

PROJECT 1

August 1, 2023

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[1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

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[2]: data = pd.read_csv('loan_data (1).csv')
```

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[3]: pd.set_option('display.max_columns', None)
data.head()
```

```
[3]: SK_ID_CURR  TARGET  NAME_CONTRACT_TYPE  CODE_GENDER  FLAG_OWN_CAR  \
0      100002      1      Cash loans      M      N
1      100003      0      Cash loans      F      N
2      100004      0      Revolving loans      M      Y
3      100006      0      Cash loans      F      N
4      100007      0      Cash loans      M      N

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  \
0                Y              0        202500.0    406597.5    24700.5
1                N              0        270000.0   1293502.5    35698.5
2                Y              0         67500.0    135000.0     6750.0
3                Y              0        135000.0    312682.5    29686.5
4                Y              0        121500.0    513000.0    21865.5

  AMT_GOODS_PRICE  NAME_TYPE_SUITE  NAME_INCOME_TYPE  \
0      351000.0    Unaccompanied      Working
1     1129500.0      Family    State servant
2      135000.0    Unaccompanied      Working
3      297000.0    Unaccompanied      Working
4      513000.0    Unaccompanied      Working

  NAME_EDUCATION_TYPE  NAME_FAMILY_STATUS  NAME_HOUSING_TYPE  \
0  Secondary / secondary special  Single / not married  House / apartment
1      Higher education      Married  House / apartment
2  Secondary / secondary special  Single / not married  House / apartment
3  Secondary / secondary special      Civil marriage  House / apartment
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4 Secondary / secondary special Single / not married House / apartment

	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED	DAYS_REGISTRATION	\
0	0.018801	-9461	-637	-3648.0	
1	0.003541	-16765	-1188	-1186.0	
2	0.010032	-19046	-225	-4260.0	
3	0.008019	-19005	-3039	-9833.0	
4	0.028663	-19932	-3038	-4311.0	

	DAYS_ID_PUBLISH	OWN_CAR_AGE	FLAG_MOBIL	FLAG_EMP_PHONE	FLAG_WORK_PHONE	\
0	-2120	NaN	1	1	0	
1	-291	NaN	1	1	0	
2	-2531	26.0	1	1	1	
3	-2437	NaN	1	1	0	
4	-3458	NaN	1	1	0	

	FLAG_CONT_MOBILE	FLAG_PHONE	FLAG_EMAIL	OCCUPATION_TYPE	CNT_FAM_MEMBERS	\
0	1	1	0	Laborers	1.0	
1	1	1	0	Core staff	2.0	
2	1	1	0	Laborers	1.0	
3	1	0	0	Laborers	2.0	
4	1	0	0	Core staff	1.0	

	REGION_RATING_CLIENT	REGION_RATING_CLIENT_W_CITY	\
0	2	2	
1	1	1	
2	2	2	
3	2	2	
4	2	2	

	WEEKDAY_APPR_PROCESS_START	hour_APPR_PROCESS_START	\
0	WEDNESDAY	10	
1	MONDAY	11	
2	MONDAY	9	
3	WEDNESDAY	17	
4	THURSDAY	11	

	REG_REGION_NOT_LIVE_REGION	REG_REGION_NOT_WORK_REGION	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	

	LIVE_REGION_NOT_WORK_REGION	REG_CITY_NOT_LIVE_CITY	\
0	0	0	
1	0	0	

2	0	0
3	0	0
4	0	0

	REG_CITY_NOT_WORK_CITY	LIVE_CITY_NOT_WORK_CITY	ORGANIZATION_TYPE \
0	0	0	Business Entity Type 3
1	0	0	School
2	0	0	Government
3	0	0	Business Entity Type 3
4	1	1	Religion

	EXT_SOURCE_1	EXT_SOURCE_2	EXT_SOURCE_3	APARTMENTS_AVG	BASEMENTAREA_AVG \
0	0.083037	0.262949	0.139376	0.0247	0.0369
1	0.311267	0.622246	NaN	0.0959	0.0529
2	NaN	0.555912	0.729567	NaN	NaN
3	NaN	0.650442	NaN	NaN	NaN
4	NaN	0.322738	NaN	NaN	NaN

	YEARS_BEGINEXPLUATATION_AVG	YEARS_BUILD_AVG	COMMONAREA_AVG \
0	0.9722	0.6192	0.0143
1	0.9851	0.7960	0.0605
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	NaN	NaN	NaN

	ELEVATORS_AVG	ENTRANCES_AVG	FLOORSMAX_AVG	FLOORSMIN_AVG	LANDAREA_AVG \
0	0.00	0.0690	0.0833	0.1250	0.0369
1	0.08	0.0345	0.2917	0.3333	0.0130
2	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN

	LIVINGAPARTMENTS_AVG	LIVINGAREA_AVG	NONLIVINGAPARTMENTS_AVG \
0	0.0202	0.0190	0.0000
1	0.0773	0.0549	0.0039
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	NaN	NaN	NaN

	NONLIVINGAREA_AVG	APARTMENTS_MODE	BASEMENTAREA_MODE \
0	0.0000	0.0252	0.0383
1	0.0098	0.0924	0.0538
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	NaN	NaN	NaN

	YEARS_BEGINEXPLUATATION_MODE	YEARS_BUILD_MODE	COMMONAREA_MODE \
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0		0.9722	0.6341	0.0144
1		0.9851	0.8040	0.0497
2		NaN	NaN	NaN
3		NaN	NaN	NaN
4		NaN	NaN	NaN

	ELEVATORS_MODE	ENTRANCES_MODE	FLOORSMAX_MODE	FLOORSMIN_MODE	\
0	0.0000	0.0690	0.0833	0.1250	
1	0.0806	0.0345	0.2917	0.3333	
2	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	

	LANDAREA_MODE	LIVINGAPARTMENTS_MODE	LIVINGAREA_MODE	\
0	0.0377	0.022	0.0198	
1	0.0128	0.079	0.0554	
2	NaN	NaN	NaN	
3	NaN	NaN	NaN	
4	NaN	NaN	NaN	

	NONLIVINGAPARTMENTS_MODE	NONLIVINGAREA_MODE	APARTMENTS_MEDI	\
0	0.0	0.0	0.0250	
1	0.0	0.0	0.0968	
2	NaN	NaN	NaN	
3	NaN	NaN	NaN	
4	NaN	NaN	NaN	

	BASEMENTAREA_MEDI	YEARS_BEGINEXPLUATATION_MEDI	YEARS_BUILD_MEDI	\
0	0.0369	0.9722	0.6243	
1	0.0529	0.9851	0.7987	
2	NaN	NaN	NaN	
3	NaN	NaN	NaN	
4	NaN	NaN	NaN	

	COMMONAREA_MEDI	ELEVATORS_MEDI	ENTRANCES_MEDI	FLOORSMAX_MEDI	\
0	0.0144	0.00	0.0690	0.0833	
1	0.0608	0.08	0.0345	0.2917	
2	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	

	FLOORSMIN_MEDI	LANDAREA_MEDI	LIVINGAPARTMENTS_MEDI	LIVINGAREA_MEDI	\
0	0.1250	0.0375	0.0205	0.0193	
1	0.3333	0.0132	0.0787	0.0558	
2	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	

	NONLIVINGAPARTMENTS_MEDI	NONLIVINGAREA_MEDI	FONDKAPREMONT_MODE	\
0	0.0000	0.00	reg oper account	
1	0.0039	0.01	reg oper account	
2	NaN	NaN	NaN	
3	NaN	NaN	NaN	
4	NaN	NaN	NaN	

	HOUSETYPE_MODE	TOTALAREA_MODE	WALLSMATERIAL_MODE	EMERGENCYSTATE_MODE	\
0	block of flats	0.0149	Stone, brick	No	
1	block of flats	0.0714	Block	No	
2	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	

	OBS_30_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	\
0	2.0	2.0	
1	1.0	0.0	
2	0.0	0.0	
3	2.0	0.0	
4	0.0	0.0	

	OBS_60_CNT_SOCIAL_CIRCLE	DEF_60_CNT_SOCIAL_CIRCLE	DAYS_LAST_PHONE_CHANGE	\
0	2.0	2.0	-1134.0	
1	1.0	0.0	-828.0	
2	0.0	0.0	-815.0	
3	2.0	0.0	-617.0	
4	0.0	0.0	-1106.0	

	FLAG_DOCUMENT_2	FLAG_DOCUMENT_3	FLAG_DOCUMENT_4	FLAG_DOCUMENT_5	\
0	0	1	0	0	
1	0	1	0	0	
2	0	0	0	0	
3	0	1	0	0	
4	0	0	0	0	

	FLAG_DOCUMENT_6	FLAG_DOCUMENT_7	FLAG_DOCUMENT_8	FLAG_DOCUMENT_9	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	1	0	

	FLAG_DOCUMENT_10	FLAG_DOCUMENT_11	FLAG_DOCUMENT_12	FLAG_DOCUMENT_13	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	

3	0	0	0	0
4	0	0	0	0

	FLAG_DOCUMENT_14	FLAG_DOCUMENT_15	FLAG_DOCUMENT_16	FLAG_DOCUMENT_17	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	FLAG_DOCUMENT_18	FLAG_DOCUMENT_19	FLAG_DOCUMENT_20	FLAG_DOCUMENT_21	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	AMT_REQ_CREDIT_BUREAU_HOUR	AMT_REQ_CREDIT_BUREAU_DAY	\
0	0.0	0.0	
1	0.0	0.0	
2	0.0	0.0	
3	NaN	NaN	
4	0.0	0.0	

	AMT_REQ_CREDIT_BUREAU_WEEK	AMT_REQ_CREDIT_BUREAU_MON	\
0	0.0	0.0	
1	0.0	0.0	
2	0.0	0.0	
3	NaN	NaN	
4	0.0	0.0	

	AMT_REQ_CREDIT_BUREAU_QRT	AMT_REQ_CREDIT_BUREAU_YEAR
0	0.0	1.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0

```
[4]: # this a binary classification problem
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[5]: data.info()
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<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
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```
[6]: data.describe()
```

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[6]:
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	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	\
count	307511.000000	307511.000000	307511.000000	3.075110e+05	
mean	278180.518577	0.080729	0.417052	1.687979e+05	
std	102790.175348	0.272419	0.722121	2.371231e+05	
min	100002.000000	0.000000	0.000000	2.565000e+04	
25%	189145.500000	0.000000	0.000000	1.125000e+05	
50%	278202.000000	0.000000	0.000000	1.471500e+05	
75%	367142.500000	0.000000	1.000000	2.025000e+05	
max	456255.000000	1.000000	19.000000	1.170000e+08	

	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	\
count	3.075110e+05	307499.000000	3.072330e+05	
mean	5.990260e+05	27108.573909	5.383962e+05	
std	4.024908e+05	14493.737315	3.694465e+05	
min	4.500000e+04	1615.500000	4.050000e+04	
25%	2.700000e+05	16524.000000	2.385000e+05	
50%	5.135310e+05	24903.000000	4.500000e+05	
75%	8.086500e+05	34596.000000	6.795000e+05	
max	4.050000e+06	258025.500000	4.050000e+06	

	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED	\
count	307511.000000	307511.000000	307511.000000	
mean		0.020868	-16036.995067	63815.045904
std		0.013831	4363.988632	141275.766519
min		0.000290	-25229.000000	-17912.000000
25%		0.010006	-19682.000000	-2760.000000
50%		0.018850	-15750.000000	-1213.000000
75%		0.028663	-12413.000000	-289.000000
max		0.072508	-7489.000000	365243.000000

	DAYS_REGISTRATION	DAYS_ID_PUBLISH	OWN_CAR_AGE	FLAG_MOBIL	\
count	307511.000000	307511.000000	104582.000000	307511.000000	
mean	-4986.120328	-2994.202373	12.061091	0.999997	
std	3522.886321	1509.450419	11.944812	0.001803	
min	-24672.000000	-7197.000000	0.000000	0.000000	
25%	-7479.500000	-4299.000000	5.000000	1.000000	
50%	-4504.000000	-3254.000000	9.000000	1.000000	
75%	-2010.000000	-1720.000000	15.000000	1.000000	
max	0.000000	0.000000	91.000000	1.000000	

	FLAG_EMP_PHONE	FLAG_WORK_PHONE	FLAG_CONT_MOBILE	FLAG_PHONE	\
count	307511.000000	307511.000000	307511.000000	307511.000000	
mean	0.819889	0.199368	0.998133	0.281066	
std	0.384280	0.399526	0.043164	0.449521	
min	0.000000	0.000000	0.000000	0.000000	

25%	1.000000	0.000000	1.000000	0.000000
50%	1.000000	0.000000	1.000000	0.000000
75%	1.000000	0.000000	1.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000

	FLAG_EMAIL	CNT_FAM_MEMBERS	REGION_RATING_CLIENT \
count	307511.000000	307509.000000	307511.000000
mean	0.056720	2.152665	2.052463
std	0.231307	0.910682	0.509034
min	0.000000	1.000000	1.000000
25%	0.000000	2.000000	2.000000
50%	0.000000	2.000000	2.000000
75%	0.000000	3.000000	2.000000
max	1.000000	20.000000	3.000000

	REGION_RATING_CLIENT_W_CITY	hour_APPR_PROCESS_START \
count	307511.000000	307511.000000
mean	2.031521	12.063419
std	0.502737	3.265832
min	1.000000	0.000000
25%	2.000000	10.000000
50%	2.000000	12.000000
75%	2.000000	14.000000
max	3.000000	23.000000

	REG_REGION_NOT_LIVE_REGION	REG_REGION_NOT_WORK_REGION \
count	307511.000000	307511.000000
mean	0.015144	0.050769
std	0.122126	0.219526
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	1.000000	1.000000

	LIVE_REGION_NOT_WORK_REGION	REG_CITY_NOT_LIVE_CITY \
count	307511.000000	307511.000000
mean	0.040659	0.078173
std	0.197499	0.268444
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	1.000000	1.000000

	REG_CITY_NOT_WORK_CITY	LIVE_CITY_NOT_WORK_CITY	EXT_SOURCE_1 \
count	307511.000000	307511.000000	134133.000000

mean	0.230454	0.179555	0.502130
std	0.421124	0.383817	0.211062
min	0.000000	0.000000	0.014568
25%	0.000000	0.000000	0.334007
50%	0.000000	0.000000	0.505998
75%	0.000000	0.000000	0.675053
max	1.000000	1.000000	0.962693

	EXT_SOURCE_2	EXT_SOURCE_3	APARTMENTS_AVG	BASEMENTAREA_AVG \
count	3.068510e+05	246546.000000	151450.000000	127568.000000
mean	5.143927e-01	0.510853	0.11744	0.088442
std	1.910602e-01	0.194844	0.10824	0.082438
min	8.173617e-08	0.000527	0.000000	0.000000
25%	3.924574e-01	0.370650	0.05770	0.044200
50%	5.659614e-01	0.535276	0.08760	0.076300
75%	6.636171e-01	0.669057	0.14850	0.112200
max	8.549997e-01	0.896010	1.000000	1.000000

	YEARS_BEGINEXPLUATATION_AVG	YEARS_BUILD_AVG	COMMONAREA_AVG \
count	157504.000000	103023.000000	92646.000000
mean	0.977735	0.752471	0.044621
std	0.059223	0.113280	0.076036
min	0.000000	0.000000	0.000000
25%	0.976700	0.687200	0.007800
50%	0.981600	0.755200	0.021100
75%	0.986600	0.823200	0.051500
max	1.000000	1.000000	1.000000

	ELEVATORS_AVG	ENTRANCES_AVG	FLOORSMAX_AVG	FLOORSMIN_AVG \
count	143620.000000	152683.000000	154491.000000	98869.000000
mean	0.078942	0.149725	0.226282	0.231894
std	0.134576	0.100049	0.144641	0.161380
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.069000	0.166700	0.083300
50%	0.000000	0.137900	0.166700	0.208300
75%	0.120000	0.206900	0.333300	0.375000
max	1.000000	1.000000	1.000000	1.000000

	LANDAREA_AVG	LIVINGAPARTMENTS_AVG	LIVINGAREA_AVG \
count	124921.000000	97312.000000	153161.000000
mean	0.066333	0.100775	0.107399
std	0.081184	0.092576	0.110565
min	0.000000	0.000000	0.000000
25%	0.018700	0.050400	0.045300
50%	0.048100	0.075600	0.074500
75%	0.085600	0.121000	0.129900
max	1.000000	1.000000	1.000000

	NONLIVINGAPARTMENTS_AVG	NONLIVINGAREA_AVG	APARTMENTS_MODE \
count	93997.000000	137829.000000	151450.000000
mean	0.008809	0.028358	0.114231
std	0.047732	0.069523	0.107936
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.052500
50%	0.000000	0.003600	0.084000
75%	0.003900	0.027700	0.143900
max	1.000000	1.000000	1.000000

	BASEMENTAREA_MODE	YEARS_BEGINEXPLUATATION_MODE	YEARS_BUILD_MODE \
count	127568.000000	157504.000000	103023.000000
mean	0.087543	0.977065	0.759637
std	0.084307	0.064575	0.110111
min	0.000000	0.000000	0.000000
25%	0.040700	0.976700	0.699400
50%	0.074600	0.981600	0.764800
75%	0.112400	0.986600	0.823600
max	1.000000	1.000000	1.000000

	COMMONAREA_MODE	ELEVATORS_MODE	ENTRANCES_MODE	FLOORSMAX_MODE \
count	92646.000000	143620.000000	152683.000000	154491.000000
mean	0.042553	0.074490	0.145193	0.222315
std	0.074445	0.132256	0.100977	0.143709
min	0.000000	0.000000	0.000000	0.000000
25%	0.007200	0.000000	0.069000	0.166700
50%	0.019000	0.000000	0.137900	0.166700
75%	0.049000	0.120800	0.206900	0.333300
max	1.000000	1.000000	1.000000	1.000000

	FLOORSMIN_MODE	LANDAREA_MODE	LIVINGAPARTMENTS_MODE	LIVINGAREA_MODE \
count	98869.000000	124921.000000	97312.000000	153161.000000
mean	0.228058	0.064958	0.105645	0.105975
std	0.161160	0.081750	0.097880	0.111845
min	0.000000	0.000000	0.000000	0.000000
25%	0.083300	0.016600	0.054200	0.042700
50%	0.208300	0.045800	0.077100	0.073100
75%	0.375000	0.084100	0.131300	0.125200
max	1.000000	1.000000	1.000000	1.000000

	NONLIVINGAPARTMENTS_MODE	NONLIVINGAREA_MODE	APARTMENTS_MEDI \
count	93997.000000	137829.000000	151450.000000
mean	0.008076	0.027022	0.117850
std	0.046276	0.070254	0.109076
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.058300

50%	0.000000	0.001100	0.086400
75%	0.003900	0.023100	0.148900
max	1.000000	1.000000	1.000000

	BASEMENTAREA_MEDI	YEARS_BEGINEXPLUATATION_MEDI	YEARS_BUILD_MEDI	\
count	127568.000000	157504.000000	103023.000000	
mean	0.087955	0.977752	0.755746	
std	0.082179	0.059897	0.112066	
min	0.000000	0.000000	0.000000	
25%	0.043700	0.976700	0.691400	
50%	0.075800	0.981600	0.758500	
75%	0.111600	0.986600	0.825600	
max	1.000000	1.000000	1.000000	

	COMMONAREA_MEDI	ELEVATORS_MEDI	ENTRANCES_MEDI	FLOORSMAX_MEDI	\
count	92646.000000	143620.000000	152683.000000	154491.000000	
mean	0.044595	0.078078	0.149213	0.225897	
std	0.076144	0.134467	0.100368	0.145067	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.007900	0.000000	0.069000	0.166700	
50%	0.020800	0.000000	0.137900	0.166700	
75%	0.051300	0.120000	0.206900	0.333300	
max	1.000000	1.000000	1.000000	1.000000	

	FLOORSMIN_MEDI	LANDAREA_MEDI	LIVINGAPARTMENTS_MEDI	LIVINGAREA_MEDI	\
count	98869.000000	124921.000000	97312.000000	153161.000000	
mean	0.231625	0.067169	0.101954	0.108607	
std	0.161934	0.082167	0.093642	0.112260	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.083300	0.018700	0.051300	0.045700	
50%	0.208300	0.048700	0.076100	0.074900	
75%	0.375000	0.086800	0.123100	0.130300	
max	1.000000	1.000000	1.000000	1.000000	

	NONLIVINGAPARTMENTS_MEDI	NONLIVINGAREA_MEDI	TOTALAREA_MODE	\
count	93997.000000	137829.000000	159080.000000	
mean	0.008651	0.028236	0.102547	
std	0.047415	0.070166	0.107462	
min	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.041200	
50%	0.000000	0.003100	0.068800	
75%	0.003900	0.026600	0.127600	
max	1.000000	1.000000	1.000000	

	OBS_30_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	\
count	306490.000000	306490.000000	
mean	1.422245	0.143421	

std	2.400989	0.446698
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	2.000000	0.000000
max	348.000000	34.000000

	OBS_60_CNT_SOCIAL_CIRCLE	DEF_60_CNT_SOCIAL_CIRCLE \
count	306490.000000	306490.000000
mean	1.405292	0.100049
std	2.379803	0.362291
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	2.000000	0.000000
max	344.000000	24.000000

	DAYS_LAST_PHONE_CHANGE	FLAG_DOCUMENT_2	FLAG_DOCUMENT_3 \
count	307510.000000	307511.000000	307511.000000
mean	-962.858788	0.000042	0.710023
std	826.808487	0.006502	0.453752
min	-4292.000000	0.000000	0.000000
25%	-1570.000000	0.000000	0.000000
50%	-757.000000	0.000000	1.000000
75%	-274.000000	0.000000	1.000000
max	0.000000	1.000000	1.000000

	FLAG_DOCUMENT_4	FLAG_DOCUMENT_5	FLAG_DOCUMENT_6	FLAG_DOCUMENT_7 \
count	307511.000000	307511.000000	307511.000000	307511.000000
mean	0.000081	0.015115	0.088055	0.000192
std	0.009016	0.122010	0.283376	0.013850
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000

	FLAG_DOCUMENT_8	FLAG_DOCUMENT_9	FLAG_DOCUMENT_10	FLAG_DOCUMENT_11 \
count	307511.000000	307511.000000	307511.000000	307511.000000
mean	0.081376	0.003896	0.000023	0.003912
std	0.273412	0.062295	0.004771	0.062424
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000

	FLAG_DOCUMENT_12	FLAG_DOCUMENT_13	FLAG_DOCUMENT_14	FLAG_DOCUMENT_15 \
count	307511.000000	307511.000000	307511.000000	307511.00000
mean	0.000007	0.003525	0.002936	0.00121
std	0.002550	0.059268	0.054110	0.03476
min	0.000000	0.000000	0.000000	0.00000
25%	0.000000	0.000000	0.000000	0.00000
50%	0.000000	0.000000	0.000000	0.00000
75%	0.000000	0.000000	0.000000	0.00000
max	1.000000	1.000000	1.000000	1.00000

	FLAG_DOCUMENT_16	FLAG_DOCUMENT_17	FLAG_DOCUMENT_18	FLAG_DOCUMENT_19 \
count	307511.000000	307511.000000	307511.000000	307511.000000
mean	0.009928	0.000267	0.008130	0.000595
std	0.099144	0.016327	0.089798	0.024387
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000

	FLAG_DOCUMENT_20	FLAG_DOCUMENT_21	AMT_REQ_CREDIT_BUREAU_HOUR \
count	307511.000000	307511.000000	265992.000000
mean	0.000507	0.000335	0.006402
std	0.022518	0.018299	0.083849
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000
max	1.000000	1.000000	4.000000

	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREAU_WEEK \
count	265992.000000	265992.000000
mean	0.007000	0.034362
std	0.110757	0.204685
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	9.000000	8.000000

	AMT_REQ_CREDIT_BUREAU_MON	AMT_REQ_CREDIT_BUREAU_QRT \
count	265992.000000	265992.000000
mean	0.267395	0.265474
std	0.916002	0.794056
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000

75%	0.000000	0.000000
max	27.000000	261.000000

	AMT_REQ_CREDIT_BUREAU_YEAR
count	265992.000000
mean	1.899974
std	1.869295
min	0.000000
25%	0.000000
50%	1.000000
75%	3.000000
max	25.000000

```
[7]: # have both variable categorical & numerical here. so , going separate the
      ↪ variable into 2.
```

```
[8]: categorical_columns = data.select_dtypes(include=['object'])
```

```
[9]: num_categorical_columns = categorical_columns.shape[1]
      num_categorical_columns
```

```
[9]: 16
```

```
[10]: categorical_variable_names = categorical_columns.columns.tolist()
```

```
[11]: categorical_variable_names
```

```
[11]: ['NAME_CONTRACT_TYPE',
      'CODE_GENDER',
      'FLAG_OWN_CAR',
      'FLAG_OWN_REALTY',
      'NAME_TYPE_SUITE',
      'NAME_INCOME_TYPE',
      'NAME_EDUCATION_TYPE',
      'NAME_FAMILY_STATUS',
      'NAME_HOUSING_TYPE',
      'OCCUPATION_TYPE',
      'WEEKDAY_APPR_PROCESS_START',
      'ORGANIZATION_TYPE',
      'FONDKAPREMONT_MODE',
      'HOUSETYPE_MODE',
      'WALLSMATERIAL_MODE',
      'EMERGENCYSTATE_MODE']
```

```
[12]: print("Number of categorical columns:", num_categorical_columns)
```

```
Number of categorical columns: 16
```

```
[13]: from sklearn import preprocessing
lb = preprocessing.LabelEncoder()
data['NAME_CONTRACT_TYPE'] = lb.fit_transform(data['NAME_CONTRACT_TYPE'])
data['CODE_GENDER'] = lb.fit_transform(data['CODE_GENDER'])
data['FLAG_OWN_REALTY'] = lb.fit_transform(data['FLAG_OWN_REALTY'])
data['FLAG_OWN_CAR'] = lb.fit_transform(data['FLAG_OWN_CAR'])
data['NAME_TYPE_SUITE'] = lb.fit_transform(data['NAME_TYPE_SUITE'])
data['NAME_INCOME_TYPE'] = lb.fit_transform(data['NAME_INCOME_TYPE'])
data['NAME_EDUCATION_TYPE'] = lb.fit_transform(data['NAME_EDUCATION_TYPE'])
data['NAME_FAMILY_STATUS'] = lb.fit_transform(data['NAME_FAMILY_STATUS'])
data['NAME_HOUSING_TYPE'] = lb.fit_transform(data['NAME_HOUSING_TYPE'])
data['OCCUPATION_TYPE'] = lb.fit_transform(data['OCCUPATION_TYPE'])
data['WEEKDAY_APPR_PROCESS_START'] = lb.
↳fit_transform(data['WEEKDAY_APPR_PROCESS_START'])
data['ORGANIZATION_TYPE'] = lb.fit_transform(data['ORGANIZATION_TYPE'])
data['FONDKAPREMONT_MODE'] = lb.fit_transform(data['FONDKAPREMONT_MODE'])
data['HOUSETYPE_MODE'] = lb.fit_transform(data['HOUSETYPE_MODE'])
data['WALLSMATERIAL_MODE'] = lb.fit_transform(data['WALLSMATERIAL_MODE'])
data['EMERGENCYSTATE_MODE'] = lb.fit_transform(data['EMERGENCYSTATE_MODE'])
```

```
[14]: pd.set_option('display.max_rows', None)
data.isnull().sum()
```

```
[14]: SK_ID_CURR          0
TARGET                  0
NAME_CONTRACT_TYPE      0
CODE_GENDER             0
FLAG_OWN_CAR            0
FLAG_OWN_REALTY         0
CNT_CHILDREN            0
AMT_INCOME_TOTAL        0
AMT_CREDIT              0
AMT_ANNUITY             12
AMT_GOODS_PRICE         278
NAME_TYPE_SUITE          0
NAME_INCOME_TYPE         0
NAME_EDUCATION_TYPE      0
NAME_FAMILY_STATUS       0
NAME_HOUSING_TYPE        0
REGION_POPULATION_RELATIVE 0
DAYS_BIRTH              0
DAYS_EMPLOYED           0
DAYS_REGISTRATION        0
DAYS_ID_PUBLISH          0
OWN_CAR_AGE             202929
FLAG_MOBIL              0
FLAG_EMP_PHONE           0
```

FLAG_WORK_PHONE	0
FLAG_CONT_MOBILE	0
FLAG_PHONE	0
FLAG_EMAIL	0
OCCUPATION_TYPE	0
CNT_FAM_MEMBERS	2
REGION_RATING_CLIENT	0
REGION_RATING_CLIENT_W_CITY	0
WEEKDAY_APPR_PROCESS_START	0
HOURLY_APPR_PROCESS_START	0
REG_REGION_NOT_LIVE_REGION	0
REG_REGION_NOT_WORK_REGION	0
LIVE_REGION_NOT_WORK_REGION	0
REG_CITY_NOT_LIVE_CITY	0
REG_CITY_NOT_WORK_CITY	0
LIVE_CITY_NOT_WORK_CITY	0
ORGANIZATION_TYPE	0
EXT_SOURCE_1	173378
EXT_SOURCE_2	660
EXT_SOURCE_3	60965
APARTMENTS_AVG	156061
BASEMENTAREA_AVG	179943
YEARS_BEGINEXPLUATATION_AVG	150007
YEARS_BUILD_AVG	204488
COMMONAREA_AVG	214865
ELEVATORS_AVG	163891
ENTRANCES_AVG	154828
FLOORSMAX_AVG	153020
FLOORSMIN_AVG	208642
LANDAREA_AVG	182590
LIVINGAPARTMENTS_AVG	210199
LIVINGAREA_AVG	154350
NONLIVINGAPARTMENTS_AVG	213514
NONLIVINGAREA_AVG	169682
APARTMENTS_MODE	156061
BASEMENTAREA_MODE	179943
YEARS_BEGINEXPLUATATION_MODE	150007
YEARS_BUILD_MODE	204488
COMMONAREA_MODE	214865
ELEVATORS_MODE	163891
ENTRANCES_MODE	154828
FLOORSMAX_MODE	153020
FLOORSMIN_MODE	208642
LANDAREA_MODE	182590
LIVINGAPARTMENTS_MODE	210199
LIVINGAREA_MODE	154350
NONLIVINGAPARTMENTS_MODE	213514

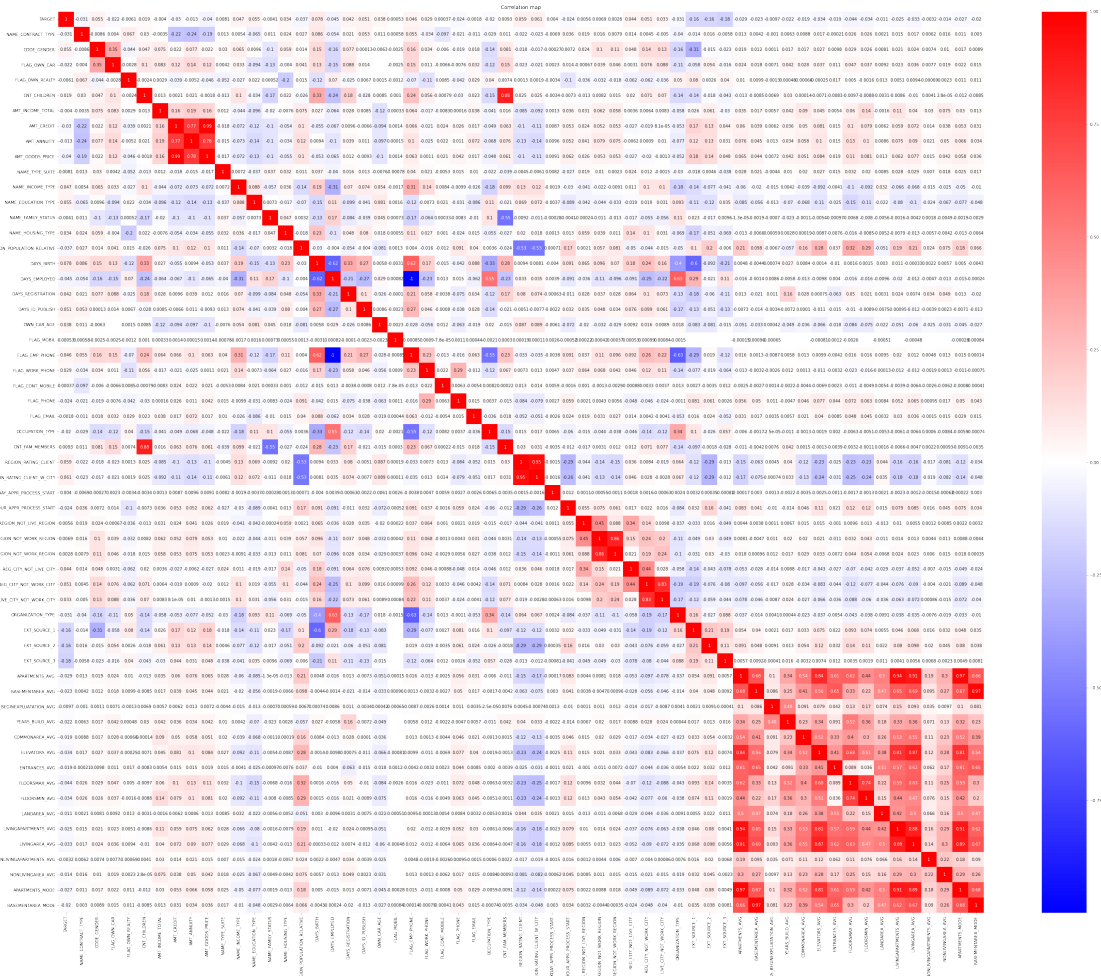
NONLIVINGAREA_MODE	169682
APARTMENTS_MEDI	156061
BASEMENTAREA_MEDI	179943
YEARS_BEGINEXPLUATATION_MEDI	150007
YEARS_BUILD_MEDI	204488
COMMONAREA_MEDI	214865
ELEVATORS_MEDI	163891
ENTRANCES_MEDI	154828
FLOORSMAX_MEDI	153020
FLOORSMIN_MEDI	208642
LANDAREA_MEDI	182590
LIVINGAPARTMENTS_MEDI	210199
LIVINGAREA_MEDI	154350
NONLIVINGAPARTMENTS_MEDI	213514
NONLIVINGAREA_MEDI	169682
FONDKAPREMONT_MODE	0
HOUSETYPE_MODE	0
TOTALAREA_MODE	148431
WALLSMATERIAL_MODE	0
EMERGENCYSTATE_MODE	0
OBS_30_CNT_SOCIAL_CIRCLE	1021
DEF_30_CNT_SOCIAL_CIRCLE	1021
OBS_60_CNT_SOCIAL_CIRCLE	1021
DEF_60_CNT_SOCIAL_CIRCLE	1021
DAYS_LAST_PHONE_CHANGE	1
FLAG_DOCUMENT_2	0
FLAG_DOCUMENT_3	0
FLAG_DOCUMENT_4	0
FLAG_DOCUMENT_5	0
FLAG_DOCUMENT_6	0
FLAG_DOCUMENT_7	0
FLAG_DOCUMENT_8	0
FLAG_DOCUMENT_9	0
FLAG_DOCUMENT_10	0
FLAG_DOCUMENT_11	0
FLAG_DOCUMENT_12	0
FLAG_DOCUMENT_13	0
FLAG_DOCUMENT_14	0
FLAG_DOCUMENT_15	0
FLAG_DOCUMENT_16	0
FLAG_DOCUMENT_17	0
FLAG_DOCUMENT_18	0
FLAG_DOCUMENT_19	0
FLAG_DOCUMENT_20	0
FLAG_DOCUMENT_21	0
AMT_REQ_CREDIT_BUREAU_HOUR	41519
AMT_REQ_CREDIT_BUREAU_DAY	41519

```
AMT_REQ_CREDIT_BUREAU_WEEK      41519
AMT_REQ_CREDIT_BUREAU_MON       41519
AMT_REQ_CREDIT_BUREAU_QRT       41519
AMT_REQ_CREDIT_BUREAU_YEAR      41519
dtype: int64
```

```
[15]: # plethora of missing values in it. after check the correlation... plan to drop
      ↳ the variables which have the least correlation with target...&
      #balance variable replace with 0 , mean, mode
```

```
[16]: # dataset contains 121 columns...so its difficult to check the correlation in a
      ↳ heatmap...going to split the into two part. each part
      # contains 60 columns
      data1=data.iloc[:,1:60]

      plt.figure(figsize=(50,40));
      sns.heatmap(data1.corr(),annot=True,cmap='bwr');
      plt.title("Correlation map")
      plt.savefig('h1.jpg')
      plt.show()
```



```
[17]: data2 = data.iloc[:, -60:]

data2['TARGET'] = data['TARGET']

# Reorder the columns to include the 'TARGET' column as the first column
columns_order = ['TARGET'] + data2.columns[:-1].tolist()

data2 = data2[columns_order]
data2.head()
```

```
[17]: TARGET COMMONAREA_MODE ELEVATORS_MODE ENTRANCES_MODE FLOORSMAX_MODE \
0 1 0.0144 0.0000 0.0690 0.0833
1 0 0.0497 0.0806 0.0345 0.2917
2 0 NaN NaN NaN NaN
3 0 NaN NaN NaN NaN
4 0 NaN NaN NaN NaN
```

	FLOORSMIN_MODE	LANDAREA_MODE	LIVINGAPARTMENTS_MODE	LIVINGAREA_MODE	\
0	0.1250	0.0377	0.022	0.0198	
1	0.3333	0.0128	0.079	0.0554	
2	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	

	NONLIVINGAPARTMENTS_MODE	NONLIVINGAREA_MODE	APARTMENTS_MEDI	\
0	0.0	0.0	0.0250	
1	0.0	0.0	0.0968	
2	NaN	NaN	NaN	
3	NaN	NaN	NaN	
4	NaN	NaN	NaN	

	BASEMENTAREA_MEDI	YEARS_BEGINEXPLUATATION_MEDI	YEARS_BUILD_MEDI	\
0	0.0369	0.9722	0.6243	
1	0.0529	0.9851	0.7987	
2	NaN	NaN	NaN	
3	NaN	NaN	NaN	
4	NaN	NaN	NaN	

	COMMONAREA_MEDI	ELEVATORS_MEDI	ENTRANCES_MEDI	FLOORSMAX_MEDI	\
0	0.0144	0.00	0.0690	0.0833	
1	0.0608	0.08	0.0345	0.2917	
2	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	

	FLOORSMIN_MEDI	LANDAREA_MEDI	LIVINGAPARTMENTS_MEDI	LIVINGAREA_MEDI	\
0	0.1250	0.0375	0.0205	0.0193	
1	0.3333	0.0132	0.0787	0.0558	
2	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	

	NONLIVINGAPARTMENTS_MEDI	NONLIVINGAREA_MEDI	FONDKAPREMONT_MODE	\
0	0.0000	0.00	2	
1	0.0039	0.01	2	
2	NaN	NaN	4	
3	NaN	NaN	4	
4	NaN	NaN	4	

	HOUSETYPE_MODE	TOTALAREA_MODE	WALLSMATERIAL_MODE	EMERGENCYSTATE_MODE	\
0	0	0.0149	5	0	
1	0	0.0714	0	0	
2	3	NaN	7	2	
3	3	NaN	7	2	

4	3	NaN	7	2
---	---	-----	---	---

	OBS_30_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	\
0	2.0	2.0	
1	1.0	0.0	
2	0.0	0.0	
3	2.0	0.0	
4	0.0	0.0	

	OBS_60_CNT_SOCIAL_CIRCLE	DEF_60_CNT_SOCIAL_CIRCLE	DAYS_LAST_PHONE_CHANGE	\
0	2.0	2.0	-1134.0	
1	1.0	0.0	-828.0	
2	0.0	0.0	-815.0	
3	2.0	0.0	-617.0	
4	0.0	0.0	-1106.0	

	FLAG_DOCUMENT_2	FLAG_DOCUMENT_3	FLAG_DOCUMENT_4	FLAG_DOCUMENT_5	\
0	0	1	0	0	
1	0	1	0	0	
2	0	0	0	0	
3	0	1	0	0	
4	0	0	0	0	

	FLAG_DOCUMENT_6	FLAG_DOCUMENT_7	FLAG_DOCUMENT_8	FLAG_DOCUMENT_9	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	1	0	

	FLAG_DOCUMENT_10	FLAG_DOCUMENT_11	FLAG_DOCUMENT_12	FLAG_DOCUMENT_13	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	FLAG_DOCUMENT_14	FLAG_DOCUMENT_15	FLAG_DOCUMENT_16	FLAG_DOCUMENT_17	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	FLAG_DOCUMENT_18	FLAG_DOCUMENT_19	FLAG_DOCUMENT_20	FLAG_DOCUMENT_21	\
0	0	0	0	0	
1	0	0	0	0	

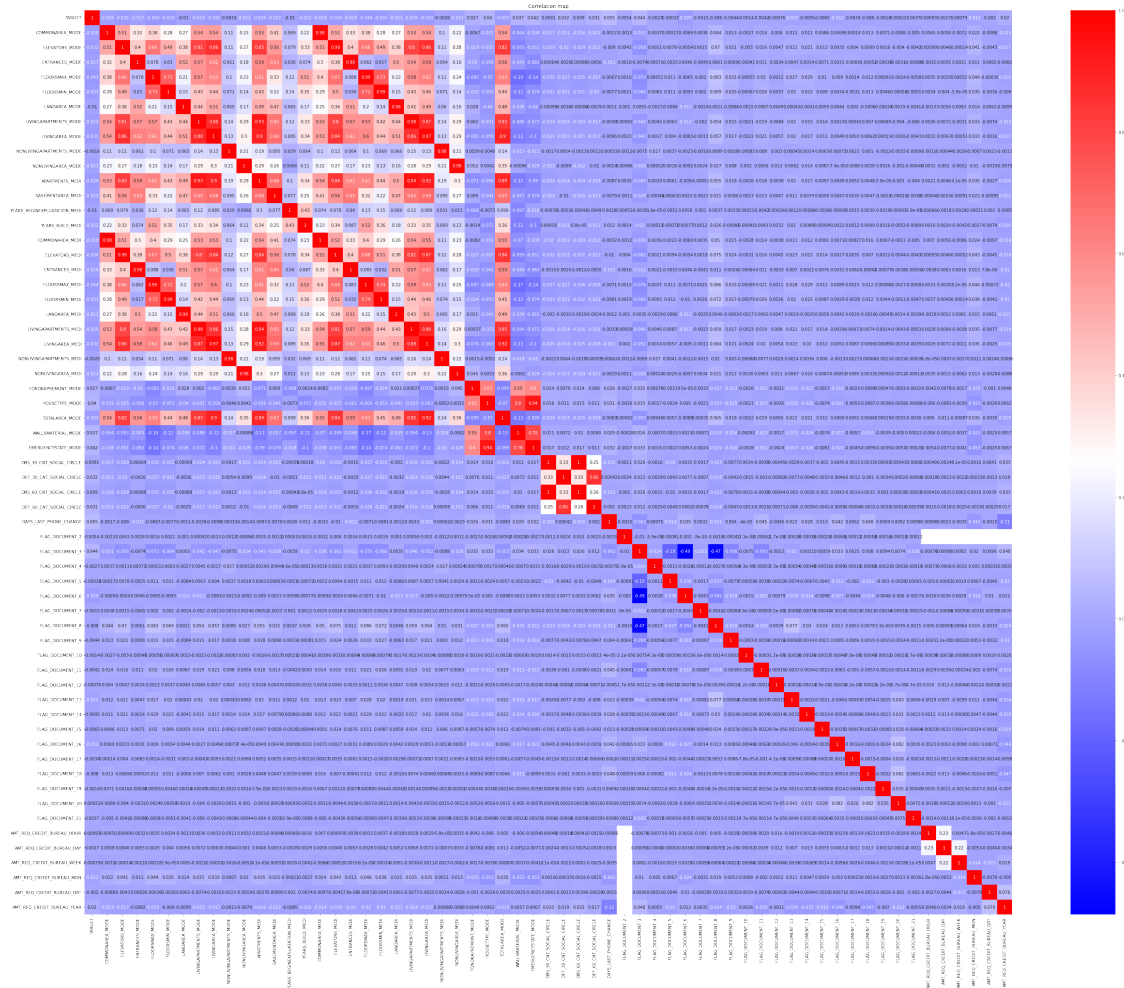
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	AMT_REQ_CREDIT_BUREAU_HOUR	AMT_REQ_CREDIT_BUREAU_DAY \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_WEEK	AMT_REQ_CREDIT_BUREAU_MON \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_QRT	AMT_REQ_CREDIT_BUREAU_YEAR
0	0.0	1.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0

```
[18]: plt.figure(figsize=(50, 40))
sns.heatmap(data2.corr(), annot=True, cmap='bwr')
plt.title("Correlation map")
plt.savefig('h1.jpg')
plt.show()
```



```
[18]: correlation = data.corr()['TARGET']
correlation_sorted = correlation.sort_values(ascending=True)
```

```
[19]: missing_values=data.isnull().sum()

result = pd.concat([correlation_sorted, missing_values], axis=1)
result.columns = ['Correlation', 'Missing Values']
result.head(123)
```

[19]:	Correlation	Missing Values
EXT_SOURCE_3	-0.178919	60965
EXT_SOURCE_2	-0.160472	660
EXT_SOURCE_1	-0.155317	173378
DAYS_EMPLOYED	-0.044932	0
FLOORSMAX_AVG	-0.044003	153020
FLOORSMAX_MEDI	-0.043768	153020

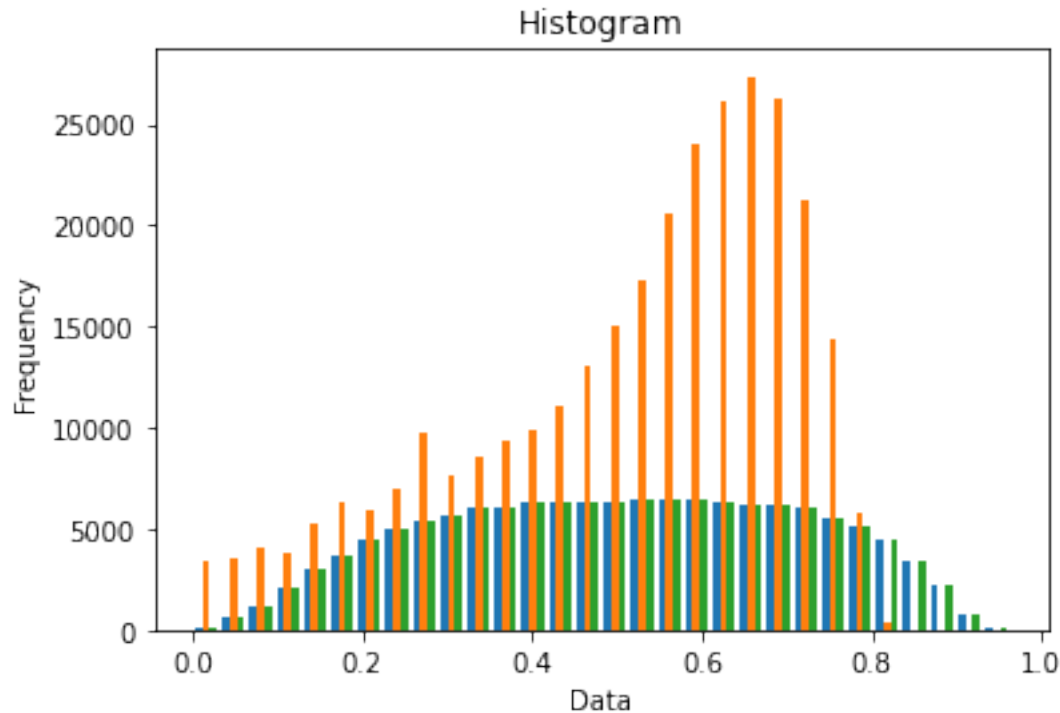
FLOORSMAX_MODE	-0.043226	153020
AMT_GOODS_PRICE	-0.039645	278
REGION_POPULATION_RELATIVE	-0.037227	0
ELEVATORS_AVG	-0.034199	163891
ELEVATORS_MEDI	-0.033863	163891
FLOORSMIN_AVG	-0.033614	208642
FLOORSMIN_MEDI	-0.033394	208642
LIVINGAREA_AVG	-0.032997	154350
LIVINGAREA_MEDI	-0.032739	154350
FLOORSMIN_MODE	-0.032698	208642
TOTALAREA_MODE	-0.032596	148431
ELEVATORS_MODE	-0.032131	163891
NAME_CONTRACT_TYPE	-0.030896	0
ORGANIZATION_TYPE	-0.030765	0
LIVINGAREA_MODE	-0.030685	154350
AMT_CREDIT	-0.030369	0
APARTMENTS_AVG	-0.029498	156061
APARTMENTS_MEDI	-0.029184	156061
FLAG_DOCUMENT_6	-0.028602	0
APARTMENTS_MODE	-0.027284	156061
LIVINGAPARTMENTS_AVG	-0.025031	210199
LIVINGAPARTMENTS_MEDI	-0.024621	210199
HOUR_APPR_PROCESS_START	-0.024166	0
FLAG_PHONE	-0.023806	0
LIVINGAPARTMENTS_MODE	-0.023393	210199
BASEMENTAREA_AVG	-0.022746	179943
YEARS_BUILD_MEDI	-0.022326	204488
YEARS_BUILD_AVG	-0.022149	204488
BASEMENTAREA_MEDI	-0.022081	179943
YEARS_BUILD_MODE	-0.022068	204488
FLAG_OWN_CAR	-0.021851	0
BASEMENTAREA_MODE	-0.019952	179943
OCCUPATION_TYPE	-0.019510	0
ENTRANCES_AVG	-0.019172	154828
ENTRANCES_MEDI	-0.019025	154828
COMMONAREA_MEDI	-0.018573	214865
COMMONAREA_AVG	-0.018550	214865
ENTRANCES_MODE	-0.017387	154828
COMMONAREA_MODE	-0.016340	214865
NONLIVINGAREA_AVG	-0.013578	169682
NONLIVINGAREA_MEDI	-0.013337	169682
AMT_ANNUITY	-0.012817	12
NONLIVINGAREA_MODE	-0.012711	169682
AMT_REQ_CREDIT_BUREAU_MON	-0.012462	41519
FLAG_DOCUMENT_16	-0.011615	0
FLAG_DOCUMENT_13	-0.011583	0
LANDAREA_MEDI	-0.011256	182590

LANDAREA_AVG	-0.010885	182590
LANDAREA_MODE	-0.010174	182590
YEARS_BEGINEXPLUATATION_MEDI	-0.009993	150007
YEARS_BEGINEXPLUATATION_AVG	-0.009728	150007
FLAG_DOCUMENT_14	-0.009464	0
YEARS_BEGINEXPLUATATION_MODE	-0.009036	150007
FLAG_DOCUMENT_8	-0.008040	0
FLAG_DOCUMENT_18	-0.007952	0
FLAG_DOCUMENT_15	-0.006536	0
FLAG_OWN_REALTY	-0.006148	0
FLAG_DOCUMENT_9	-0.004352	0
FLAG_DOCUMENT_11	-0.004229	0
NAME_FAMILY_STATUS	-0.004127	0
AMT_INCOME_TOTAL	-0.003982	0
FLAG_DOCUMENT_17	-0.003378	0
NONLIVINGAPARTMENTS_AVG	-0.003176	213514
NONLIVINGAPARTMENTS_MEDI	-0.002757	213514
FLAG_DOCUMENT_4	-0.002672	0
SK_ID_CURR	-0.002108	0
AMT_REQ_CREDIT_BUREAU_QRT	-0.002022	41519
FLAG_EMAIL	-0.001758	0
NONLIVINGAPARTMENTS_MODE	-0.001557	213514
FLAG_DOCUMENT_7	-0.001520	0
FLAG_DOCUMENT_10	-0.001414	0
FLAG_DOCUMENT_19	-0.001358	0
FLAG_DOCUMENT_12	-0.000756	0
FLAG_DOCUMENT_5	-0.000316	0
FLAG_DOCUMENT_20	0.000215	0
FLAG_CONT_MOBILE	0.000370	0
FLAG_MOBIL	0.000534	0
AMT_REQ_CREDIT_BUREAU_WEEK	0.000788	41519
AMT_REQ_CREDIT_BUREAU_HOUR	0.000930	41519
AMT_REQ_CREDIT_BUREAU_DAY	0.002704	41519
LIVE_REGION_NOT_WORK_REGION	0.002819	0
FLAG_DOCUMENT_21	0.003709	0
WEEKDAY_APPR_PROCESS_START	0.004002	0
FLAG_DOCUMENT_2	0.005417	0
REG_REGION_NOT_LIVE_REGION	0.005576	0
REG_REGION_NOT_WORK_REGION	0.006942	0
NAME_TYPE_SUITE	0.008074	0
OBS_60_CNT_SOCIAL_CIRCLE	0.009022	1021
OBS_30_CNT_SOCIAL_CIRCLE	0.009131	1021
CNT_FAM_MEMBERS	0.009308	2
CNT_CHILDREN	0.019187	0
AMT_REQ_CREDIT_BUREAU_YEAR	0.019930	41519
FONDKAPREMONT_MODE	0.026924	0
FLAG_WORK_PHONE	0.028524	0

DEF_60_CNT_SOCIAL_CIRCLE	0.031276	1021
DEF_30_CNT_SOCIAL_CIRCLE	0.032248	1021
LIVE_CITY_NOT_WORK_CITY	0.032518	0
NAME_HOUSING_TYPE	0.034489	0
WALLSMATERIAL_MODE	0.037076	0
OWN_CAR_AGE	0.037612	202929
HOUSETYPE_MODE	0.040211	0
EMERGENCYSTATE_MODE	0.041955	0
DAYS_REGISTRATION	0.041975	0
FLAG_DOCUMENT_3	0.044346	0
REG_CITY_NOT_LIVE_CITY	0.044395	0
FLAG_EMP_PHONE	0.045982	0
NAME_INCOME_TYPE	0.046829	0
REG_CITY_NOT_WORK_CITY	0.050994	0
DAYS_ID_PUBLISH	0.051457	0
CODE_GENDER	0.054692	0
NAME_EDUCATION_TYPE	0.054699	0
DAYS_LAST_PHONE_CHANGE	0.055218	1
REGION_RATING_CLIENT	0.058899	0
REGION_RATING_CLIENT_W_CITY	0.060893	0
DAYS_BIRTH	0.078239	0
TARGET	1.000000	0

```
[20]: import matplotlib.pyplot as plt

# Plot a histogram
plt.hist(data[['EXT_SOURCE_1', 'EXT_SOURCE_2', 'EXT_SOURCE_1']], bins=30)
plt.xlabel('Data')
plt.ylabel('Frequency')
plt.title('Histogram')
plt.show()
```



```
[21]: #im not planning to drop the independent variable...will do feature feature
      ↪selection.
      # missing values replace with mode, mean, 0
      data['EXT_SOURCE_2'].fillna(0, inplace=True)
```

```
[21]: data['AMT_REQ_CREDIT_BUREAU_YEAR'].replace([np.nan],
      ↪data['AMT_REQ_CREDIT_BUREAU_YEAR'].mean(), inplace=True)
      data['EXT_SOURCE_1'].replace([np.nan], data['EXT_SOURCE_1'].mean(),
      ↪inplace=True)
      data['EXT_SOURCE_2'].replace([np.nan], data['EXT_SOURCE_2'].mean(),
      ↪inplace=True)
      data['EXT_SOURCE_3'].replace([np.nan], data['EXT_SOURCE_3'].mean(),
      ↪inplace=True)
      data['YEARS_BEGINEXPLUATATION_AVG'].replace([np.nan],
      ↪data['YEARS_BEGINEXPLUATATION_AVG'].mean(), inplace=True)
      data['YEARS_BUILD_AVG'].replace([np.nan], data['YEARS_BUILD_AVG'].mean(),
      ↪inplace=True)
      data['NAME_CONTRACT_TYPE'].replace([np.nan], data['NAME_CONTRACT_TYPE'].mean(),
      ↪inplace=True)
      data['COMMONAREA_MODE'].replace([np.nan], data['COMMONAREA_MODE'].mean(),
      ↪inplace=True)
      data['ELEVATORS_MODE'].replace([np.nan], data['ELEVATORS_MODE'].mean(),
      ↪inplace=True)
```

```
data['ENTRANCES_MODE'].replace([np.nan], data['ENTRANCES_MODE'].mean(),
    ↳inplace=True)
data['FLOORSMAX_MODE'].replace([np.nan], data['FLOORSMAX_MODE'].mean(),
    ↳inplace=True)
```

```
[22]: data['FLOORSMIN_MODE'].replace([np.nan], data['FLOORSMIN_MODE'].mean(),
    ↳inplace=True)
data['LANDAREA_MODE'].replace([np.nan], data['LANDAREA_MODE'].mean(),
    ↳inplace=True)
data['LIVINGAPARTMENTS_MODE'].replace([np.nan], data['LIVINGAPARTMENTS_MODE'].
    ↳mean(), inplace=True)
data['LIVINGAREA_MODE'].replace([np.nan], data['LIVINGAREA_MODE'].mean(),
    ↳inplace=True)
data['NONLIVINGAPARTMENTS_MODE'].replace([np.nan],
    ↳data['NONLIVINGAPARTMENTS_MODE'].mean(), inplace=True)
data['NONLIVINGAREA_MODE'].replace([np.nan], data['NONLIVINGAREA_MODE'].mean(),
    ↳inplace=True)
data['APARTMENTS_MEDI'].replace([np.nan], data['APARTMENTS_MEDI'].mean(),
    ↳inplace=True)
data['BASEMENTAREA_MEDI'].replace([np.nan], data['BASEMENTAREA_MEDI'].mean(),
    ↳inplace=True)
data['YEARS_BEGINEXPLUATATION_MEDI'].replace([np.nan],
    ↳data['YEARS_BEGINEXPLUATATION_MEDI'].mean(), inplace=True)
data['YEARS_BUILD_MEDI'].replace([np.nan], data['YEARS_BUILD_MEDI'].mean(),
    ↳inplace=True)
```

```
[23]: data['COMMONAREA_MEDI'].replace([np.nan], data['COMMONAREA_MEDI'].mean(),
    ↳inplace=True)
data['ELEVATORS_MEDI'].replace([np.nan], data['ELEVATORS_MEDI'].mean(),
    ↳inplace=True)
data['ENTRANCES_MEDI'].replace([np.nan], data['ENTRANCES_MEDI'].mean(),
    ↳inplace=True)
data['FLOORSMAX_MEDI'].replace([np.nan], data['FLOORSMAX_MEDI'].mean(),
    ↳inplace=True)
data['FLOORSMIN_MEDI'].replace([np.nan], data['FLOORSMIN_MEDI'].mean(),
    ↳inplace=True)
data['LANDAREA_MEDI'].replace([np.nan], data['LANDAREA_MEDI'].mean(),
    ↳inplace=True)
data['LIVINGAPARTMENTS_MEDI'].replace([np.nan], data['LIVINGAPARTMENTS_MEDI'].
    ↳mean(), inplace=True)
data['LIVINGAREA_MEDI'].replace([np.nan], data['LIVINGAREA_MEDI'].mean(),
    ↳inplace=True)
data['NONLIVINGAREA_MEDI'].replace([np.nan], data['NONLIVINGAREA_MEDI'].mean(),
    ↳inplace=True)
```

```

data['NONLIVINGAPARTMENTS_MEDI'].replace([np.nan],
↳data['NONLIVINGAPARTMENTS_MEDI'].mean(), inplace=True)
data['FONDKAPREMONT_MODE'].replace([np.nan], data['FONDKAPREMONT_MODE'].mean(),
↳inplace=True)
data['HOUSETYPE_MODE'].replace([np.nan], data['HOUSETYPE_MODE'].mean(),
↳inplace=True)
data['TOTALAREA_MODE'].replace([np.nan], data['TOTALAREA_MODE'].mean(),
↳inplace=True)
data['WALLSMATERIAL_MODE'].replace([np.nan], data['WALLSMATERIAL_MODE'].mean(),
↳inplace=True)
data['EMERGENCYSTATE_MODE'].replace([np.nan], data['EMERGENCYSTATE_MODE'].
↳mean(), inplace=True)
data['OWN_CAR_AGE'].replace([np.nan], data['OWN_CAR_AGE'].mean(), inplace=True)
data['APARTMENTS_AVG'].replace([np.nan], data['APARTMENTS_AVG'].mean(),
↳inplace=True)
data['BASEMENTAREA_AVG'].replace([np.nan], data['BASEMENTAREA_AVG'].mean(),
↳inplace=True)
data['COMMONAREA_MEDI'].replace([np.nan], data['COMMONAREA_MEDI'].mean(),
↳inplace=True)

```

```

[24]: data['COMMONAREA_AVG'].replace([np.nan], data['COMMONAREA_AVG'].mean(),
↳inplace=True)
data['ELEVATORS_AVG'].replace([np.nan], data['ELEVATORS_AVG'].mean(),
↳inplace=True)
data['ENTRANCES_AVG'].replace([np.nan], data['ENTRANCES_AVG'].mean(),
↳inplace=True)
data['FLOORSMAX_AVG'].replace([np.nan], data['FLOORSMAX_AVG'].mean(),
↳inplace=True)
data['FLOORSMIN_AVG'].replace([np.nan], data['FLOORSMIN_AVG'].mean(),
↳inplace=True)
data['LANDAREA_AVG'].replace([np.nan], data['LANDAREA_AVG'].mean(),
↳inplace=True)
data['LIVINGAPARTMENTS_AVG'].replace([np.nan], data['LIVINGAPARTMENTS_AVG'].
↳mean(), inplace=True)
data['LIVINGAREA_AVG'].replace([np.nan], data['LIVINGAREA_AVG'].mean(),
↳inplace=True)
data['NONLIVINGAPARTMENTS_AVG'].replace([np.nan],
↳data['NONLIVINGAPARTMENTS_AVG'].mean(), inplace=True)
data['NONLIVINGAREA_AVG'].replace([np.nan], data['NONLIVINGAREA_AVG'].mean(),
↳inplace=True)
data['BASEMENTAREA_MODE'].replace([np.nan], data['BASEMENTAREA_MODE'].mean(),
↳inplace=True)
data['YEARS_BEGINEXPLUATATION_MODE'].replace([np.nan],
↳data['YEARS_BEGINEXPLUATATION_MODE'].mean(), inplace=True)

```

```
data['YEARS_BUILD_MODE'].replace([np.nan], data['YEARS_BUILD_MODE'].mean(),
↳ inplace=True)
```

```
[25]: data['AMT_REQ_CREDIT_BUREAU_HOUR'].replace([np.nan],
↳ data['AMT_REQ_CREDIT_BUREAU_HOUR'].mean(), inplace=True)
data['AMT_REQ_CREDIT_BUREAU_DAY'].replace([np.nan],
↳ data['AMT_REQ_CREDIT_BUREAU_DAY'].mean(), inplace=True)
data['AMT_REQ_CREDIT_BUREAU_WEEK'].replace([np.nan],
↳ data['AMT_REQ_CREDIT_BUREAU_WEEK'].mean(), inplace=True)
data['AMT_REQ_CREDIT_BUREAU_MON'].replace([np.nan],
↳ data['AMT_REQ_CREDIT_BUREAU_MON'].mean(), inplace=True)
data['AMT_REQ_CREDIT_BUREAU_QRT'].replace([np.nan],
↳ data['AMT_REQ_CREDIT_BUREAU_QRT'].mean(), inplace=True)
data['APARTMENTS_MODE'].replace([np.nan], data['APARTMENTS_MODE'].mean(),
↳ inplace=True)
```

```
[27]: # splitting the data
```

```
[26]: X=data.iloc[:,2:]
X.head()
```

```
[26]:
```

	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	\
0	0	1	0	1	
1	0	0	0	0	
2	1	1	1	1	
3	0	0	0	1	
4	0	1	0	1	

	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	\
0	0	202500.0	406597.5	24700.5	351000.0	
1	0	270000.0	1293502.5	35698.5	1129500.0	
2	0	67500.0	135000.0	6750.0	135000.0	
3	0	135000.0	312682.5	29686.5	297000.0	
4	0	121500.0	513000.0	21865.5	513000.0	

	NAME_TYPE_SUITE	NAME_INCOME_TYPE	NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS	\
0	6	7	4	3	
1	1	4	1	1	
2	6	7	4	3	
3	6	7	4	0	
4	6	7	4	3	

	NAME_HOUSING_TYPE	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED	\
0	1	0.018801	-9461	-637	
1	1	0.003541	-16765	-1188	
2	1	0.010032	-19046	-225	

3	1	0.008019	-19005	-3039
4	1	0.028663	-19932	-3038

	DAYS_REGISTRATION	DAYS_ID_PUBLISH	OWN_CAR_AGE	FLAG_MOBIL	\
0	-3648.0	-2120	12.061091	1	
1	-1186.0	-291	12.061091	1	
2	-4260.0	-2531	26.000000	1	
3	-9833.0	-2437	12.061091	1	
4	-4311.0	-3458	12.061091	1	

	FLAG_EMP_PHONE	FLAG_WORK_PHONE	FLAG_CONT_MOBILE	FLAG_PHONE	FLAG_EMAIL	\
0	1	0	1	1	0	
1	1	0	1	1	0	
2	1	1	1	1	0	
3	1	0	1	0	0	
4	1	0	1	0	0	

	OCCUPATION_TYPE	CNT_FAM_MEMBERS	REGION_RATING_CLIENT	\
0	8	1.0	2	
1	3	2.0	1	
2	8	1.0	2	
3	8	2.0	2	
4	3	1.0	2	

	REGION_RATING_CLIENT_W_CITY	WEEKDAY_APPR_PROCESS_START	\
0	2	6	
1	1	1	
2	2	1	
3	2	6	
4	2	4	

	HOURL_APPR_PROCESS_START	REG_REGION_NOT_LIVE_REGION	\
0	10	0	
1	11	0	
2	9	0	
3	17	0	
4	11	0	

	REG_REGION_NOT_WORK_REGION	LIVE_REGION_NOT_WORK_REGION	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	

	REG_CITY_NOT_LIVE_CITY	REG_CITY_NOT_WORK_CITY	LIVE_CITY_NOT_WORK_CITY	\
0	0	0	0	

1	0	0	0
2	0	0	0
3	0	0	0
4	0	1	1

	ORGANIZATION_TYPE	EXT_SOURCE_1	EXT_SOURCE_2	EXT_SOURCE_3 \
0	5	0.083037	0.262949	0.139376
1	39	0.311267	0.622246	0.510853
2	11	0.502130	0.555912	0.729567
3	5	0.502130	0.650442	0.510853
4	37	0.502130	0.322738	0.510853

	APARTMENTS_AVG	BASEMENTAREA_AVG	YEARS_BEGINEXPLUATATION_AVG \
0	0.02470	0.036900	0.972200
1	0.09590	0.052900	0.985100
2	0.11744	0.088442	0.977735
3	0.11744	0.088442	0.977735
4	0.11744	0.088442	0.977735

	YEARS_BUILD_AVG	COMMONAREA_AVG	ELEVATORS_AVG	ENTRANCES_AVG \
0	0.619200	0.014300	0.000000	0.069000
1	0.796000	0.060500	0.080000	0.034500
2	0.752471	0.044621	0.078942	0.149725
3	0.752471	0.044621	0.078942	0.149725
4	0.752471	0.044621	0.078942	0.149725

	FLOORSMAX_AVG	FLOORSMIN_AVG	LANDAREA_AVG	LIVINGAPARTMENTS_AVG \
0	0.083300	0.125000	0.036900	0.020200
1	0.291700	0.333300	0.013000	0.077300
2	0.226282	0.231894	0.066333	0.100775
3	0.226282	0.231894	0.066333	0.100775
4	0.226282	0.231894	0.066333	0.100775

	LIVINGAREA_AVG	NONLIVINGAPARTMENTS_AVG	NONLIVINGAREA_AVG \
0	0.019000	0.000000	0.000000
1	0.054900	0.003900	0.009800
2	0.107399	0.008809	0.028358
3	0.107399	0.008809	0.028358
4	0.107399	0.008809	0.028358

	APARTMENTS_MODE	BASEMENTAREA_MODE	YEARS_BEGINEXPLUATATION_MODE \
0	0.025200	0.038300	0.972200
1	0.092400	0.053800	0.985100
2	0.114231	0.087543	0.977065
3	0.114231	0.087543	0.977065
4	0.114231	0.087543	0.977065

	YEARS_BUILD_MODE	COMMONAREA_MODE	ELEVATORS_MODE	ENTRANCES_MODE	\
0	0.634100	0.014400	0.00000	0.069000	
1	0.804000	0.049700	0.08060	0.034500	
2	0.759637	0.042553	0.07449	0.145193	
3	0.759637	0.042553	0.07449	0.145193	
4	0.759637	0.042553	0.07449	0.145193	

	FLOORSMAX_MODE	FLOORSMIN_MODE	LANDAREA_MODE	LIVINGAPARTMENTS_MODE	\
0	0.083300	0.125000	0.037700	0.022000	
1	0.291700	0.333300	0.012800	0.079000	
2	0.222315	0.228058	0.064958	0.105645	
3	0.222315	0.228058	0.064958	0.105645	
4	0.222315	0.228058	0.064958	0.105645	

	LIVINGAREA_MODE	NONLIVINGAPARTMENTS_MODE	NONLIVINGAREA_MODE	\
0	0.019800		0.000000	0.000000
1	0.055400		0.000000	0.000000
2	0.105975		0.008076	0.027022
3	0.105975		0.008076	0.027022
4	0.105975		0.008076	0.027022

	APARTMENTS_MEDI	BASEMENTAREA_MEDI	YEARS_BEGINEXPLUATATION_MEDI	\
0	0.02500	0.036900		0.972200
1	0.09680	0.052900		0.985100
2	0.11785	0.087955		0.977752
3	0.11785	0.087955		0.977752
4	0.11785	0.087955		0.977752

	YEARS_BUILD_MEDI	COMMONAREA_MEDI	ELEVATORS_MEDI	ENTRANCES_MEDI	\
0	0.624300	0.014400	0.000000	0.069000	
1	0.798700	0.060800	0.080000	0.034500	
2	0.755746	0.044595	0.078078	0.149213	
3	0.755746	0.044595	0.078078	0.149213	
4	0.755746	0.044595	0.078078	0.149213	

	FLOORSMAX_MEDI	FLOORSMIN_MEDI	LANDAREA_MEDI	LIVINGAPARTMENTS_MEDI	\
0	0.083300	0.125000	0.037500	0.020500	
1	0.291700	0.333300	0.013200	0.078700	
2	0.225897	0.231625	0.067169	0.101954	
3	0.225897	0.231625	0.067169	0.101954	
4	0.225897	0.231625	0.067169	0.101954	

	LIVINGAREA_MEDI	NONLIVINGAPARTMENTS_MEDI	NONLIVINGAREA_MEDI	\
0	0.019300		0.000000	0.000000
1	0.055800		0.003900	0.010000
2	0.108607		0.008651	0.028236
3	0.108607		0.008651	0.028236

4 0.108607 0.008651 0.028236

	FONDKAPREMONT_MODE	HOUSETYPE_MODE	TOTALAREA_MODE	WALLSMATERIAL_MODE \
0	2	0	0.014900	5
1	2	0	0.071400	0
2	4	3	0.102547	7
3	4	3	0.102547	7
4	4	3	0.102547	7

	EMERGENCYSTATE_MODE	OBS_30_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE \
0	0	2.0	2.0
1	0	1.0	0.0
2	2	0.0	0.0
3	2	2.0	0.0
4	2	0.0	0.0

	OBS_60_CNT_SOCIAL_CIRCLE	DEF_60_CNT_SOCIAL_CIRCLE	DAYS_LAST_PHONE_CHANGE \
0	2.0	2.0	-1134.0
1	1.0	0.0	-828.0
2	0.0	0.0	-815.0
3	2.0	0.0	-617.0
4	0.0	0.0	-1106.0

	FLAG_DOCUMENT_2	FLAG_DOCUMENT_3	FLAG_DOCUMENT_4	FLAG_DOCUMENT_5 \
0	0	1	0	0
1	0	1	0	0
2	0	0	0	0
3	0	1	0	0
4	0	0	0	0

	FLAG_DOCUMENT_6	FLAG_DOCUMENT_7	FLAG_DOCUMENT_8	FLAG_DOCUMENT_9 \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	1	0

	FLAG_DOCUMENT_10	FLAG_DOCUMENT_11	FLAG_DOCUMENT_12	FLAG_DOCUMENT_13 \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	FLAG_DOCUMENT_14	FLAG_DOCUMENT_15	FLAG_DOCUMENT_16	FLAG_DOCUMENT_17 \
0	0	0	0	0
1	0	0	0	0

2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	FLAG_DOCUMENT_18	FLAG_DOCUMENT_19	FLAG_DOCUMENT_20	FLAG_DOCUMENT_21 \
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	AMT_REQ_CREDIT_BUREAU_HOUR	AMT_REQ_CREDIT_BUREAU_DAY \
0	0.000000	0.000
1	0.000000	0.000
2	0.000000	0.000
3	0.006402	0.007
4	0.000000	0.000

	AMT_REQ_CREDIT_BUREAU_WEEK	AMT_REQ_CREDIT_BUREAU_MON \
0	0.000000	0.000000
1	0.000000	0.000000
2	0.000000	0.000000
3	0.034362	0.267395
4	0.000000	0.000000

	AMT_REQ_CREDIT_BUREAU_QRT	AMT_REQ_CREDIT_BUREAU_YEAR
0	0.000000	1.000000
1	0.000000	0.000000
2	0.000000	0.000000
3	0.265474	1.899974
4	0.000000	0.000000

```
[27]: y=data.TARGET
```

```
[28]: X.shape
```

```
[28]: (307511, 120)
```

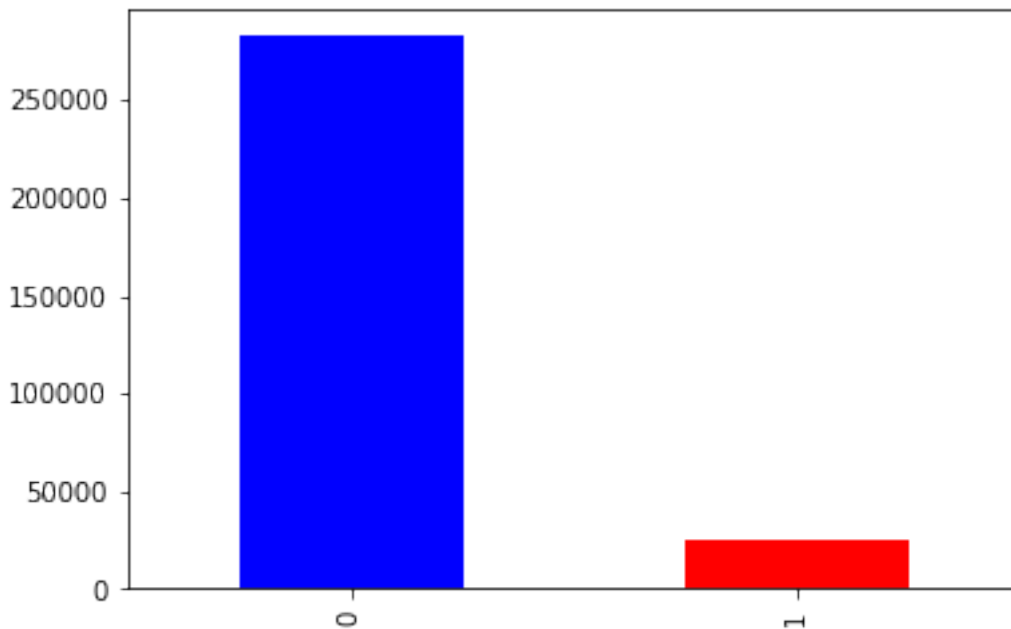
```
[29]: y.shape
```

```
[29]: (307511,)
```

```
[30]: y.value_counts()*100/data.shape[0]
```

```
[30]: 0    91.927118
      1     8.072882
      Name: TARGET, dtype: float64
```

```
[31]: y.value_counts().plot(kind='bar', color=["blue","red"])
plt.show()
```



```
[32]: # target is imbalance..
```

```
[37]: # inorder to overcome imbalance im using the SMOTE technique
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.
↪25,random_state=0)
st= StandardScaler()

X_train_std=st.fit_transform(X_train)
X_test_std= st.fit_transform(X_test)
```

```
[40]: from imblearn.over_sampling import SMOTE
from sklearn.impute import SimpleImputer
```

```
[41]: imputer = SimpleImputer(strategy='constant')
X = pd.DataFrame(imputer.fit_transform(X), columns=X.columns)

smk = SMOTE()
X_train_smote, y_train_smote = smk.fit_resample(X, y)
```

```
[42]: X_train, X_test, y_train, y_test = train_test_split(X_train_smote, y_train_smote, test_size=0.25, random_state=0)
```

```
[43]: scaler = StandardScaler()
X_train_std = scaler.fit_transform(X_train)
X_test_std = scaler.transform(X_test)
```

```
[44]: from tensorflow.keras.layers import Dense, BatchNormalization, Input
from tensorflow.keras.models import Sequential
from livelossplot import PlotLossesKerasTF
from tensorflow.keras.metrics import Precision, Recall
from tensorflow.keras.regularizers import l2
```

```
[45]: model = Sequential()
model.add(Input(shape=(120,)))

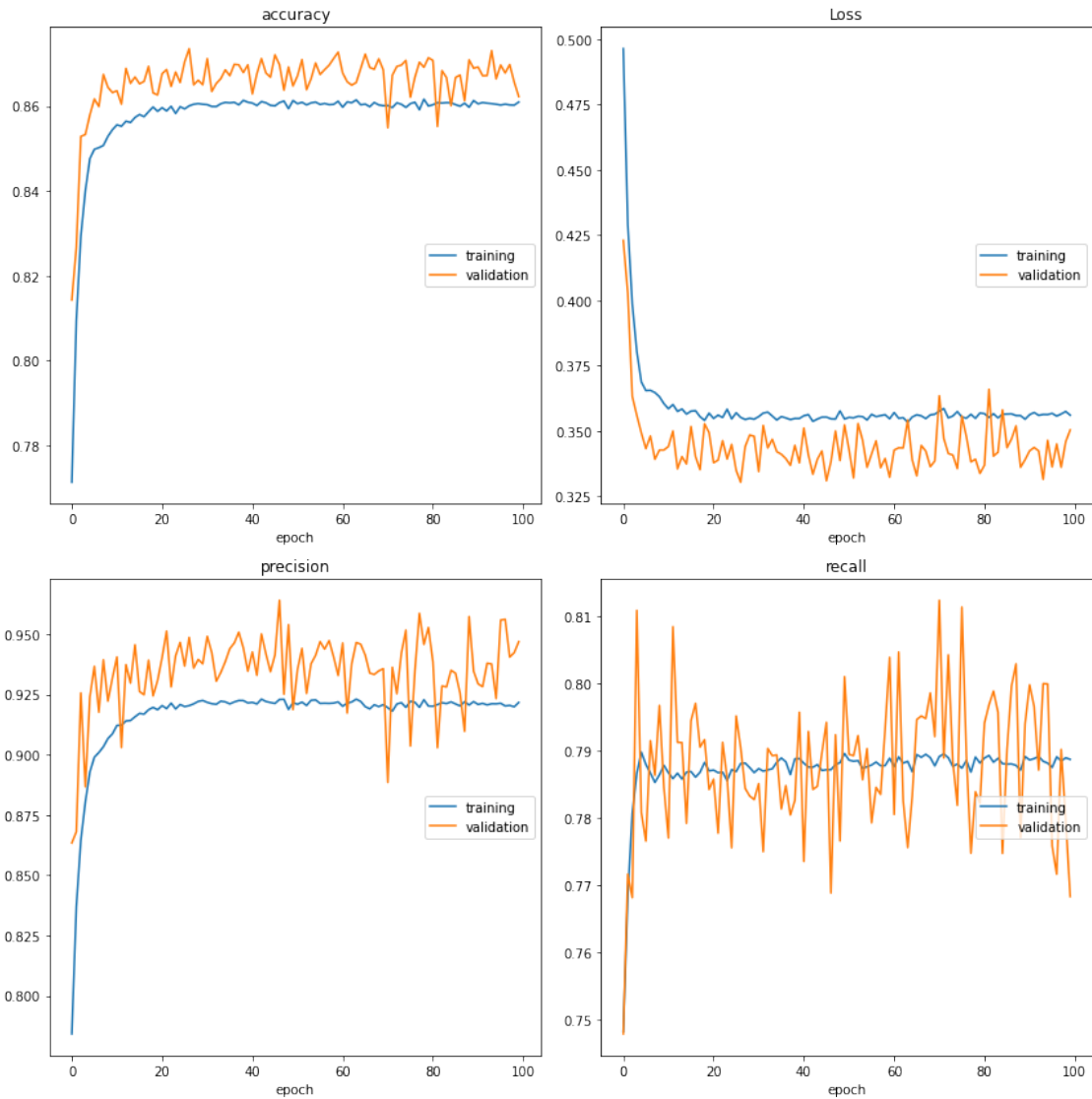
model.add(Dense(20, activation='relu', kernel_regularizer=l2(l2=0.001)))
model.add(Dense(20, activation='relu'))
model.add(BatchNormalization())

model.add(Dense(20, activation='relu', kernel_regularizer=l2(l2=0.001)))
model.add(BatchNormalization())

model.add(Dense(1, activation='sigmoid'))
```

```
[46]: model.compile(loss='binary_crossentropy', optimizer='adam',
                    metrics=['accuracy', Precision(), Recall()])
```

```
[47]: model.fit(X_train_std, y_train, epochs=100, batch_size=32, callbacks=[PlotLossesKerasTF()], validation_data=(X_test_std, y_test))
```



```

accuracy
    training      (min: 0.771, max: 0.862, cur: 0.861)
    validation    (min: 0.814, max: 0.874, cur: 0.862)
Loss
    training      (min: 0.353, max: 0.496, cur: 0.356)
    validation    (min: 0.330, max: 0.423, cur: 0.350)
precision
    training      (min: 0.784, max: 0.923, cur: 0.922)
    validation    (min: 0.863, max: 0.964, cur: 0.947)
recall
    training      (min: 0.748, max: 0.790, cur: 0.789)
    validation    (min: 0.748, max: 0.812, cur: 0.768)
13251/13251 [=====] - 98s 7ms/step - loss: 0.3560 -

```

```
accuracy: 0.8610 - precision: 0.9217 - recall: 0.7887 - val_loss: 0.3504 -  
val_accuracy: 0.8623 - val_precision: 0.9469 - val_recall: 0.7683
```

```
[47]: <keras.callbacks.History at 0x7f71cd2a9210>
```

The deep learning model for loan default prediction has demonstrated strong performance based on the training and validation results. Throughout the training process, the model achieved accuracy ranging from 77.1% to 86.2%, while validation accuracy ranged from 81.4% to 87.4%. This indicates that the model generalizes well to unseen data, reducing the risk of overfitting. The model's precision during training ranged from 78.4% to 92.3% and during validation from 86.3% to 96.4%, demonstrating its ability to make accurate positive predictions. Additionally, the recall ranged from 74.8% to 79.0% during training and from 74.8% to 81.2% during validation, indicating the model's capacity to correctly identify positive cases.

In the final evaluation on the validation set, the deep learning model achieved an accuracy of 86.23%, precision of 94.69%, and recall of 76.83%. These metrics highlight the model's effectiveness in predicting loan default risk, making it a valuable tool for financial institutions in decision-making and risk management processes.

```
[ ]:
```