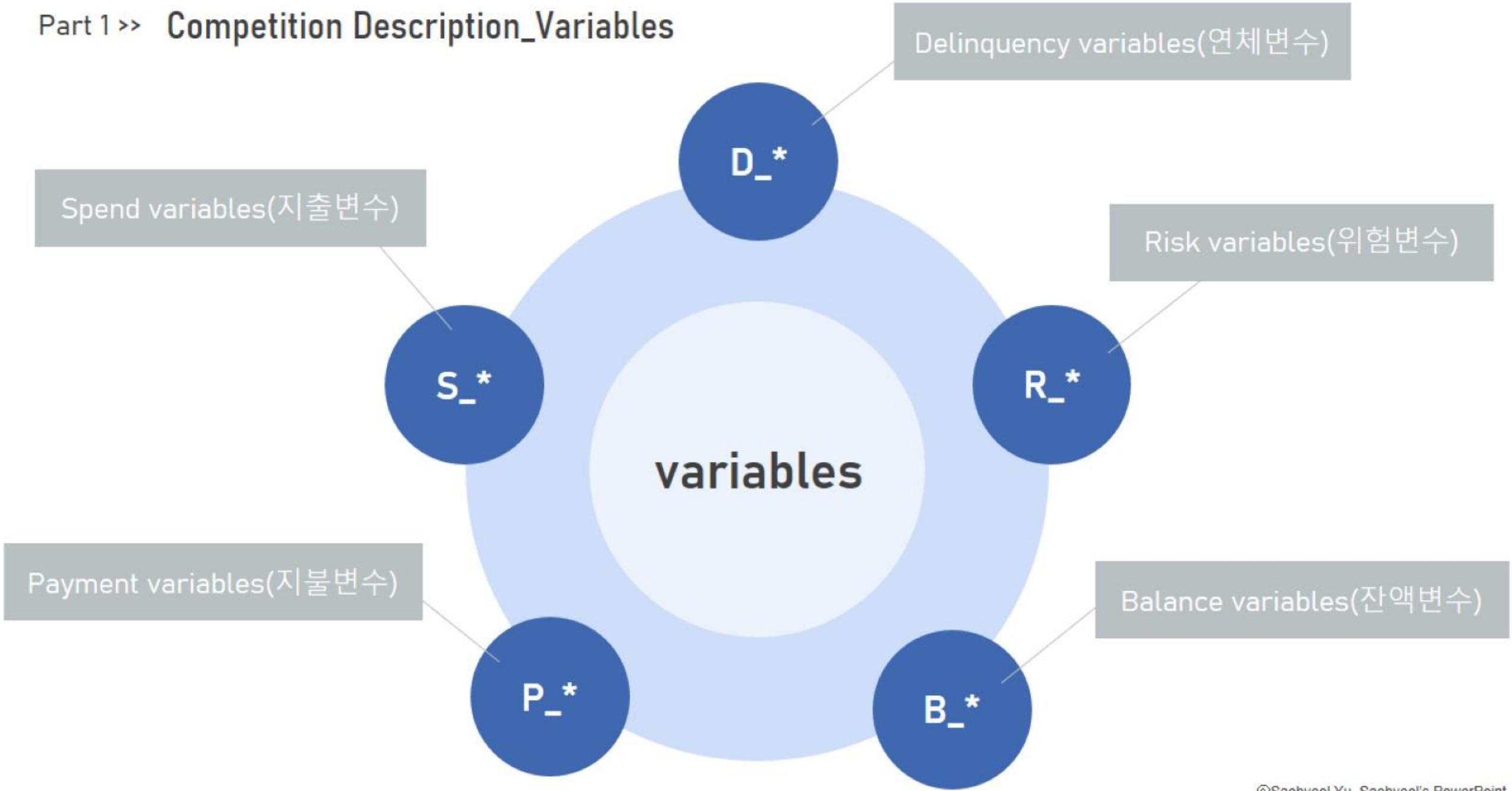
C : 'B_30', 'B_38', 'D_114', 'D_116', 'D_117', 'D_120',
'D_126', 'D_63', 'D_64', 'D_66', 'D_68'

predict 'target = 1' for each customer_ID

Part 1 >> Competition Description_Variables



Part 1 >> **Competition Description_Variables**



2

Data Preprocessing and EDA

Part 2 >> Exploratory Data Analysis

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

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

Part 2 >> 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 : dtype기억 o

>>

Reduce dtypes

- column 'customer_ID'
- column 'S_2'
  · pd.to_datetime()
  · 10 → 4byte
- categorical column (11)
  : int8로 변환 [8 → 1byte]
- numerical column (171)
  : float64 → float32

>>

File Saving type

Multiple Files
or
Not

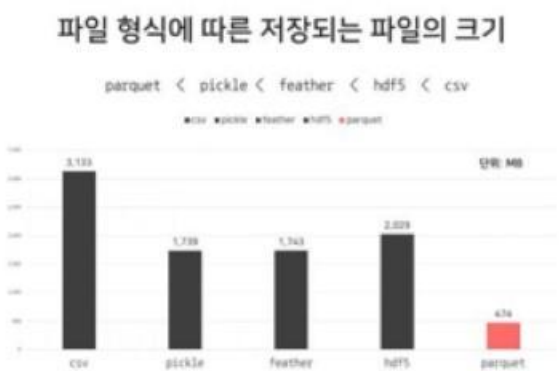
>>

Remove Noise

Features
- integers
- random noise injected
  ↓
- float32(4byte)
  → int8(1byte)

Part 2 >> 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) 인코딩을 사용가능
- 특정 column을 선택해서 가져오는 형식
  → 선택하지 않은 column 데이터는 I/O가 발생하지 않음
  → 시간, 메모리 사용량 줄일 수 있음



Part 2 >> Exploratory Data Analysis_ Methods of data reduction(1) : File Format

- 행 기반 압축 → 데이터 압축률 우수
- 특정 column의 데이터만 읽고 처리 가능
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  → 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

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

- 행 기반 압축 → 데이터 압축률 우수
- 특정 column의 데이터만 읽고 처리 가능
  → 데이터 처리에 들어가는 자원 절약됨
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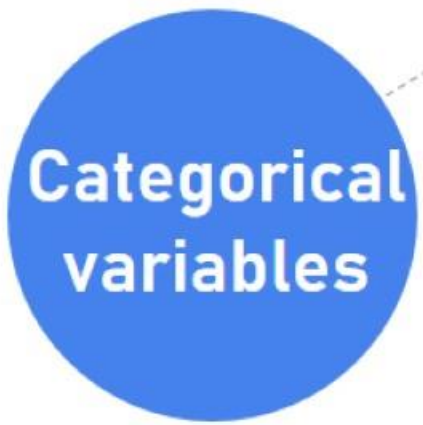
  → int64에서 int8로 downcast하면 다음에도 파일을 int8로 불러옴

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

문자열 [64byte] → int64 [8byte]

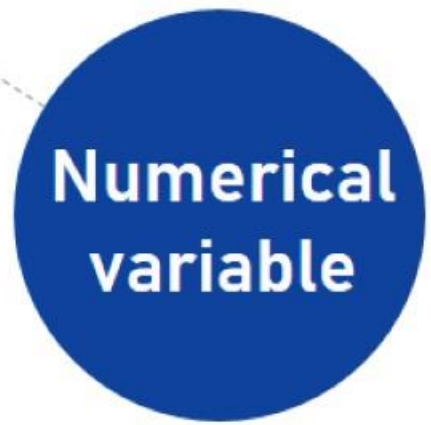
문자열 [10byte] → pd.to_datetime() [4byte]



최대 8개의 값 가짐

→ int8로 변경

[8byte → 1byte]

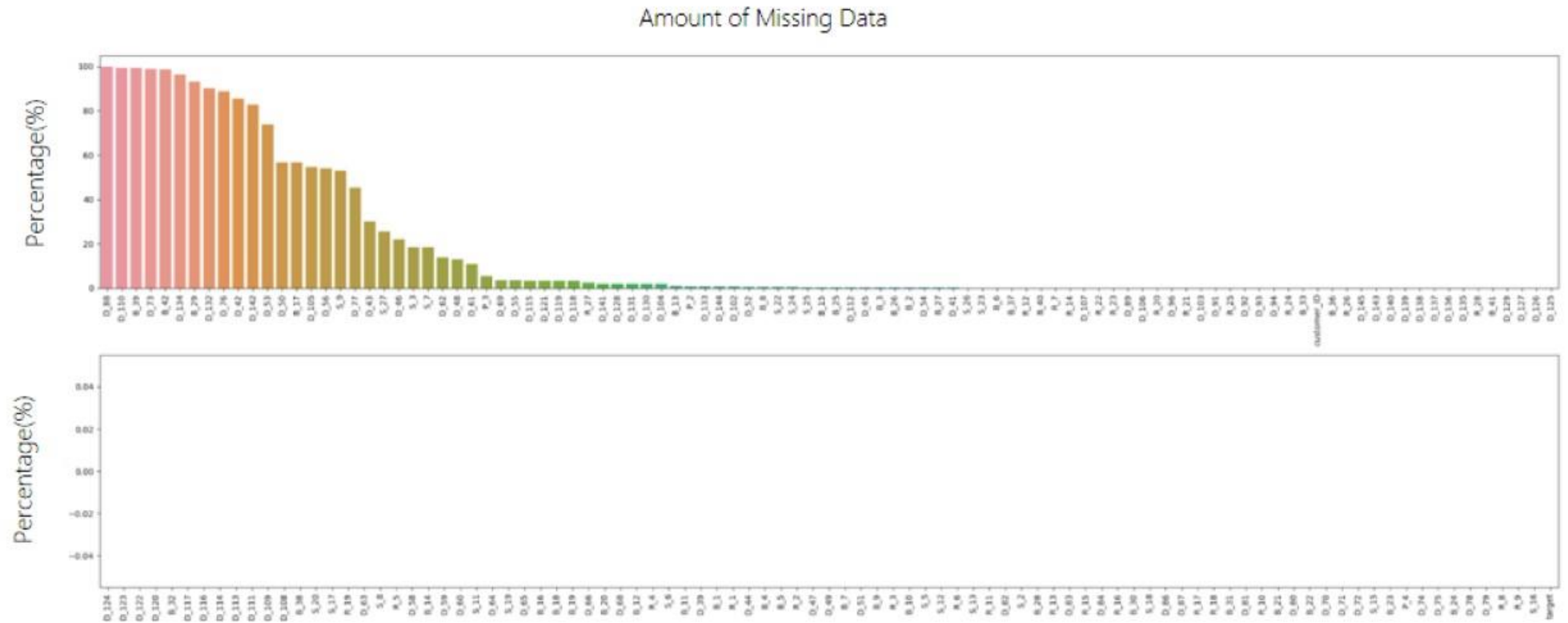


float64 → float32로 변경

[8byte → 4byte]

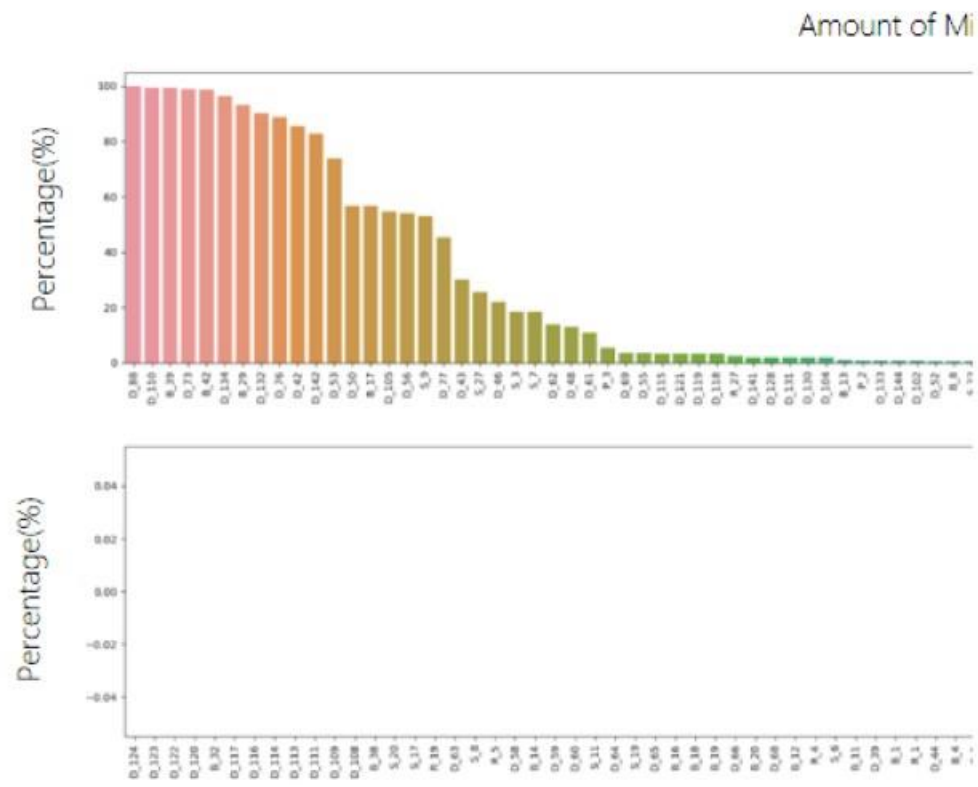
Part 2 >> Exploratory Data Analysis_Missing Value

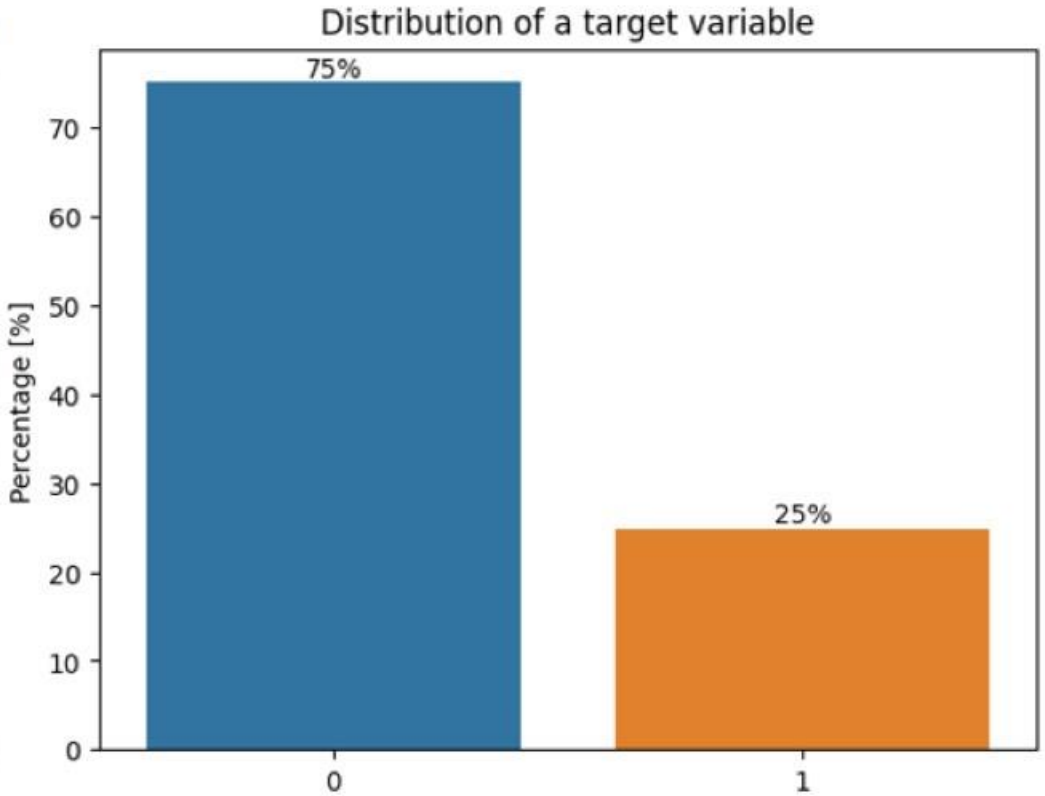
Verification_Missing Value



Part 2 >> Exploratory Data Analysis_Missing Value

Verification_Missing Value





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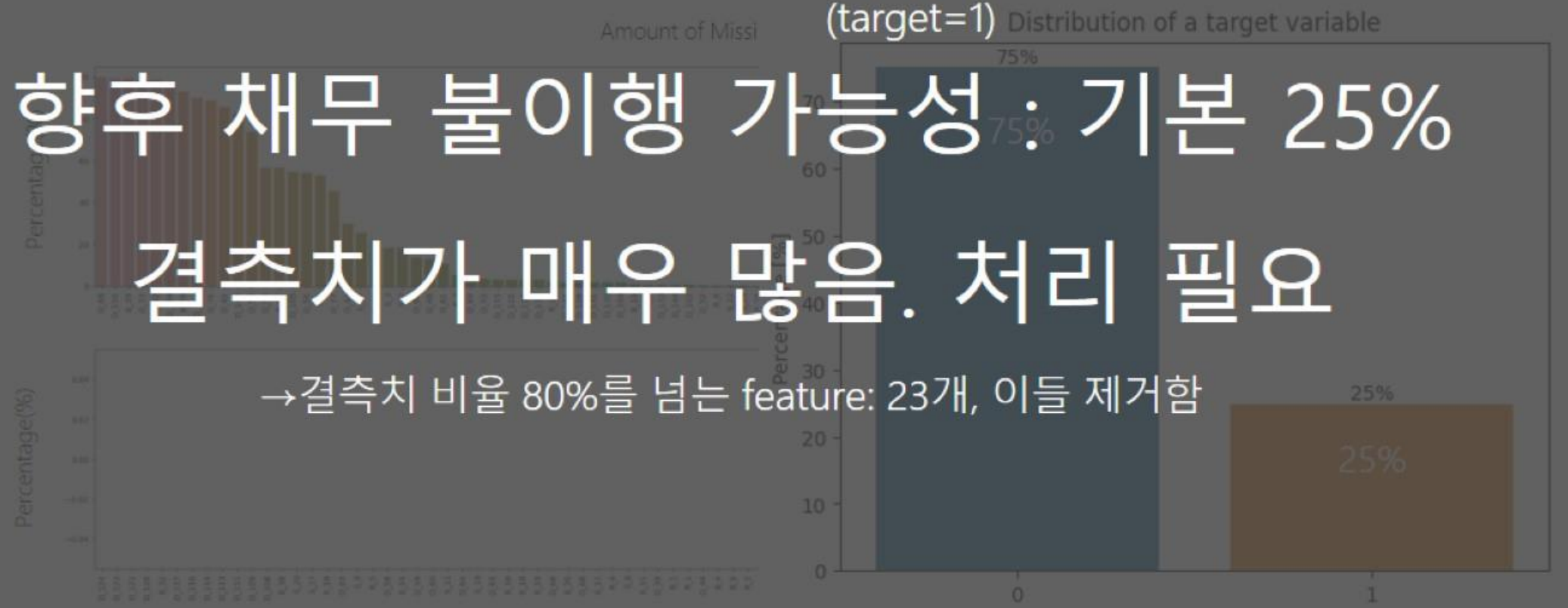
Verification_Missing Value



향후 채무 불이행 가능성 : 기본 25%

결측치가 매우 많음. 처리 필요

→결측치 비율 80%를 넘는 feature: 23개, 이들 제거함

”

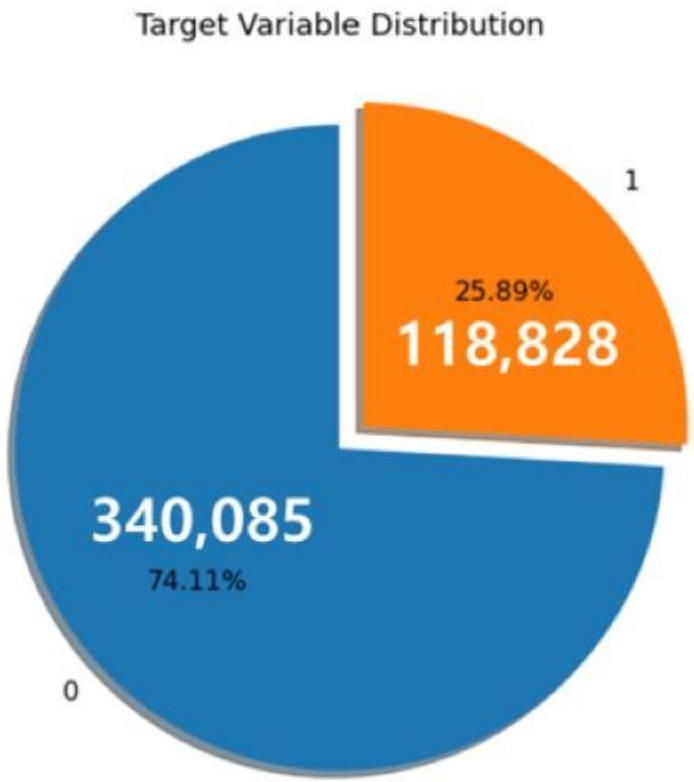
Verification_Missing Value for 1000 customers

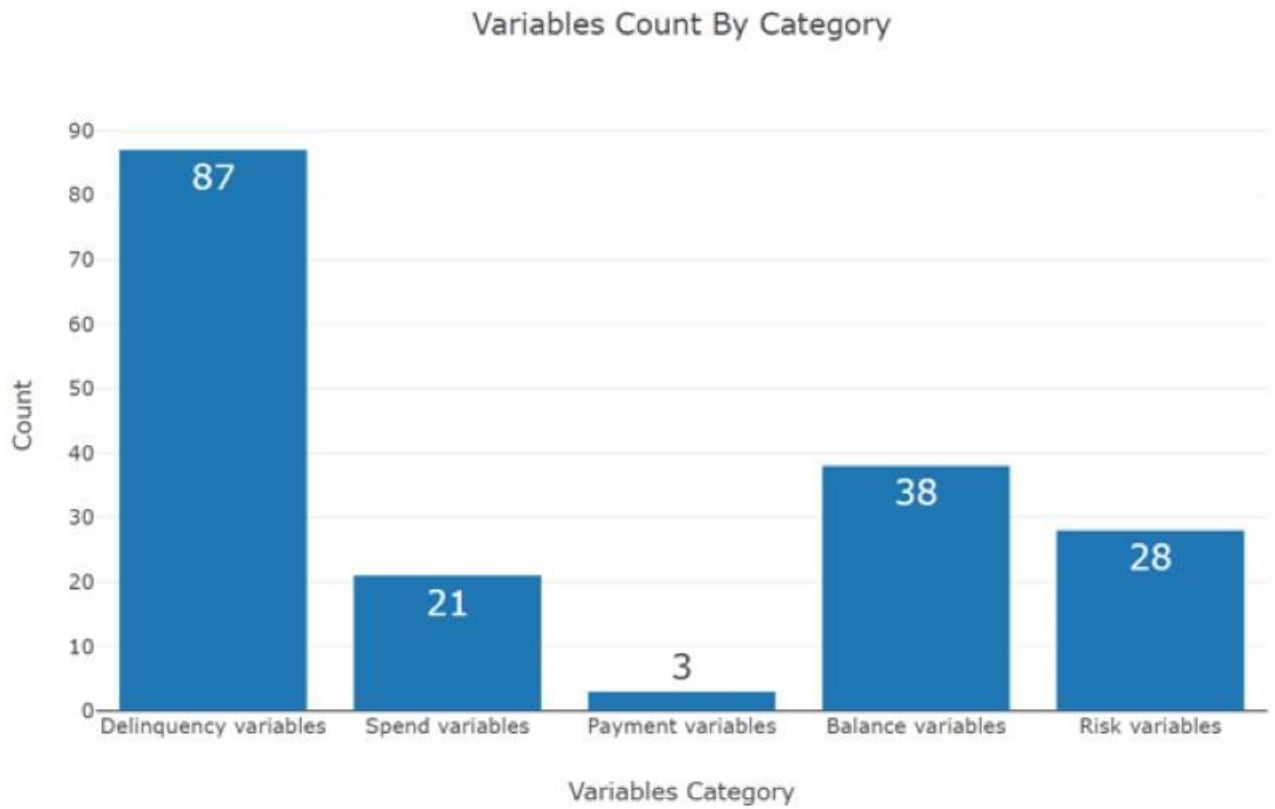
```
# Removing Columns With NaNs Rate Higher Than Threshold
nan_pct_threshold = 80
to_remove_cols = list(nan_values_pct[nan_values_pct > nan_pct_threshold].index)
print(f"Columns With NaN Values Rate > {nan_pct_threshold}%: {len(to_remove_cols)} Columns")
train_data = train_data.drop(columns=to_remove_cols).reset_index(drop=True)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

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

Part 2 >> Exploratory Data Analysis_Missing Value

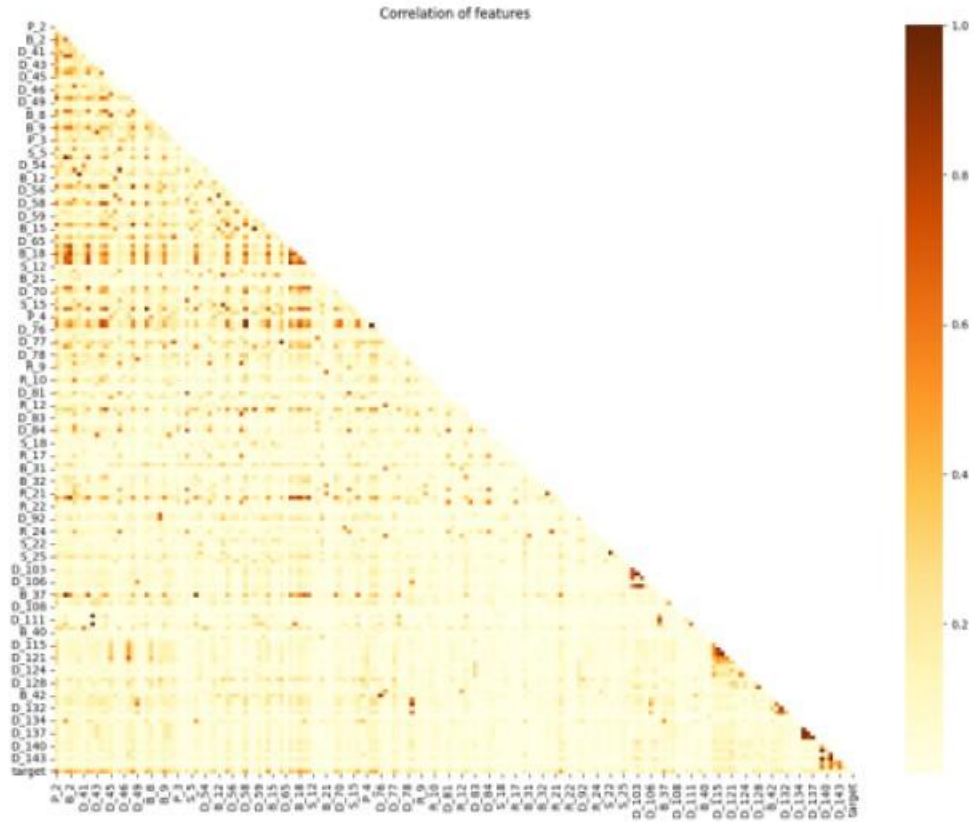
Verification_After Missing Value Processing





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

Part 2 >> Exploratory Data Analysis_ Statistical Values

Verification_Correlation between Unstacked Variables

In [38]:
```
unstacked = correlations.unstack()
unstacked = unstacked.sort_values(ascending=False, kind="quicksort").drop_duplicates().hea
d(25)
unstacked
```

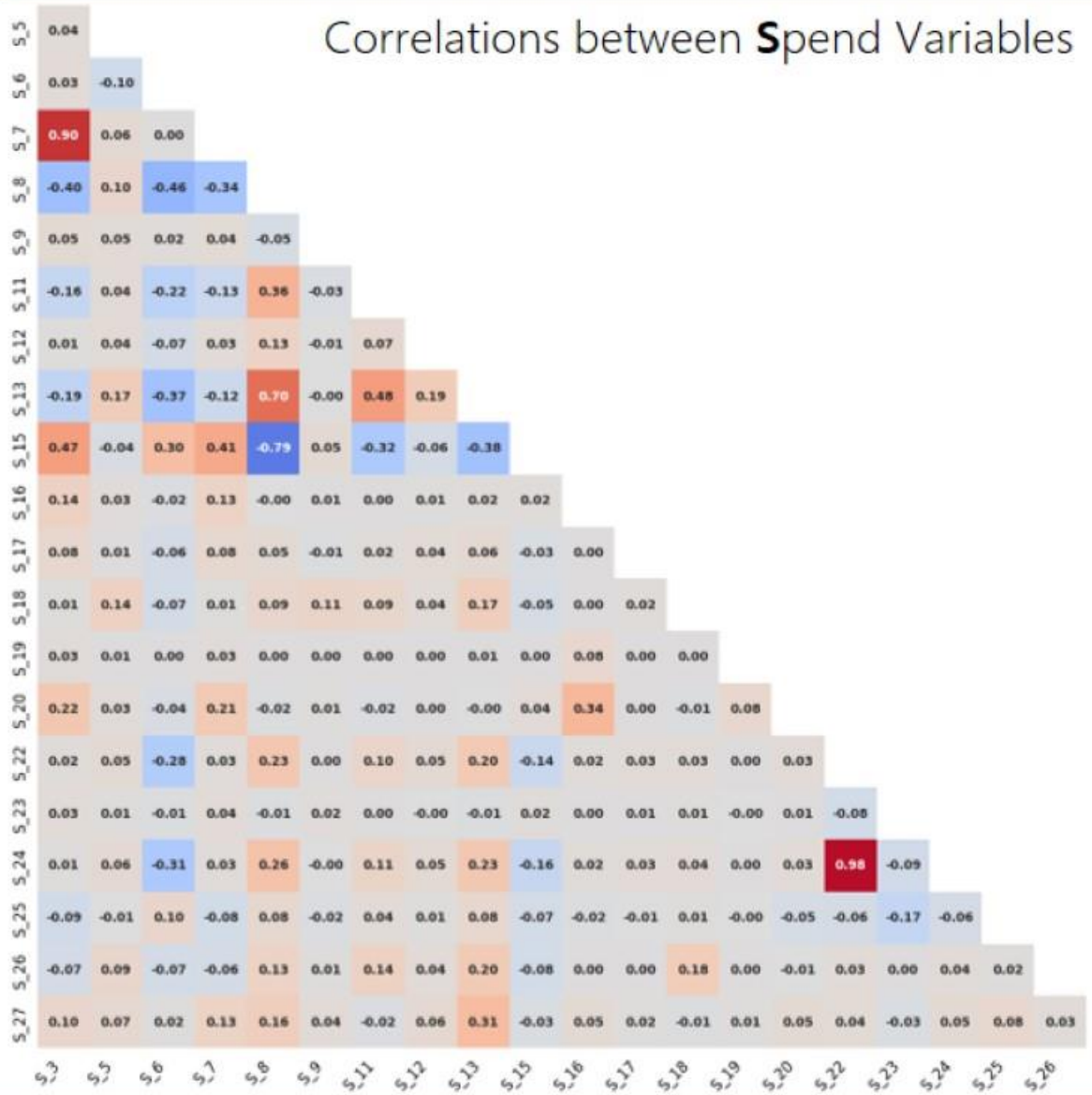
Out[38]:

P_2	P_2	1.000000
D_103	D_104	0.999779
D_77	D_62	0.999774
D_139	D_143	0.999629
	D_141	0.998261
D_143	D_141	0.997794
B_11	B_1	0.995475
B_23	B_7	0.995041
D_119	D_118	0.994861
B_1	B_37	0.993209
B_37	B_11	0.988153
D_75	D_74	0.987574
D_137	D_135	0.983981
S_22	S_24	0.978798
D_58	D_75	0.925743
	D_74	0.922671
D_138	D_137	0.918552
B_14	B_15	0.913476
B_33	B_2	0.912731
D_135	D_138	0.908674
D_137	D_136	0.907234
S_7	S_3	0.903646
D_135	D_136	0.903043
B_42	D_76	0.888606
B_20	B_16	0.888382

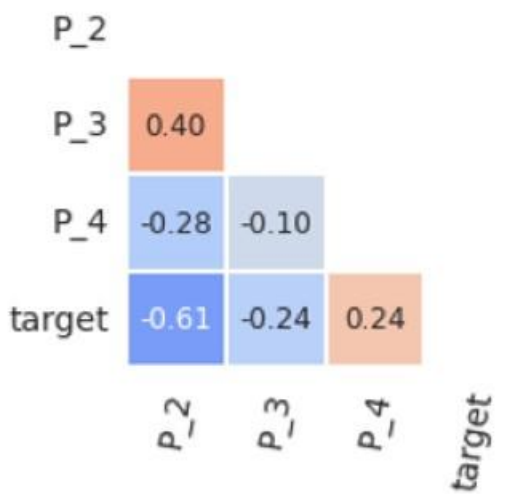
dtype: float64

Part 2 >> Exploratory Data Analysis_ Statistical Values

Correlations between **S**pend Variables

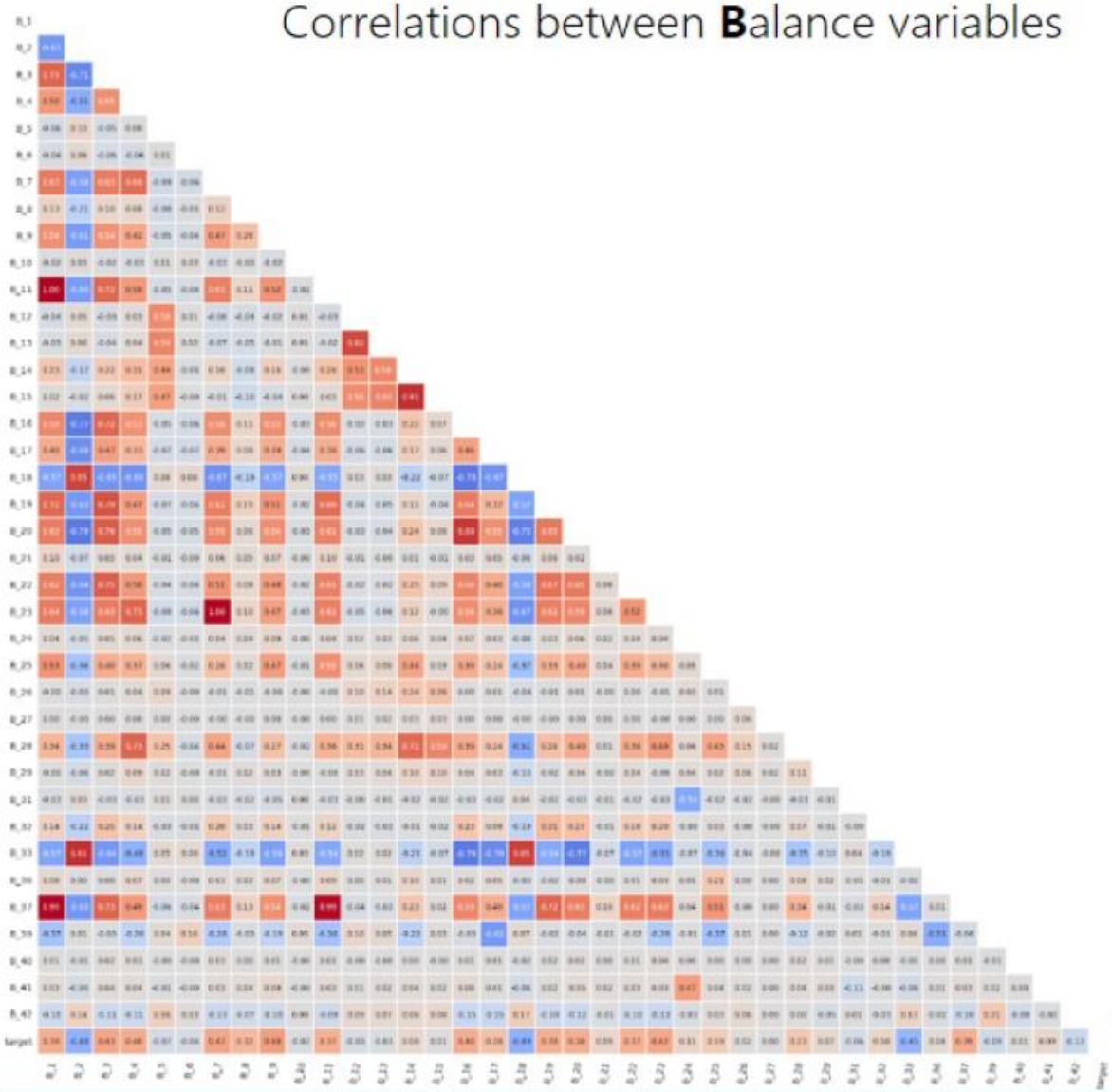


Correlations between **P**ayment variables

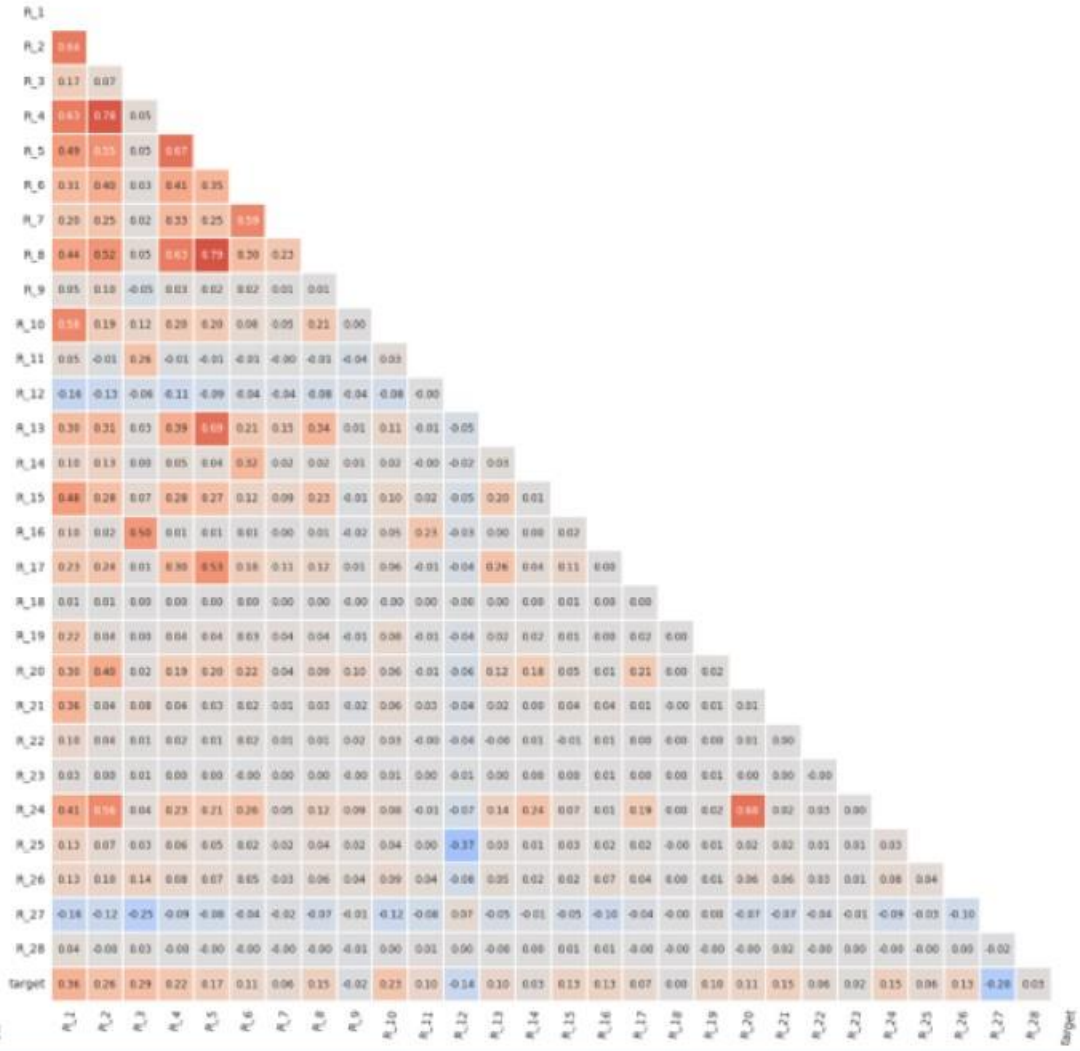


Part 2 >> Exploratory Data Analysis_ Statistical Values

Correlations between **B**alance variables



Correlations between **R**isk variables



Part 2 >> 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	0.161069	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

Part 2 >> Exploratory Data Analysis_ Statistical Values

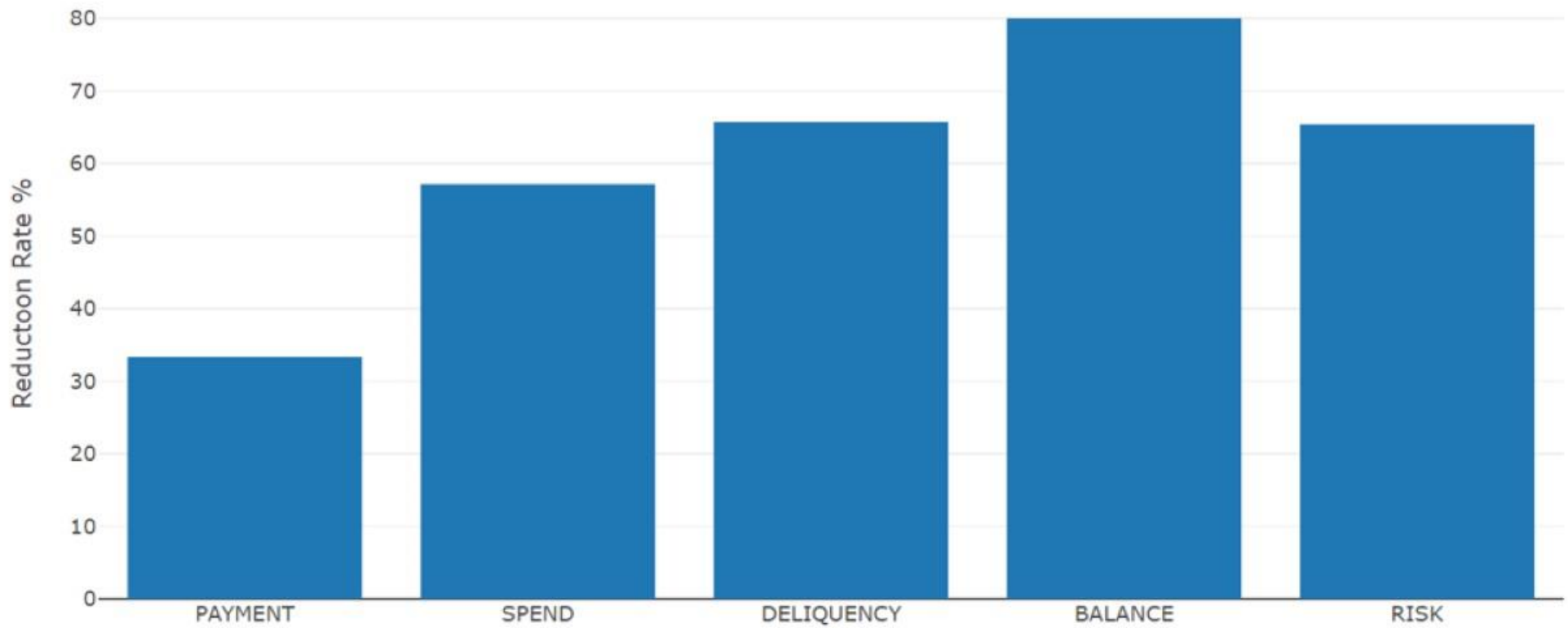
Verification_Statistical value (count,mean,std,min,max,Quantiles)_target '1'

```
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	-0.046796	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

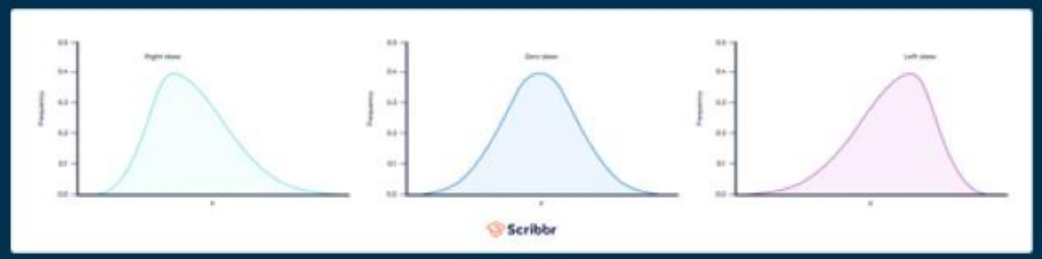
Part 2 >> Exploratory Data Analysis_Outlier detection for skewed data

Verification_Skewness Reduction Rate for each Variable Category



Part 2 >> Exploratory Data Analysis_Outlier detection for skewed data

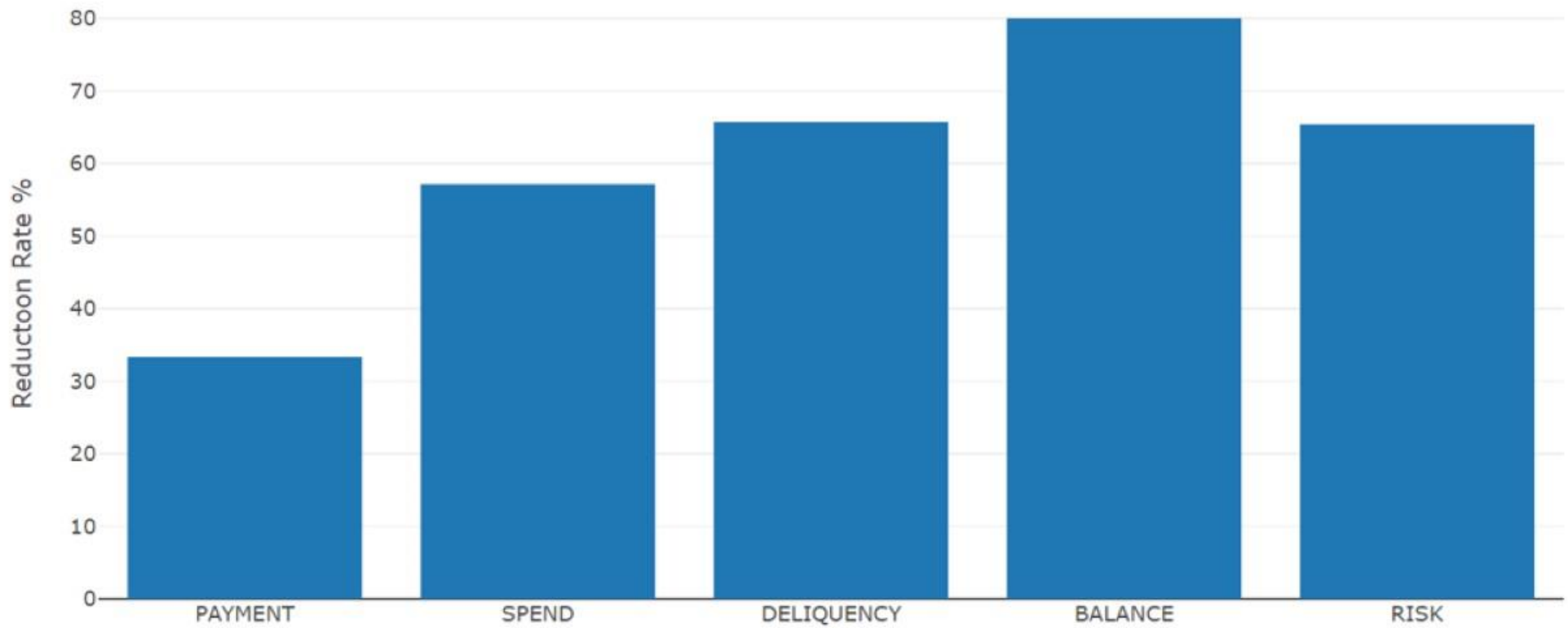
Verification_Skewness R... Rate for each Variable Category



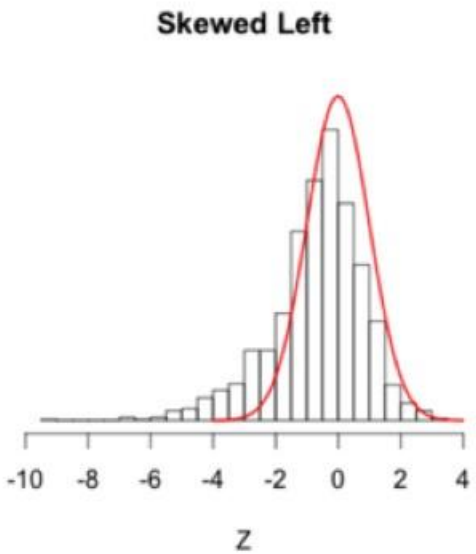
- deviate from the symmetrical bell curve
- Outliers(nonsense) → skewness

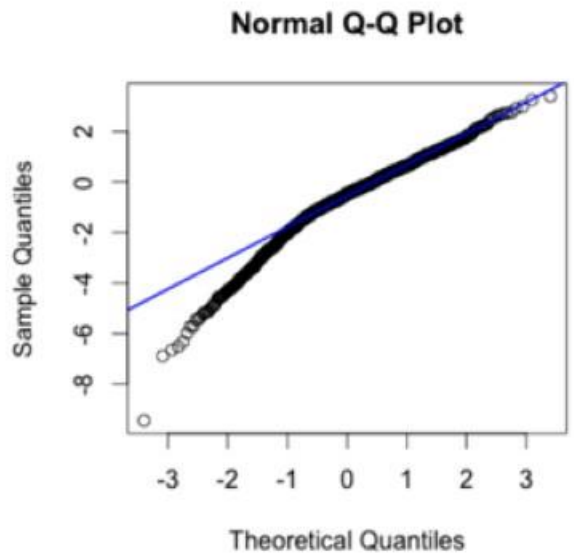
Part 2 >> Exploratory Data Analysis_Outlier detection for skewed data

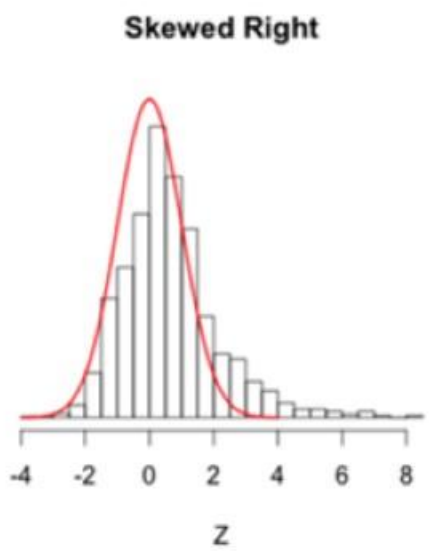
Verification_Skewness Reduction Rate for each Variable Category

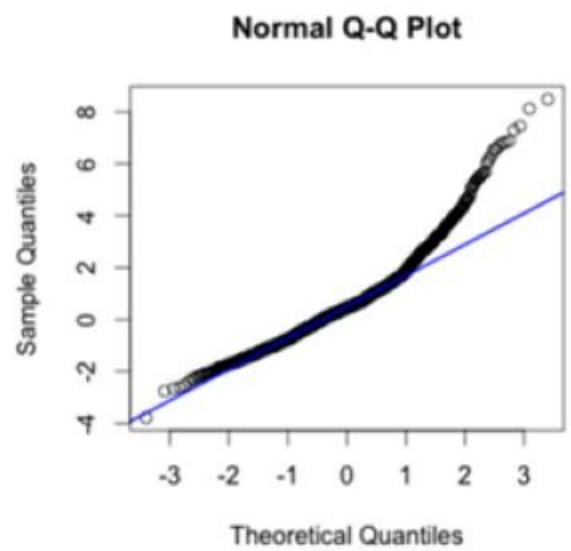


Verification_Quantile-Quantile plot

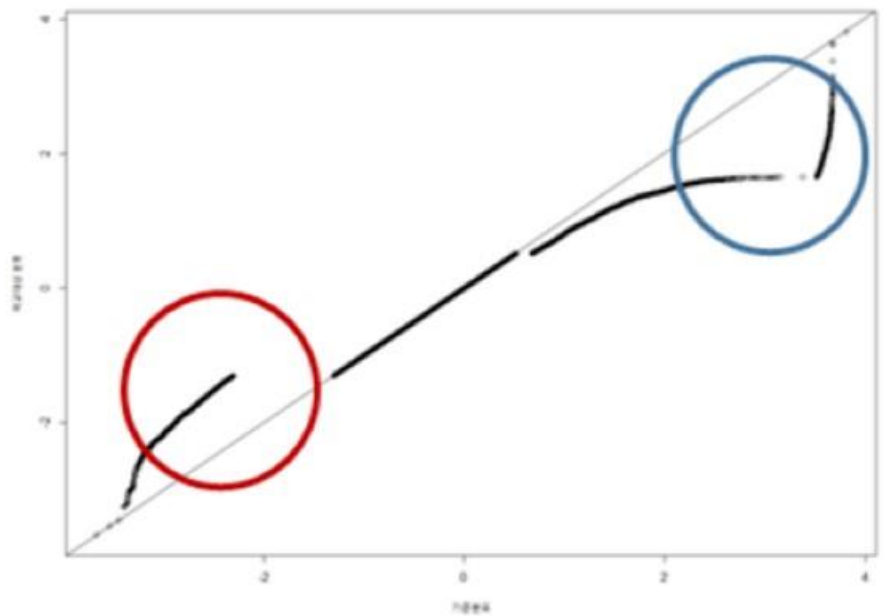


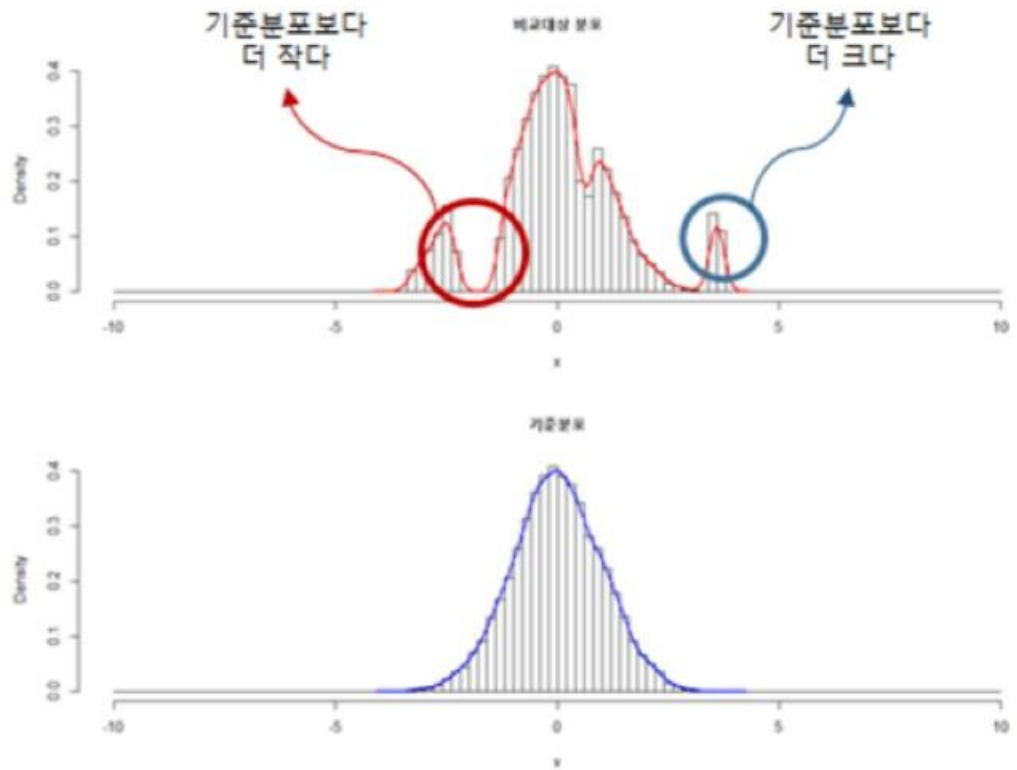






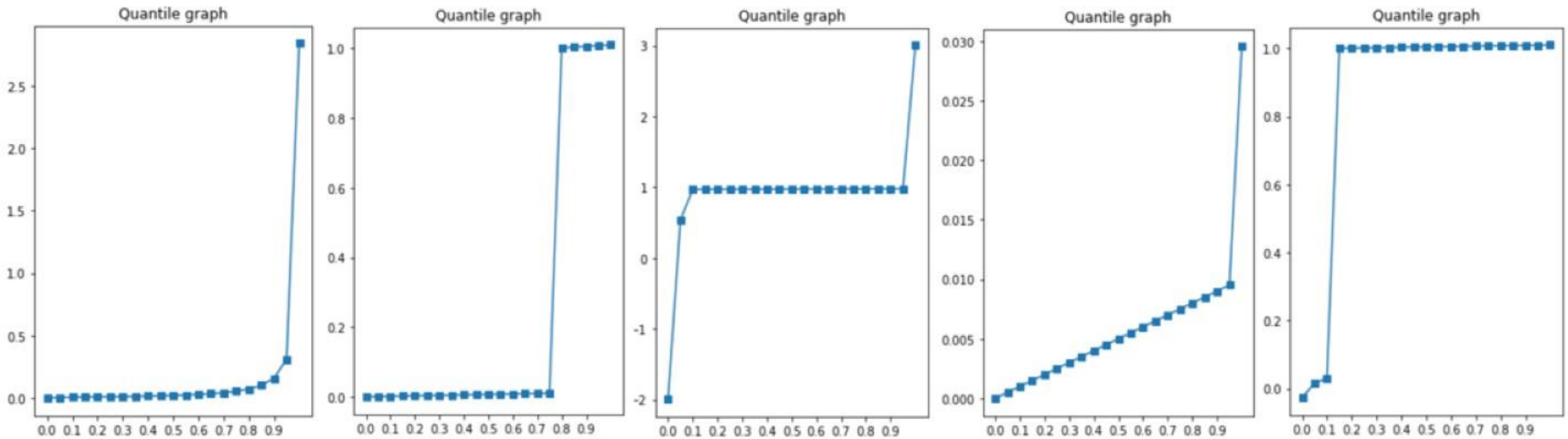
Verification_Quantile-Quantile plot





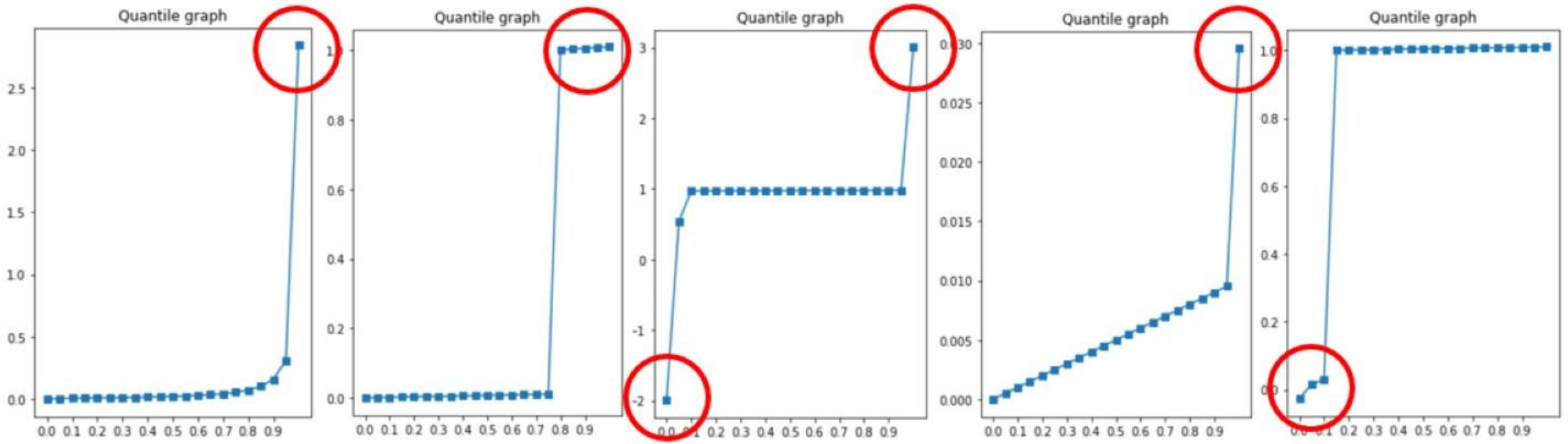
Part 2 >> Exploratory Data Analysis_ Understanding Features with Quantiles

Verification_Quantile graph for Outlier detection



Part 2 >> # Exploratory Data Analysis_ Understanding Features with Quantiles

Verification_Quantile graph for Outlier detection



Verification_Quantile graph for Outlier detection

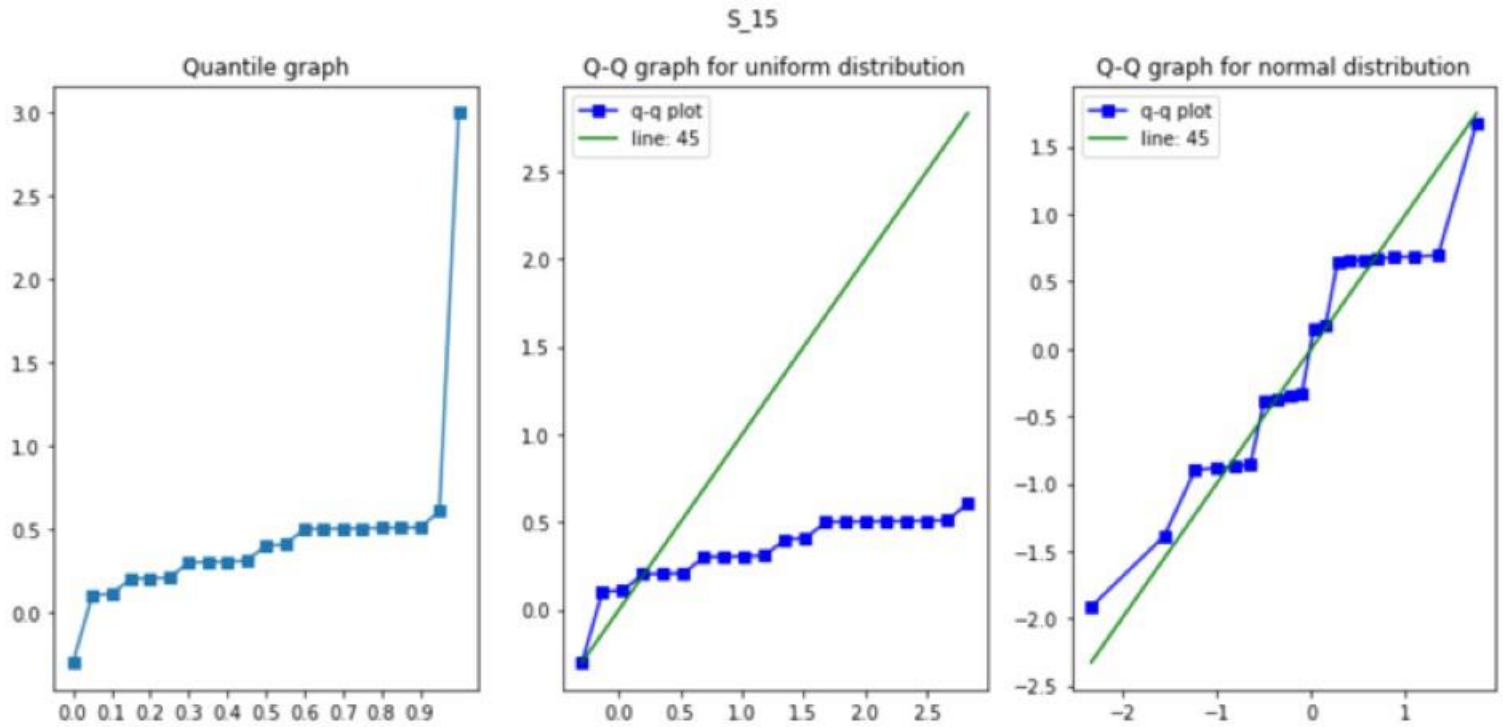
“

Outlier(이상치) 갖는 feature 많음

”

Part 2 >> Exploratory Data Analysis_ Understanding Features with Quantiles

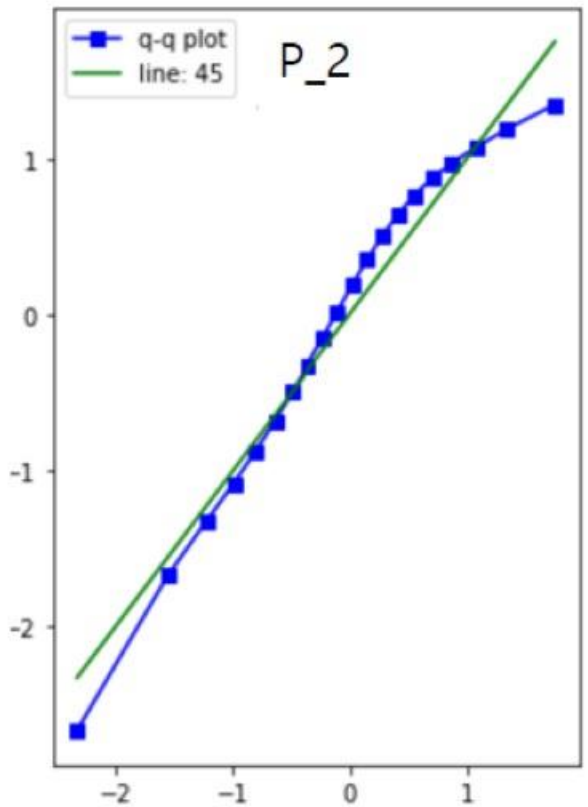
Verification_HIghly discrete values

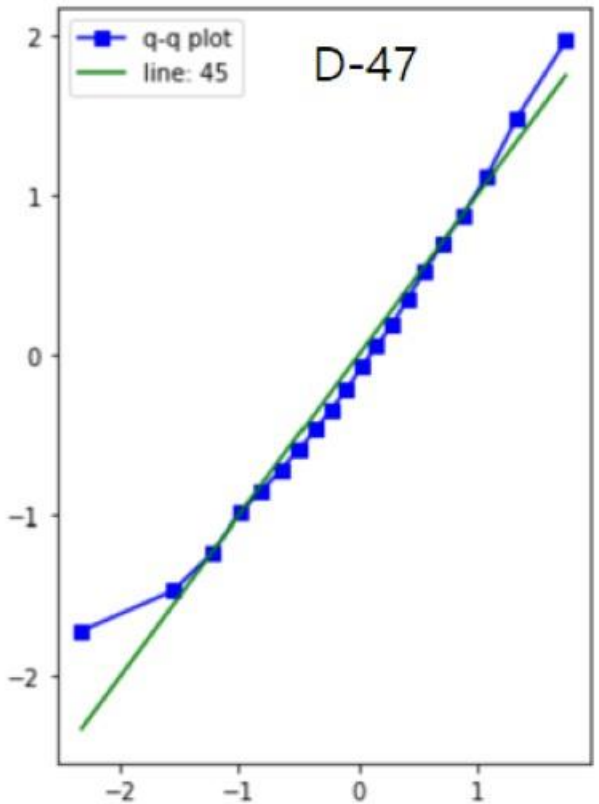


insight

S15는 최소 7개의 이산 값들을 가지는 것으로 보임

Verification_Q-Q graph for Normal Distribution





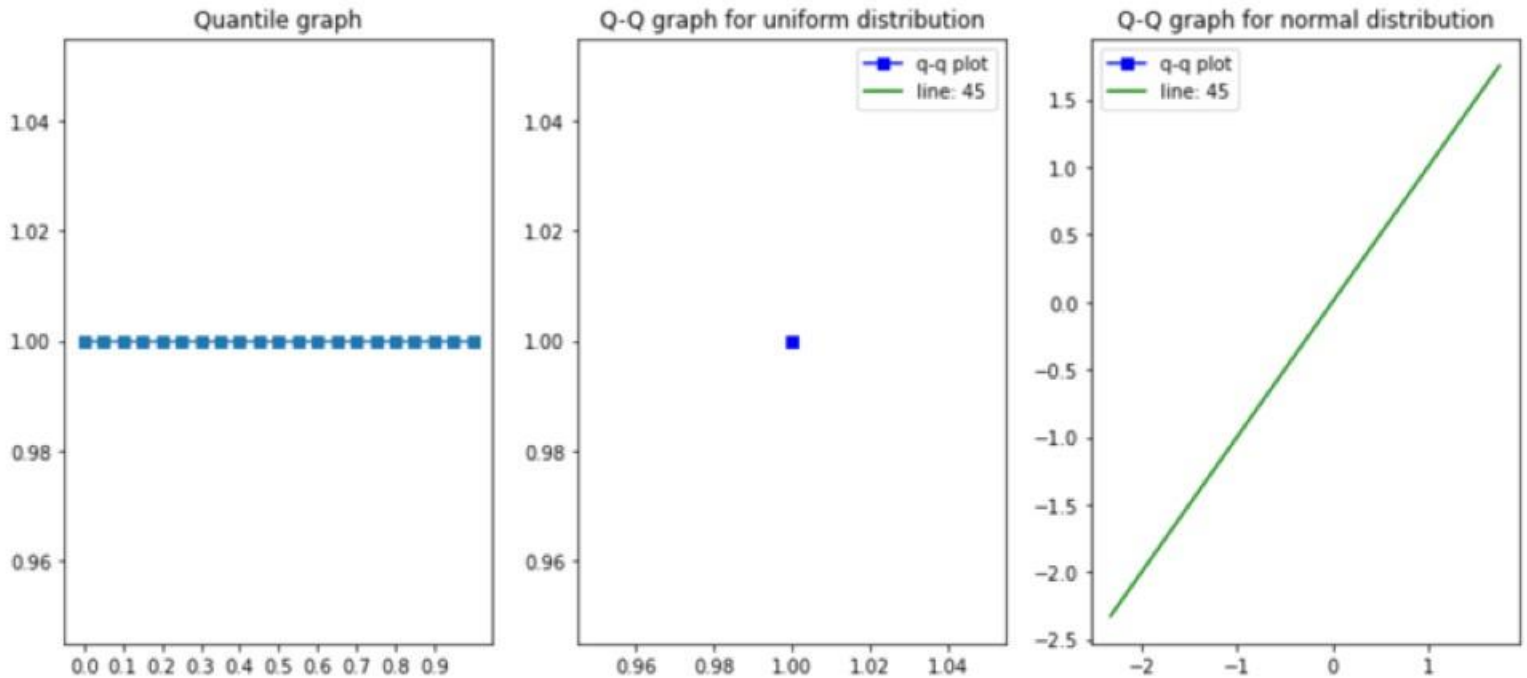
insight

P_2, D_47은
가우시안분포(=정규분포)
를 따르는 것으로 판단됨

Part 2 >> Exploratory Data Analysis_ Understanding Features with Quantiles

Verification_Q-Q graph for some Features

B_31



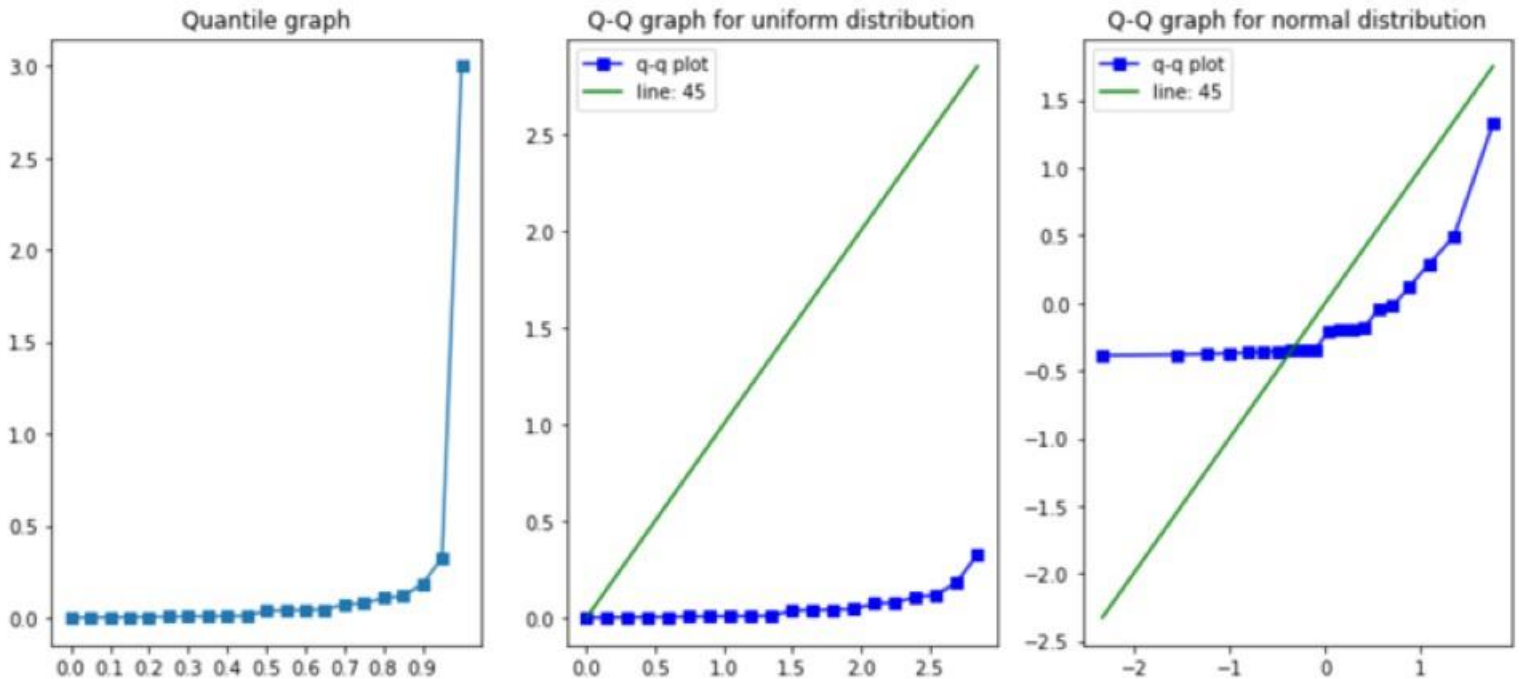
insight

B_31 는 모든 분위 수에서
단일 값을 가진다고 판단됨

Part 2 >> Exploratory Data Analysis_ Understanding Features with Quantiles

Verification_Q-Q graph for some Features

R_26



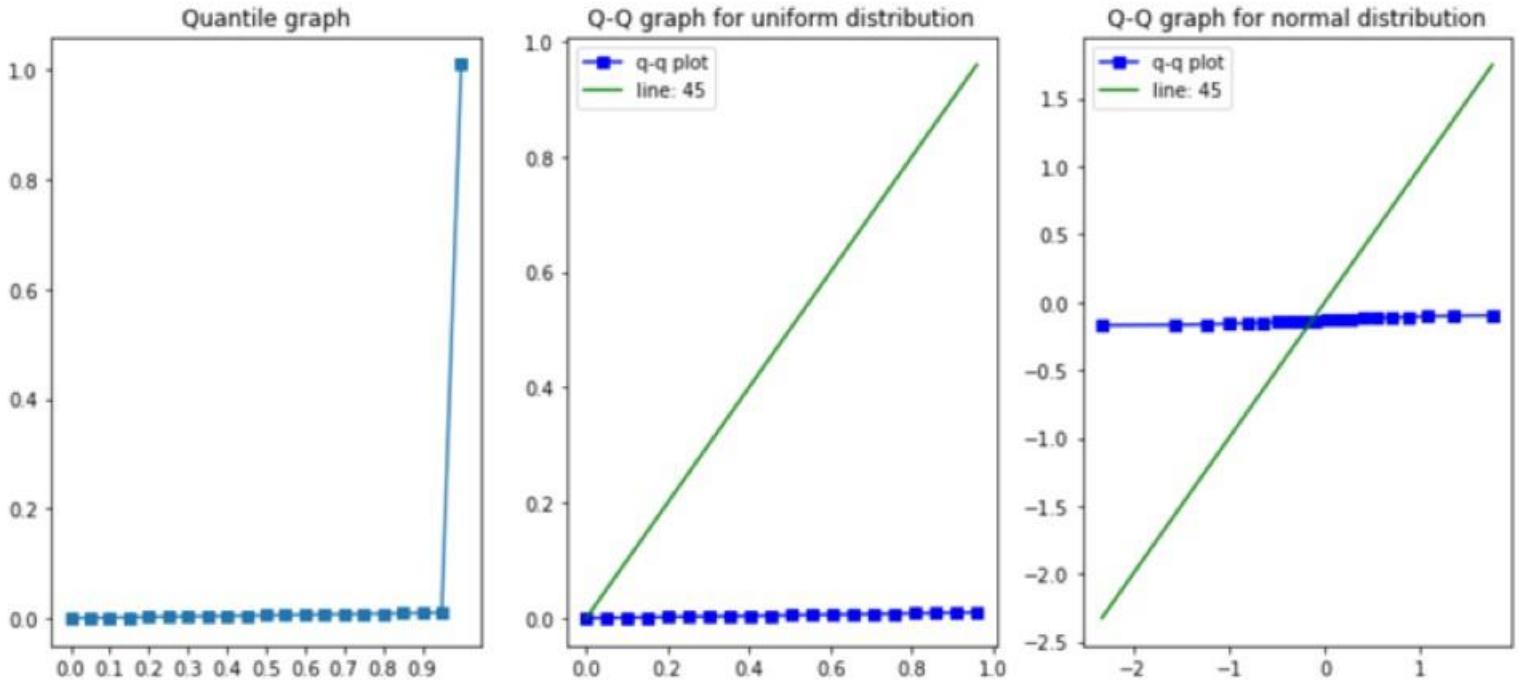
insight

R_26 는 확대 시 6개의 discrete value가 있는 것으로 판단됨

Part 2 >> Exploratory Data Analysis_ Understanding Features with Quantiles

Verification_Q-Q graph for some Features

D_94



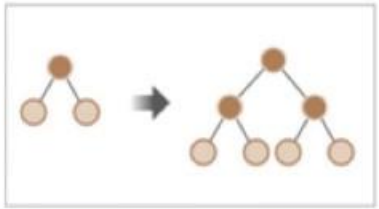
insight

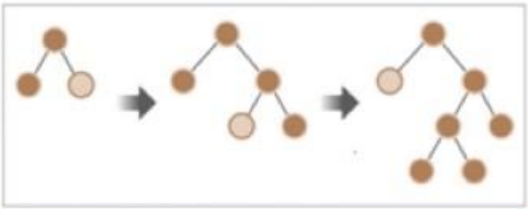
D_94, S_26 기울기 거의 0
→ 이상치 값이 매우 크다고 판단됨

3

Insight about Machine Learning Model

Part 3 >> # 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

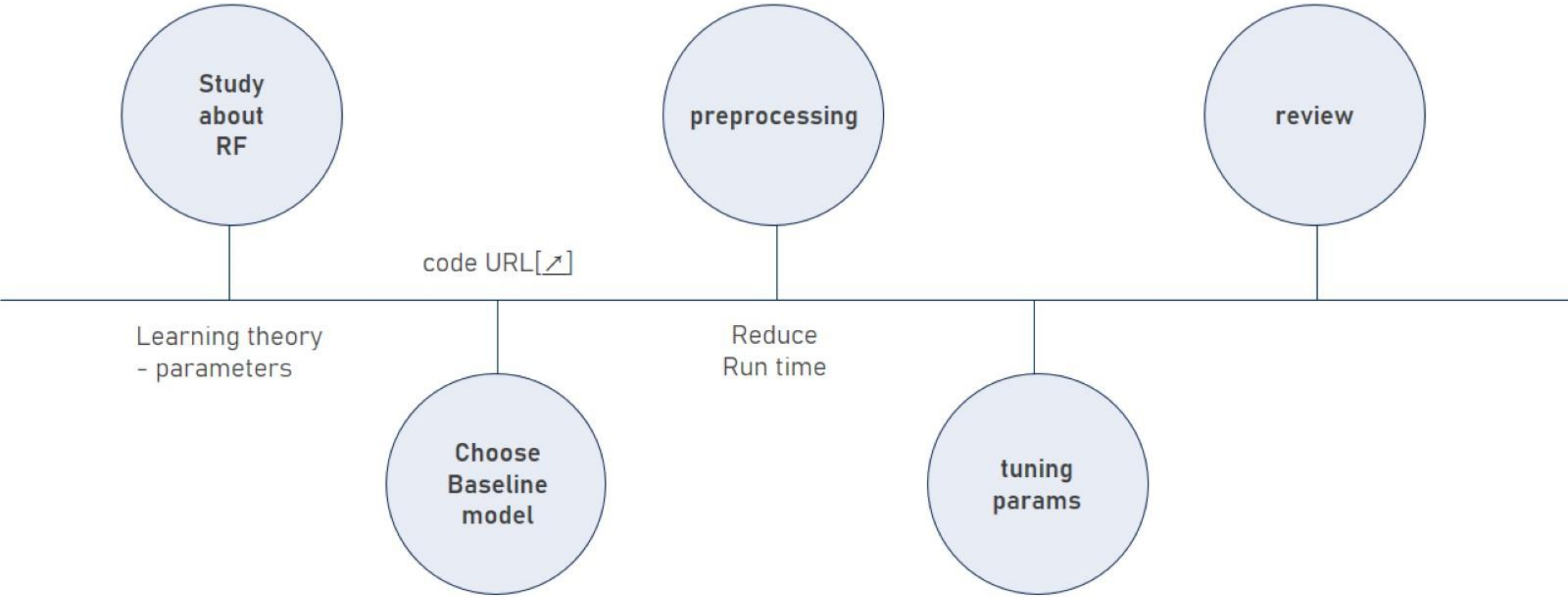
3 LightGBM

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

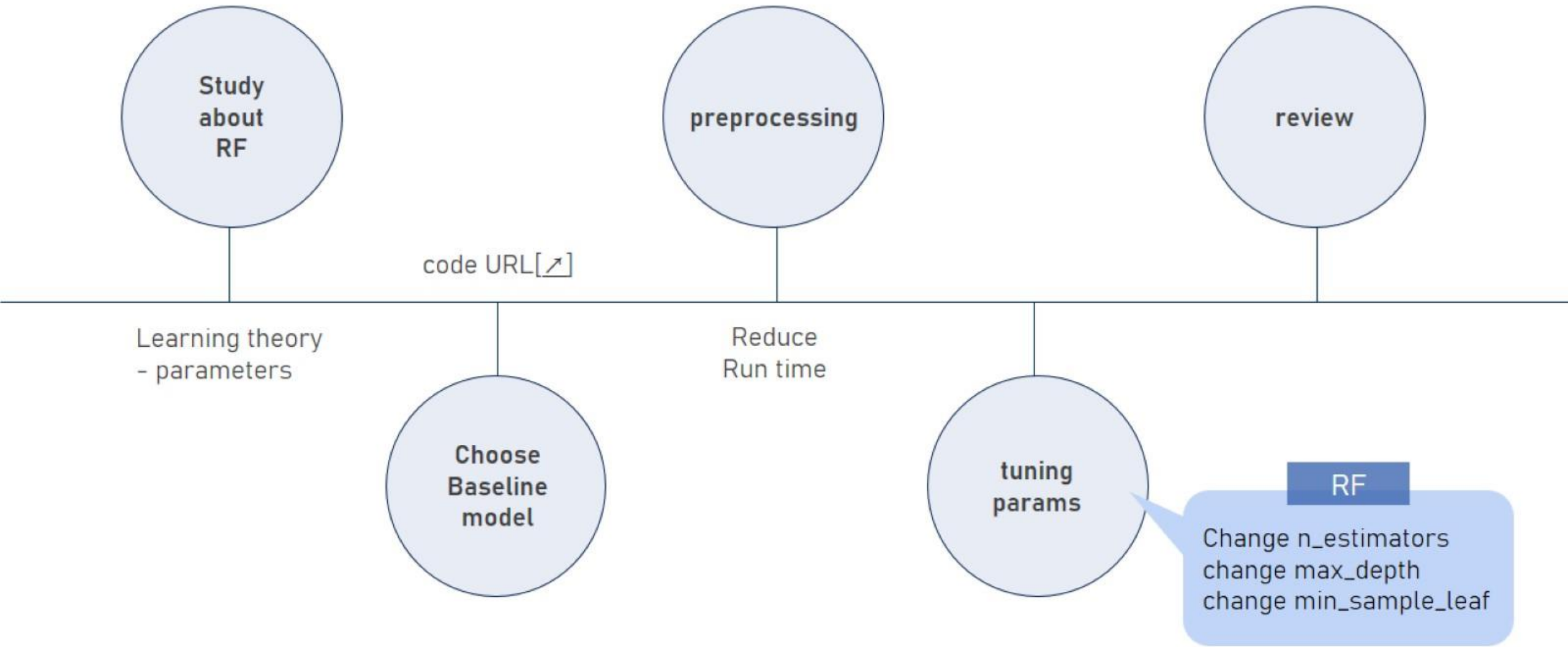
4 CatBoost

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

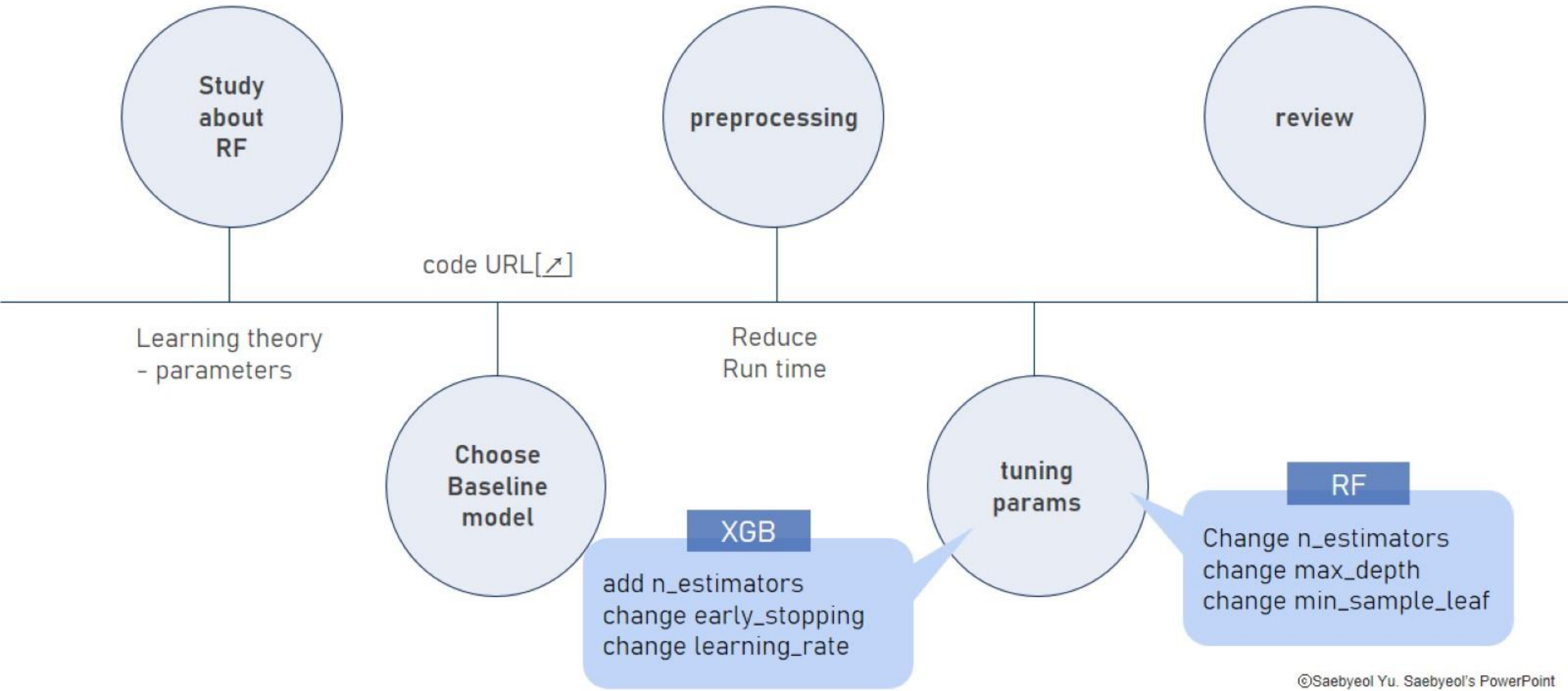
Part 3 >> Generate Machine Learning Model



Part 3 >> Generate Machine Learning Model



Part 3 >> Generate Machine Learning Model



Part 3 >> 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	-
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	-
9		-	max_depth → 20	-
10	add random_state (v3)	383.9s - CPU	random_state = 77	-
11	change min_samples_leaf (v4)	-	min_samples_leaf →	-

Part 3 >> Generate Machine Learning Model_XGBoost

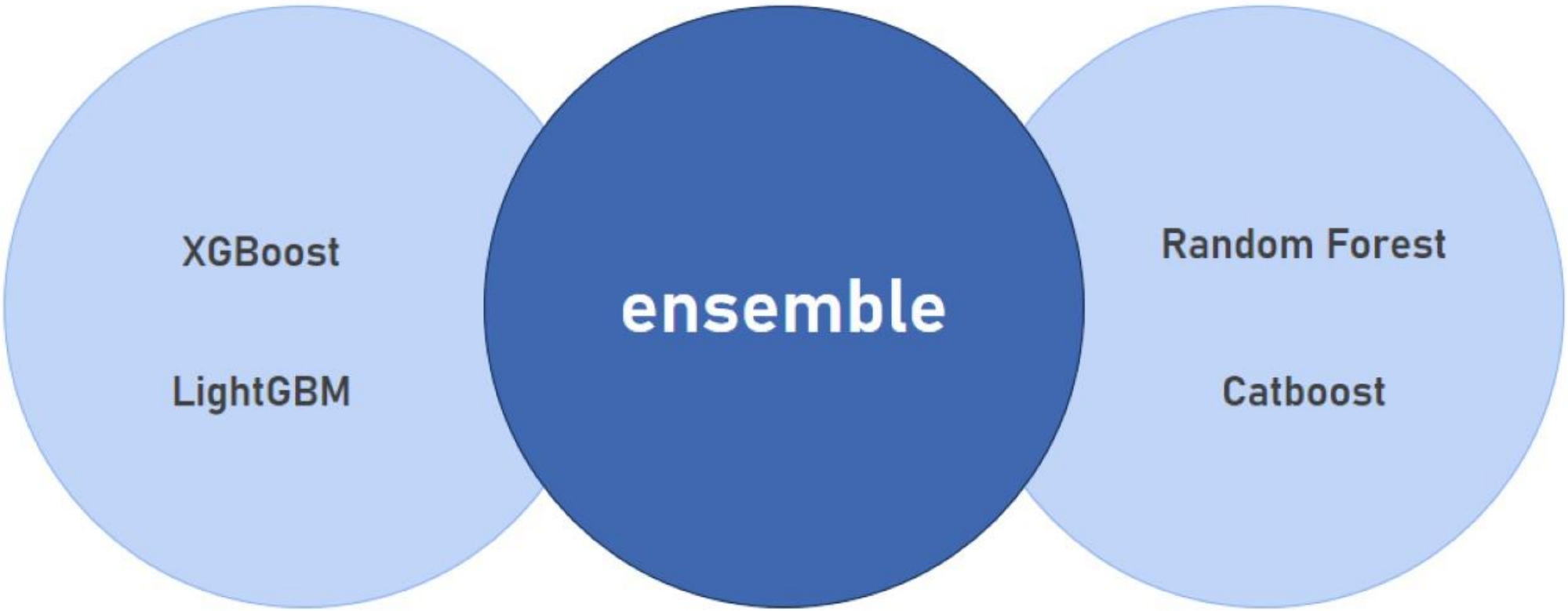
No.	내용요약	소요시간	parameters	scores
1	basic XGB model	190.8s(GPU)	(n_estimators : default 100, early_stopping_rounds=100, learning_rate=0.05)	변동없음
2	add n_estimators	186.6s(GPU)	n_estimators=110	
3		176.8s(GPU)	n_estimators=120	
4		190.4s(GPU)	n_estimators=130	
5		191.8s(GPU)	n_estimators=140	
6		196.2s(GPU)	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	

Part 3 >> Generate Machine Learning Model_CatBoost

4

Conclusion

Part 4 >> Insight about ML models & TODO




Q&A