# Case Study: Statistical Test ¶

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## In [ ]:

```
import pandas as pd
import numpy as np
```

### In [3]:

```
application_record = pd.read_csv('application_record.csv')
credit_record = pd.read_csv('credit_record.csv')
```

#### In [4]:

application\_record

#### Out[4]:

0         5008804         M         Y         Y         Q         427500.0         Working           1         5008805         M         Y         Y         Q         427500.0         Working           2         5008806         M         Y         Y         Q         112500.0         Working           3         5008808         F         N         Y         Q         270000.0         Commercial associate           4         5008809         F         N         Y         Q         270000.0         Commercial associate                     438552         6840104         M         N         Y         Q         135000.0         Pensioner           438553         6840222         F         N         N         Q         103500.0         Working           438554         6841878         F         N         N         Q         72000.0         Pensioner           438556         6842865         F         N         Y         Q         121500.0         Working		ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE	NA
2       5008806       M       Y       Y       Q       112500.0       Working         3       5008808       F       N       Y       Q       270000.0       Commercial associate         4       5008809       F       N       Y       Q       270000.0       Commercial associate                   438552       6840104       M       N       Y       Q       135000.0       Pensioner         438553       6840222       F       N       N       Q       54000.0       Commercial associate         438554       6841878       F       N       N       Q       54000.0       Pensioner         438555       6842765       F       N       Y       Q       121500.0       Working	0	5008804	М	Y	Υ	0	427500.0	Working	
3         5008808         F         N         Y         0         270000.0         Commercial associate           4         5008809         F         N         Y         0         270000.0         Commercial associate                     438552         6840104         M         N         Y         0         135000.0         Pensioner           438553         6840222         F         N         N         0         54000.0         Commercial associate           438554         6841878         F         N         N         0         54000.0         Commercial associate           438555         6842765         F         N         Y         0         72000.0         Pensioner           438556         6842885         F         N         Y         0         121500.0         Working	1	5008805	М	Υ	Υ	0	427500.0	Working	
4       5008809       F       N       Y       0       270000.0       Commercial associate                     438552       6840104       M       N       Y       0       135000.0       Pensioner         438553       6840222       F       N       N       0       103500.0       Commercial associate         438554       6841878       F       N       N       0       54000.0       Commercial associate         438555       6842765       F       N       Y       0       72000.0       Pensioner         438556       6842885       F       N       Y       0       121500.0       Working	2	5008806	М	Y	Y	0	112500.0	Working	
<td>3</td> <td>5008808</td> <td>F</td> <td>N</td> <td>Υ</td> <td>0</td> <td>270000.0</td> <td>Commercial associate</td> <td></td>	3	5008808	F	N	Υ	0	270000.0	Commercial associate	
438552       6840104       M       N       Y       0       135000.0       Pensioner         438553       6840222       F       N       N       0       103500.0       Working         438554       6841878       F       N       N       0       54000.0       Commercial associate         438555       6842765       F       N       Y       0       72000.0       Pensioner         438556       6842885       F       N       Y       0       121500.0       Working	4	5008809	F	N	Υ	0	270000.0	Commercial associate	
438553       6840222       F       N       N       0       103500.0       Working         438554       6841878       F       N       N       0       54000.0       Commercial associate         438555       6842765       F       N       Y       0       72000.0       Pensioner         438556       6842885       F       N       Y       0       121500.0       Working									
438554         6841878         F         N         N         0         54000.0         Commercial associate           438555         6842765         F         N         Y         0         72000.0         Pensioner           438556         6842885         F         N         Y         0         121500.0         Working	438552	6840104	М	N	Y	0	135000.0	Pensioner	
438555         6842765         F         N         Y         0         72000.0         Pensioner           438556         6842885         F         N         Y         0         121500.0         Working	438553	6840222	F	N	N	0	103500.0	Working	
438556 6842885 F N Y 0 121500.0 Working	438554	6841878	F	N	N	0	54000.0	Commercial associate	
· · · · · · · · · · · · · · · · · · ·	438555	6842765	F	N	Y	0	72000.0	Pensioner	
	438556	6842885	F	N	Υ	0	121500.0	Working	
438557 rows × 18 columns	438557 rows × 18 columns								

```
In [5]:
```

credit\_record

#### Out[5]:

	ID	MONTHS_BALANCE	STATUS
0	5001711	0	X
1	5001711	-1	0
2	5001711	-2	0
3	5001711	-3	0
4	5001712	0	С
		***	
1048570	5150487	-25	С
1048571	5150487	-26	С
1048572	5150487	-27	С
1048573	5150487	-28	С
1048574	5150487	-29	С

1048575 rows × 3 columns

## In [6]:

```
# Replace X,C values with 0 as they are identified as Good clients
credit_record.replace(['X','C'], 0,inplace=True)
```

#### In [7]:

```
credit_record.STATUS = pd.to_numeric(credit_record.STATUS)
```

#### In [8]:

```
# Searching for customers who have at least one late month
drop_ls = []
for i in range(len(credit_record)):
    if credit_record.STATUS[i] != 0:
        drop_ls.append(credit_record.ID[i])
```

### In [9]:

```
len(drop_ls)
```

### Out[9]:

14194

#### In [10]:

```
# Changing the STATUS of any client with at least one late month to 1
for i in range(len(credit_record)):
    if credit_record.ID[i] in drop_ls:
        credit_record.STATUS[i] = 1
```

#### In [11]:

```
credit_record.STATUS.value_counts()
```

#### Out[11]:

```
904764143811
```

Name: STATUS, dtype: int64

```
In [12]:
```

```
credit_record.drop_duplicates(inplace=True)
credit_record
```

#### Out[12]:

	ID	MONTHS_BALANCE	STATUS
0	5001711	0	0
1	5001711	-1	0
2	5001711	-2	0
3	5001711	-3	0
4	5001712	0	0
1048570	5150487	-25	0
1048571	5150487	-26	0
1048572	5150487	-27	0
1048573	5150487	-28	0
1048574	5150487	-29	0

1048575 rows × 3 columns

#### In [13]:

```
print(f'No. of IDs in application_record = {len(application_record.ID)} No. of IDs in credit_record = {len(credit_record.ID)}'
```

No. of IDs in application\_record = 438557 No. of IDs in credit\_record = 1048575

#### In [14]:

```
dataset = application_record.merge(credit_record, on=['ID'], how='inner')
# on to choose which column to merger on
# How to get merge only the intersection between them
```

### In [15]:

```
dataset.drop(['ID'],inplace=True,axis=1)
```

### In [16]:

```
dataset.duplicated().sum()
```

### Out[16]:

412393

### In [17]:

```
dataset.drop_duplicates(inplace=True)
```

## In [18]:

dataset

## Out[18]:

	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE	NAME_EDUC
0	М	Y	Υ	0	427500.0	Working	Hig
1	M	Υ	Υ	0	427500.0	Working	Hig
2	М	Υ	Υ	0	427500.0	Working	Hig
3	M	Υ	Υ	0	427500.0	Working	Hig
4	M	Υ	Υ	0	427500.0	Working	Hig
	***			***			
777710	М	N	Y	0	112500.0	Working	Seconda
777711	М	N	Υ	0	112500.0	Working	Seconda
777712	М	N	Υ	0	112500.0	Working	Seconda
777713	М	N	Υ	0	112500.0	Working	Seconda
777714	М	N	Υ	0	112500.0	Working	Seconda
365322 1	rows × 19 colum	าร					
4							<b>+</b>

## In [19]:

dataset.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 365322 entries, 0 to 777714
Data columns (total 19 columns):

	COZU ( COCUZ Z CO.						
#	Column	Non-Null Count	Dtype				
0	CODE_GENDER	365322 non-null	object				
1	FLAG_OWN_CAR	365322 non-null	object				
2	FLAG_OWN_REALTY	365322 non-null	object				
3	CNT_CHILDREN	365322 non-null	int64				
4	AMT_INCOME_TOTAL	365322 non-null	float64				
5	NAME_INCOME_TYPE	365322 non-null	object				
6	NAME_EDUCATION_TYPE	365322 non-null	object				
7	NAME_FAMILY_STATUS	365322 non-null	object				
8	NAME_HOUSING_TYPE	365322 non-null	object				
9	DAYS_BIRTH	365322 non-null	int64				
10	DAYS_EMPLOYED	365322 non-null	int64				
11	FLAG_MOBIL	365322 non-null	int64				
12	FLAG_WORK_PHONE	365322 non-null	int64				
13	FLAG_PHONE	365322 non-null	int64				
14	FLAG_EMAIL	365322 non-null	int64				
15	OCCUPATION_TYPE	252192 non-null	object				
16	CNT_FAM_MEMBERS	365322 non-null	float64				
17	MONTHS_BALANCE	365322 non-null	int64				
18	STATUS	365322 non-null	int64				
dtypos: $float64(2) int64(0) object(9)$							

dtypes: float64(2), int64(9), object(8)
memory usage: 55.7+ MB

```
In [20]:
```

```
dataset.describe()
```

### Out[20]:

	CNT_CHILDREN	AMT_INCOME_TOTAL	DAYS_BIRTH	DAYS_EMPLOYED	FLAG_MOBIL	FLAG_WORK_PHONE	FLAG_PHONE	FLAG
count	365322.000000	3.653220e+05	365322.000000	365322.000000	365322.0	365322.000000	365322.000000	365322
mean	0.425742	1.848982e+05	-16161.482656	60776.306365	1.0	0.221878	0.294214	0
std	0.768540	1.017316e+05	4144.182785	139028.719425	0.0	0.415510	0.455689	0
min	0.000000	2.700000e+04	-25152.000000	-15713.000000	1.0	0.000000	0.000000	0
25%	0.000000	1.170000e+05	-19614.000000	-3208.000000	1.0	0.000000	0.000000	0
50%	0.000000	1.575000e+05	-15849.000000	-1566.000000	1.0	0.000000	0.000000	0
75%	1.000000	2.250000e+05	-12676.000000	-378.000000	1.0	0.000000	1.000000	0
max	19.000000	1.575000e+06	-7489.000000	365243.000000	1.0	1.000000	1.000000	1
4								<b>•</b>

#### In [21]:

```
dataset.isna().sum()
```

#### Out[21]:

```
CODE_GENDER
                             0
FLAG_OWN_CAR
                             0
FLAG_OWN_REALTY
CNT_CHILDREN
AMT_INCOME_TOTAL
                             0
                             0
NAME_INCOME_TYPE
                             0
NAME_EDUCATION_TYPE
                             0
NAME_FAMILY_STATUS
                             0
NAME_HOUSING_TYPE
                             0
DAYS_BIRTH
                             0
DAYS_EMPLOYED
                             0
FLAG_MOBIL
                             0
FLAG_WORK_PHONE
                             0
FLAG_PHONE
                             0
FLAG_EMAIL
                             0
OCCUPATION_TYPE
                        113130
CNT_FAM_MEMBERS
                             0
MONTHS_BALANCE
                             0
STATUS
                             0
dtype: int64
```

### In [22]:

```
dataset.isna().sum().sum()
```

# Out[22]:

113130

## In [23]:

dataset.OCCUPATION\_TYPE

## Out[23]:

```
0
               NaN
1
               NaN
               NaN
2
3
               NaN
4
               NaN
777710
          Laborers
777711
          Laborers
777712
          Laborers
777713
          Laborers
777714
          Laborers
```

Name: OCCUPATION\_TYPE, Length: 365322, dtype: object

#### In [24]:

```
dataset.OCCUPATION_TYPE.value_counts()
```

#### Out[24]:

62839 Laborers Core staff 34175 Sales staff 33786 Managers 31066 Drivers 23349 High skill tech staff 14459 Medicine staff 11937 11926 Accountants  ${\tt Security \ staff}$ 6851 Cooking staff 6663 Cleaning staff 5201 Private service staff 2989 Low-skill Laborers 2000 Secretaries 1523 Waiters/barmen staff 1272 HR staff 973 IT staff 617 Realty agents 566 Name: OCCUPATION\_TYPE, dtype: int64

### In [25]:

```
dataset.OCCUPATION_TYPE.replace(np.nan, 'Other', inplace = True)
```

#### In [26]:

```
dataset.OCCUPATION_TYPE.value_counts()
```

#### Out[26]:

0ther 113130 Laborers 62839 Core staff 34175 Sales staff 33786 Managers 31066 Drivers 23349 High skill tech staff 14459 Medicine staff 11937 Accountants 11926 Security staff 6851 Cooking staff 6663 Cleaning staff 5201 Private service staff 2989 Low-skill Laborers 2000 Secretaries 1523 Waiters/barmen staff 1272 HR staff 973 IT staff 617 Realty agents 566 Name: OCCUPATION\_TYPE, dtype: int64

```
dataset
Out[28]:
         CODE_GENDER FLAG_OWN_CAR FLAG_OWN_REALTY CNT_CHILDREN AMT_INCOME_TOTAL NAME_INCOME_TYPE NAME_EDUC
     0
                    М
                                      Υ
                                                          Υ
                                                                         0
                                                                                        427500.0
                                                                                                             Working
                                                                                                                               Hig
                                                                                                                               Hig
                                      Υ
                                                          Υ
                                                                          0
                                                                                        427500.0
     1
                    M
                                                                                                             Working
                                      Υ
                                                                          0
                                                                                        427500.0
     2
                    M
                                                                                                             Working
                                                                                                                               Hig
     3
                                                                          0
                    M
                                                                                        427500.0
                                                                                                             Working
                                                                                                                               Hig
                                      Υ
                                                                          0
                                                                                        427500.0
                    M
                                                                                                             Working
                                                                                                                               Hig
                                                                                                                          Seconda
 777710
                    М
                                      Ν
                                                                          0
                                                                                        112500.0
                                                                                                             Working
                                                                                                                          Seconda
                                                                          0
 777711
                    М
                                      Ν
                                                                                        112500.0
                                                                                                             Working
                                                                                                                          Seconda
                                                                          0
                                                                                        112500.0
                                                                                                             Working
777712
                    М
                                      Ν
                                                                                                                          Seconda
777713
                                                                                        112500.0
                                                                                                              Working
                                                                                                                          Seconda
 777714
                    М
                                      Ν
                                                                          0
                                                                                        112500.0
                                                                                                             Working
365322 rows × 19 columns
In [ ]:
dataset.to_csv('credit.csv')
```

# **One Sample**

In [28]:

# **Test for Proportion**

```
In [89]:
sample = dataset.sample(frac=0.10)

In [91]:
sample.describe()
Out[91]:
```

CNT\_CHILDREN AMT\_INCOME\_TOTAL DAYS\_BIRTH DAYS\_EMPLOYED FLAG\_MOBIL FLAG\_WORK\_PHONE FLAG\_PHONE FLAG\_I count 36532.000000 3.653200e+04 36532.000000 36532.000000 36532.0 36532.000000 36532.000000 36532.0 mean 0.429131 1.844514e+05 -16186.627724 61935.026443 1.0 0.221422 0.294810 0.0 std 0.769898 1.019580e+05 4154.943376 140002.017208 0.0 0.415210 0.455964 0.2 min 0.000000 2.700000e+04 -25152.000000 -15713.000000 1.0 0.000000 0.000000 0.0 25% 0.000000 1.170000e+05 -19661.000000 -3174.000000 1.0 0.000000 0.000000 0.0 50% 0.000000 1.575000e+05 -15849.000000 -1555.000000 1.0 0.000000 0.000000 0.0 75% 1.000000 2.250000e+05 -12705.000000 -356.000000 1.0 0.000000 1.000000 0.0 max 19.000000 1.575000e+06 -7757.000000 365243.000000 1.0 1.000000 1.000000 1.0 4

In [93]:

sample.CODE\_GENDER.value\_counts()

Out[93]:

F 23937 M 12595

Name: CODE\_GENDER, dtype: int64

```
In [101]:
proportions_ztest(count=23937, nobs=36532, value=0.66)
Out[101]:
(-1.9166880588315112, 0.05527757319676388)
In [102]:
dataset['CODE_GENDER'].value_counts(normalize=True)
Out[102]:
     0.655737
    0.344263
Name: CODE_GENDER, dtype: float64
Test for mean
In [103]:
from statsmodels.stats.weightstats import ztest
In [124]:
ztest(x1=sample['AMT_INCOME_TOTAL'], value=190000)
Out[124]:
(-10.401568432043778, 2.4388536106918665e-25)
In [125]:
dataset['AMT_INCOME_TOTAL'].mean()
Out[125]:
184898.23890157178
Two Sample
In [156]:
sample1 = dataset.sample(frac=0.10)
sample2 = dataset.sample(frac=0.10)
```

In [157]:

sample1

Out[157]:

	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE	NAME_EDUC
183834	М	N	Υ	0	135000.0	Working	Seconda
98641	М	Y	N	1	157500.0	Commercial associate	Seconda
573812	М	Y	Υ	0	157500.0	Working	Seconda
577461	F	Υ	Υ	2	90000.0	Commercial associate	Seconda
383968	F	Υ	Υ	0	337500.0	Working	Seconda
	•••			***			
381732	F	N	Υ	0	90000.0	Working	Inco
34201	F	Υ	Υ	0	112500.0	Pensioner	Hig
515880	F	N	Υ	0	72000.0	Pensioner	Seconda
211624	М	N	Υ	0	112500.0	Commercial associate	Seconda
294057	М	N	N	3	58500.0	Working	Seconda
36532 rd	ows × 19 columns	3					
4							<b>&gt;</b>

In [158]:

sample2

Out[158]:

	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE	NAME_EDUCATIO
1281	М	Υ	Υ	2	450000.0	Working	Higher e
9724	М	N	N	0	135000.0	Commercial associate	Secondary / se
)776	М	Υ	N	1	450000.0	Working	Higher e
9221	F	N	Y	0	135000.0	Working	Secondary / se
3349	М	Y	Y	0	270000.0	Working	Secondary / se
1323	F	N	N	0	180000.0	Working	Higher e
3185	F	N	Υ	1	117000.0	Working	Secondary / se
5643	F	N	Y	3	67500.0	Commercial associate	Secondary / se
2972	М	N	Υ	2	207000.0	Commercial associate	Secondary / se
3662	М	Υ	Υ	0	540000.0	Working	Secondary / se

32 rows × 19 columns

In [159]:

sample1['CODE\_GENDER'].value\_counts()

Out[159]:

F 23976 M 12556 Name: CODE\_GENDER, dtype: int64

```
In [160]:
sample2['CODE_GENDER'].value_counts()
Out[160]:
     23955
    12577
Name: CODE_GENDER, dtype: int64
Difference of Two Proportions
In [161]:
count = np.array([23976,23955])
nobs = np.array([36532,36532])
proportions_ztest(count, nobs)
Out[161]:
(0.16354625601354528, 0.8700883563502826)
In [162]:
sample1['CODE_GENDER'].value_counts(normalize=True)
Out[162]:
    0.656301
    0.343699
Name: CODE_GENDER, dtype: float64
In [163]:
sample2['CODE_GENDER'].value_counts(normalize=True)
Out[163]:
    0.655726
    0.344274
Name: CODE_GENDER, dtype: float64
In [165]:
sample1['FLAG_OWN_CAR'].value_counts()
Out[165]:
    13815
Name: FLAG_OWN_CAR, dtype: int64
In [166]:
sample2['FLAG_OWN_CAR'].value_counts()
Out[166]:
     22526
     14006
Name: FLAG_OWN_CAR, dtype: int64
In [168]:
count = np.array([22717,22526])
nobs = np.array([36532,36532])
proportions_ztest(count, nobs, value=0.01)
Out[168]:
(-1.3281186463712324, 0.18413891442018981)
Difference of Two means
In [169]:
ztest(x1=sample1['AMT_INCOME_TOTAL'], x2=sample2['AMT_INCOME_TOTAL'], value=0)
Out[169]:
(-1.2696213576394317, 0.2042195378968562)
```

```
In [170]:

sample1['AMT_INCOME_TOTAL'].mean()

Out[170]:

184719.69859301436

In [171]:

sample2['AMT_INCOME_TOTAL'].mean()

Out[171]:

185672.07594711485

One Sample, Two Measures

Chisquare Test for independence

In [172]:

from statsmodels.stats.proportion import proportions_chisquare

In [176]:

np.array([23976,23955])
```

# **Regression Analysis**

```
In [180]:
from statsmodels.api import OLS

In [181]:
mod = OLS(dataset['DAYS_BIRTH'], dataset['AMT_INCOME_TOTAL'])

In [182]:
res = mod.fit()
```

```
In [183]:
```

print(res.summary())

```
OLS Regression Results
Dep. Variable: DAYS_BIRTH R-squared (uncentered):
                OLS Adj. R-squared (uncentered):
Least Squares F-statistic:
Model:
                                                             0.703
                                                        8.668e+05
Method:
              Tue, 07 Mar 2023 Prob (F-statistic):
                                                             0.00
Date:
                     18:02:42 Log-Likelihood:
365322 AIC:
                                                        -3.8481e+06
Time:
No. Observations:
                                                          7.696e+06
Df Residuals:
                      365321 BIC:
                                                          7.696e+06
Df Model:
                          1
                   nonrobust
Covariance Type:
------
                coef std err t P>|t| [0.025 0.975]
______
AMT_INCOME_TOTAL -0.0663 7.12e-05 -931.013 0.000 -0.066 -0.066
______

        Omnibus:
        132324.664
        Durbin-Watson:

        Prob(Omnibus):
        0.000
        Jarque-Bera (JB):

        Skew:
        1.457
        Prob(JB):

                                                     0.042
                                                  1329668.249
                      11.881 Cond. No.
Kurtosis:
                                                       1.00
______
```

#### Notes:

- [1]  $R^2$  is computed without centering (uncentered) since the model does not contain a constant.
- [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

### Difference of means

```
In [211]:
ztest(x1=sample1['CNT_FAM_MEMBERS'], x2=sample2['CNT_CHILDREN'], value=1.8)
Out[211]:
(-5.180909056271185, 2.208071348369464e-07)
```

In [ ]: