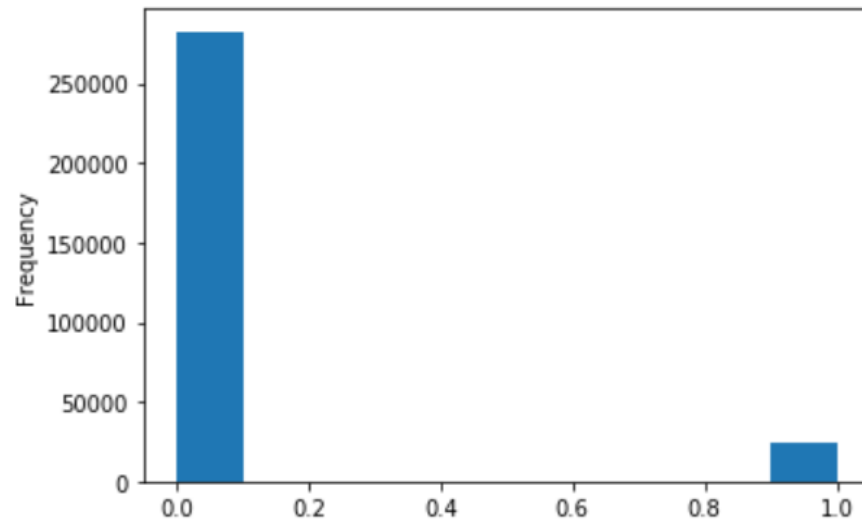


Distribution of Target :

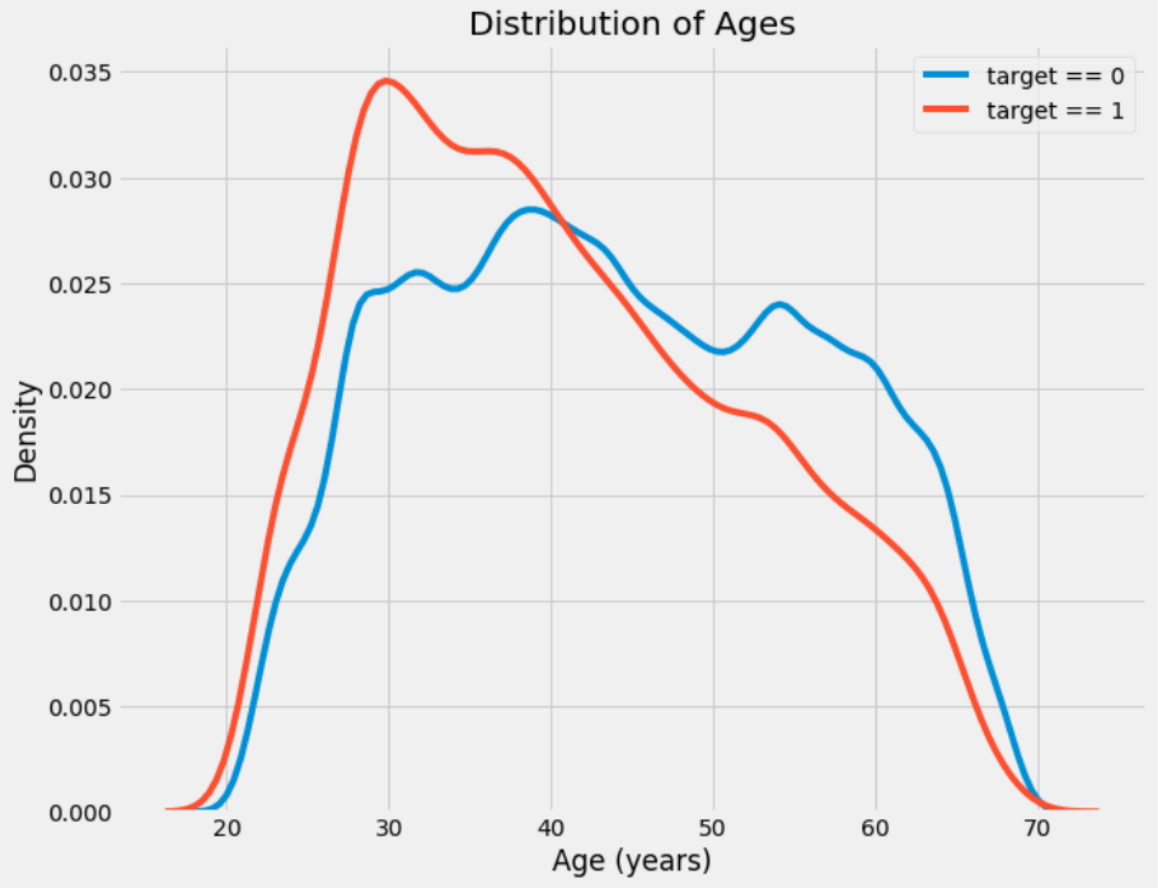
```
In [47]: df['TARGET'].plot.hist();
```

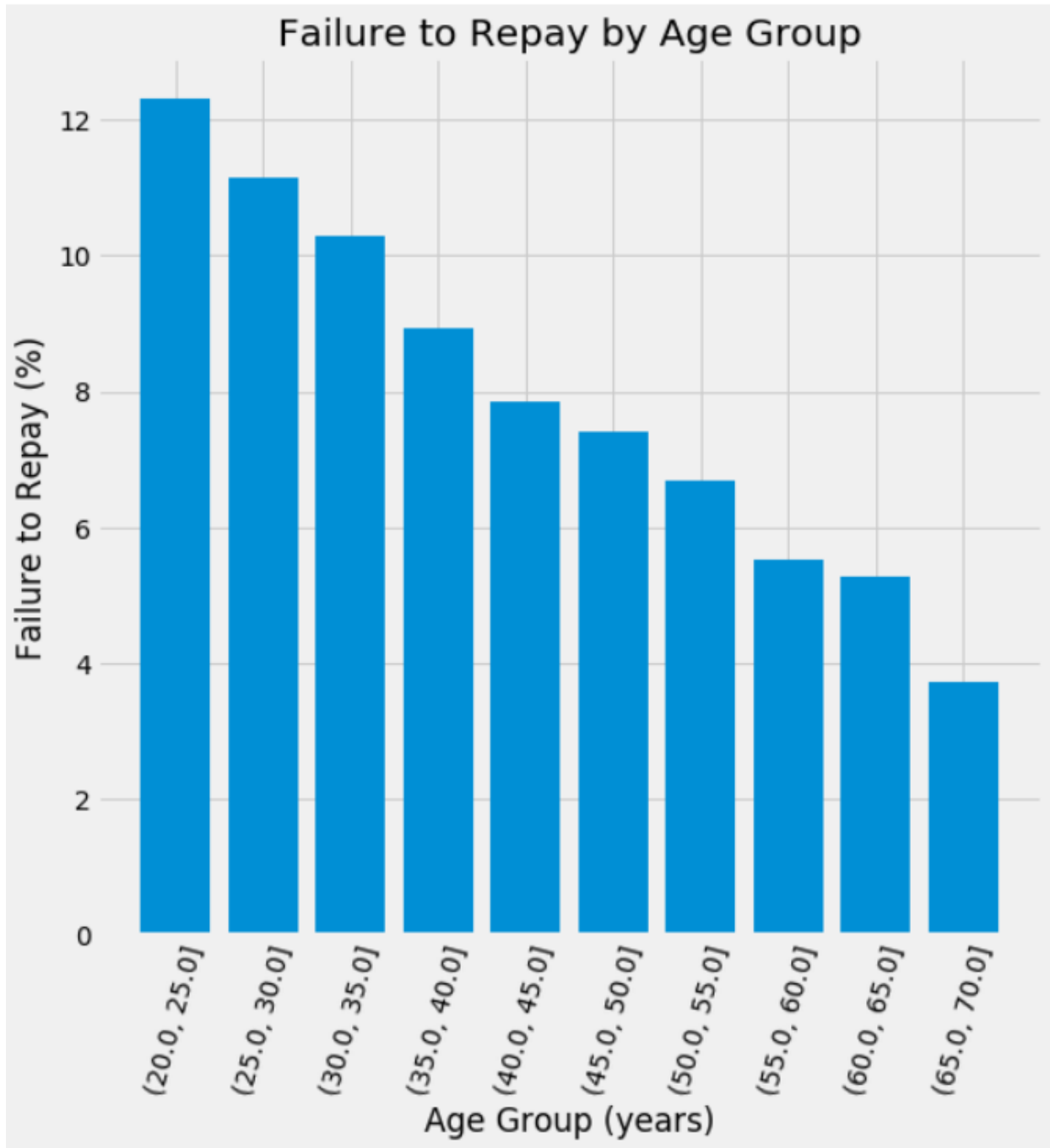


Effect on Age of Repayment:

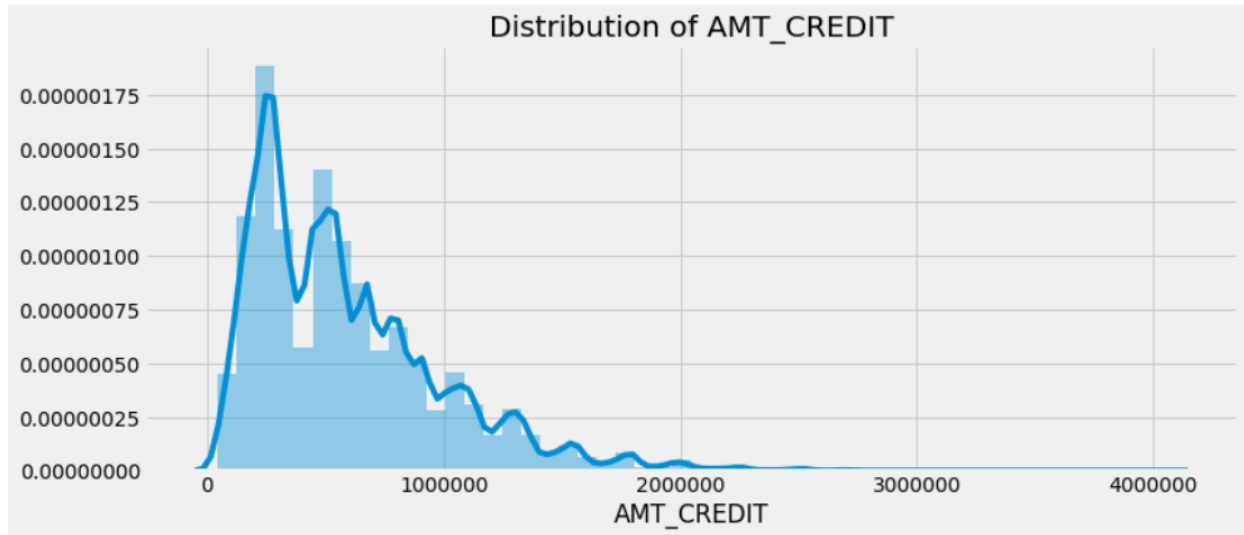


Distribution of Ages :

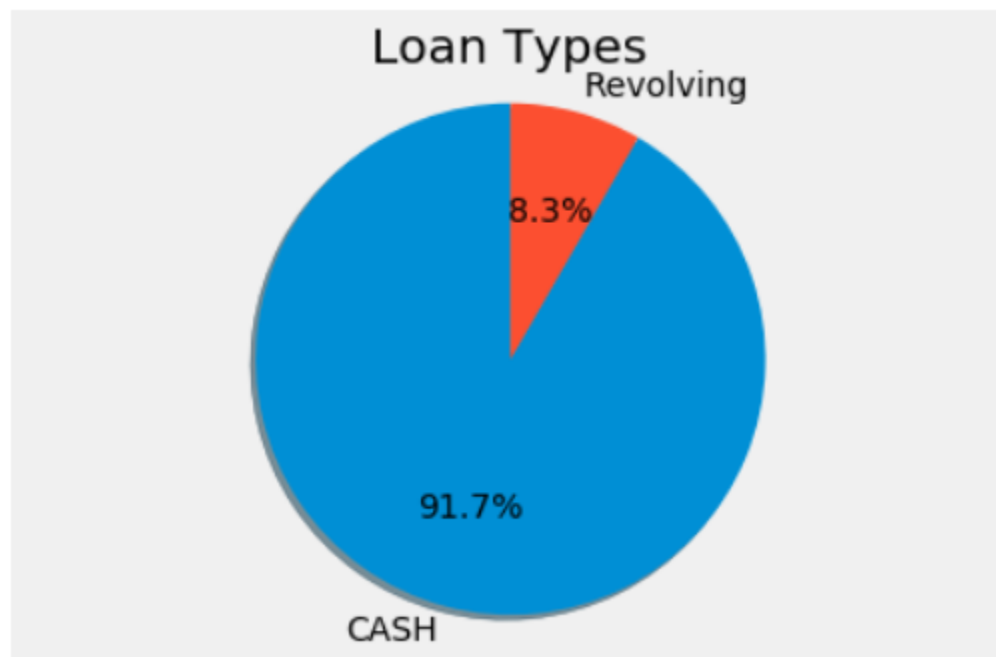




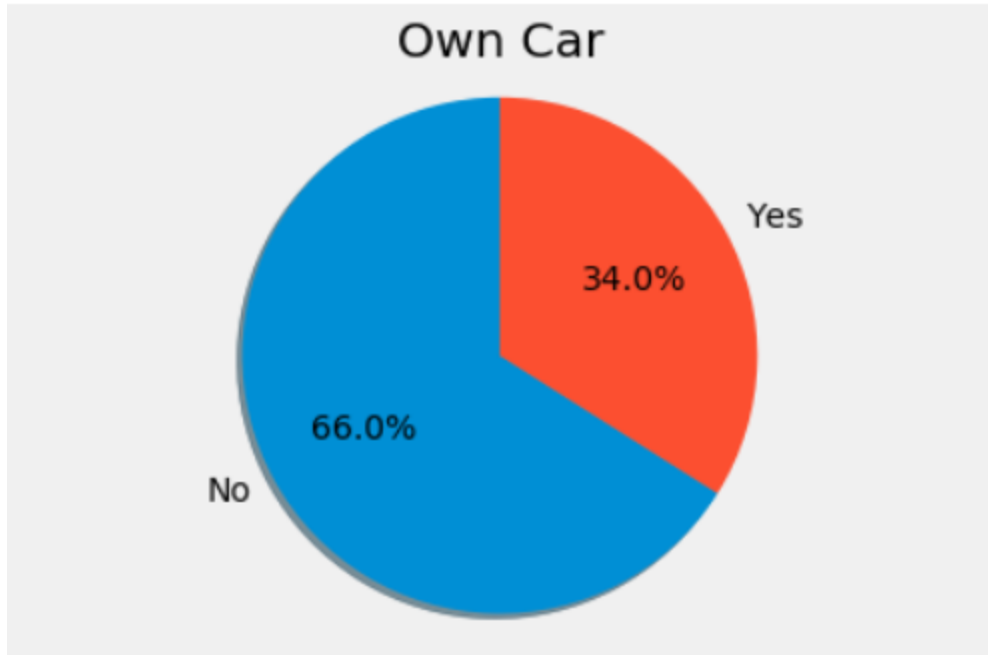
Distribution of Amount Credit :



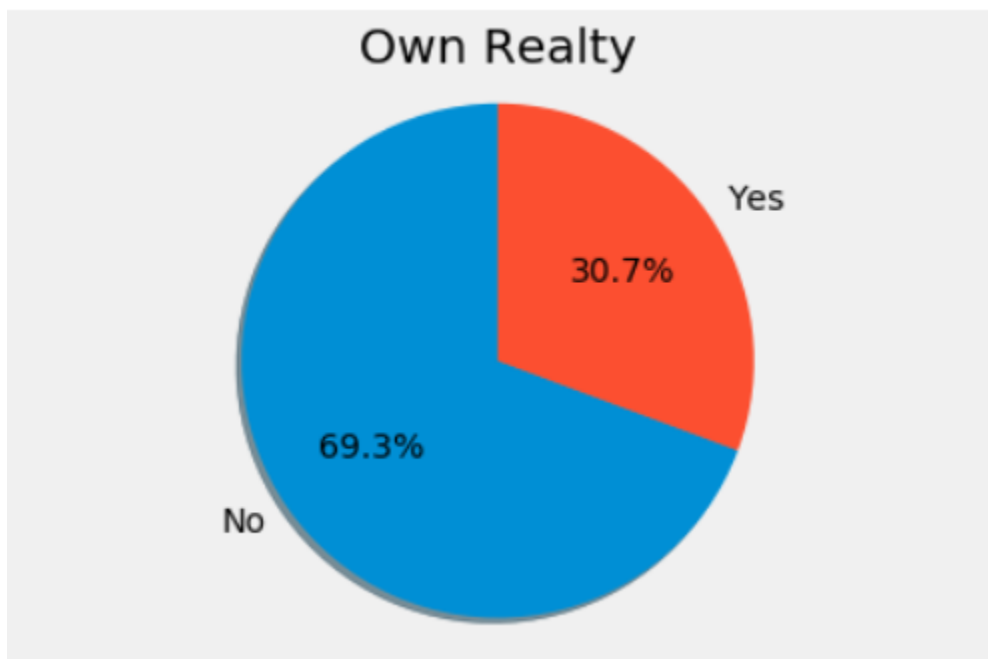
Type of Loans :



Car Ownership:



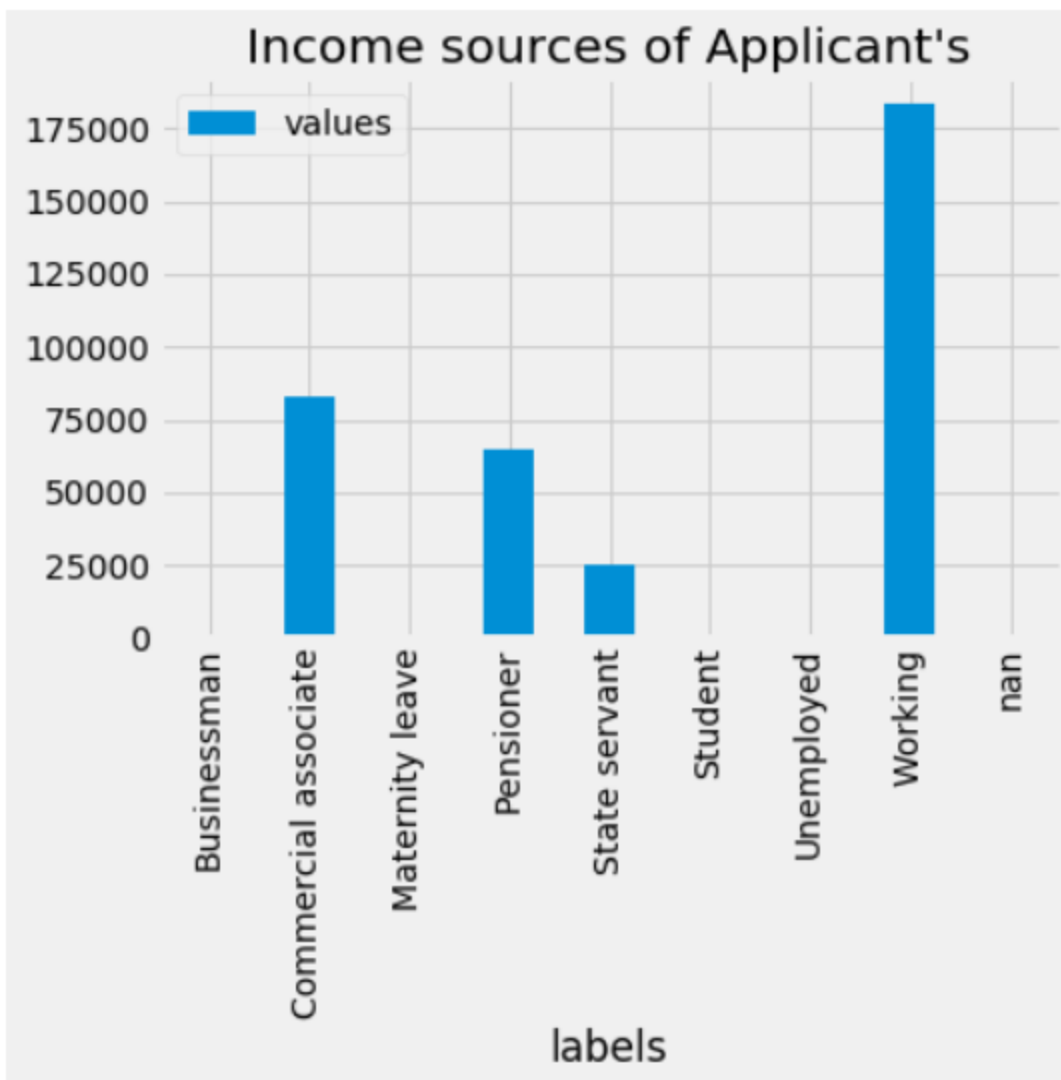
Realty Ownership:



Income Source of Applicant's:

	labels	values
0	Businessman	11.0
1	Commercial associate	83018.0
2	Maternity leave	5.0
3	Pensioner	64635.0
4	State servant	25235.0
5	Student	20.0
6	Unemployed	23.0
7	Working	183304.0
8	nan	NaN

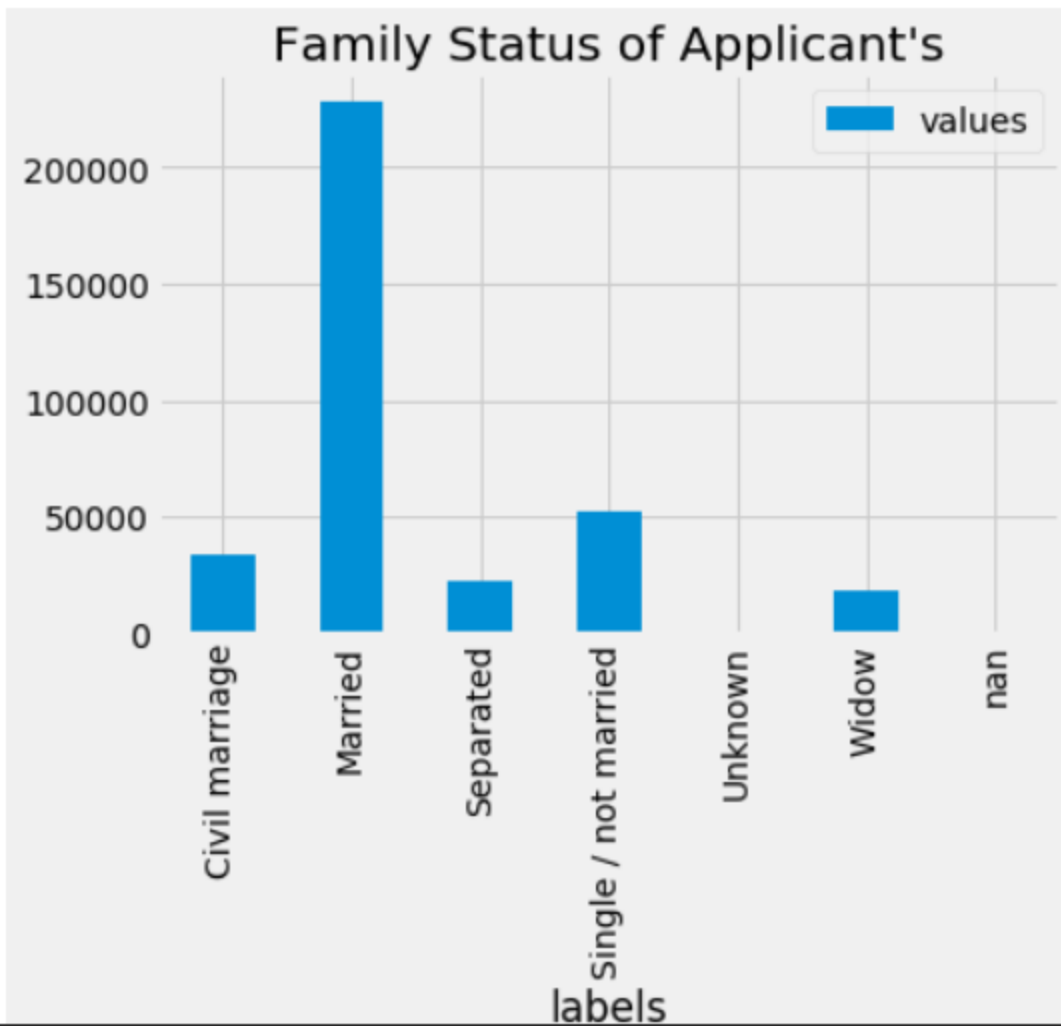
<matplotlib.axes.\_subplots.AxesSubplot at 0x218709819c8>



Family Status of Applicant's :

	labels	values
0	Civil marriage	34035.0
1	Married	228712.0
2	Separated	22725.0
3	Single / not married	52480.0
4	Unknown	2.0
5	Widow	18297.0
6	nan	NaN

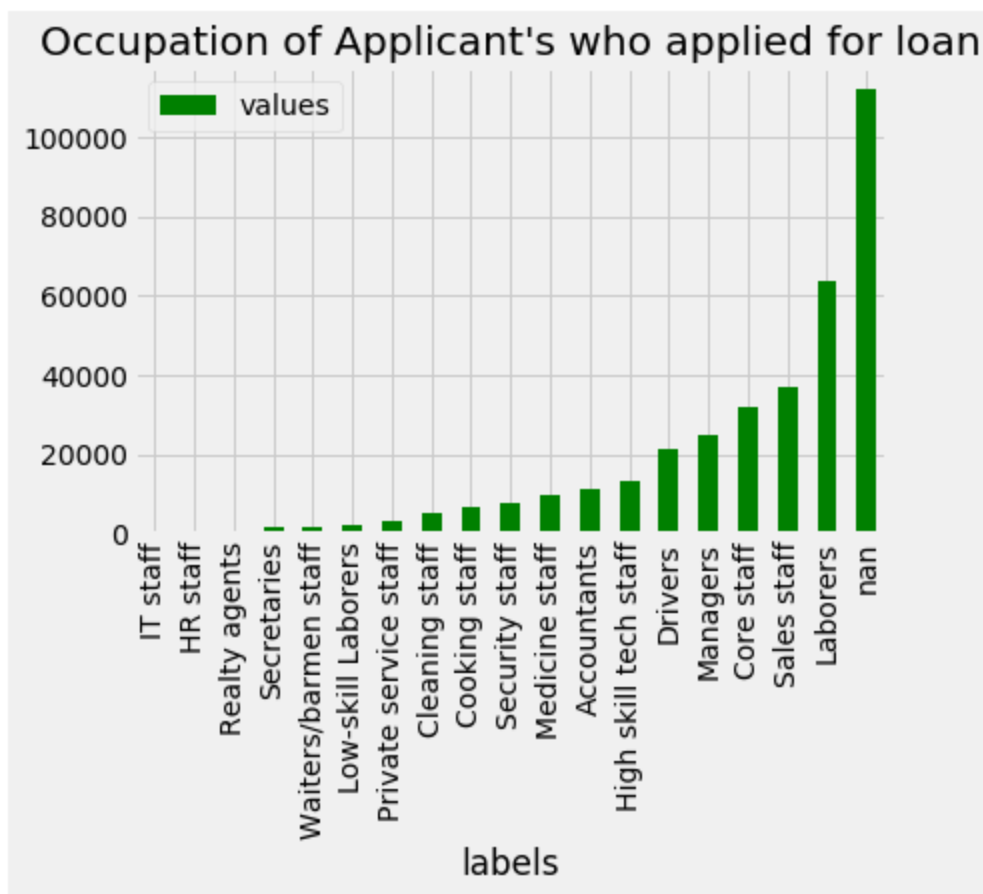
<matplotlib.axes.\_subplots.AxesSubplot at 0x21806ad16c8>



Occupation of the Applicant's:

	labels	values
7	IT staff	607
5	HR staff	667
13	Realty agents	889
15	Secretaries	1518
17	Waiters/barmen staff	1526
9	Low-skill Laborers	2364
12	Private service staff	3107
1	Cleaning staff	5309
2	Cooking staff	6840
16	Security staff	7636
11	Medicine staff	9853
0	Accountants	11441
6	High skill tech staff	13234
4	Drivers	21376
10	Managers	24945
3	Core staff	31930
14	Sales staff	37174
8	Laborers	63841
18	nan	111994

: <matplotlib.axes.\_subplots.AxesSubplot at 0x218709fe748>

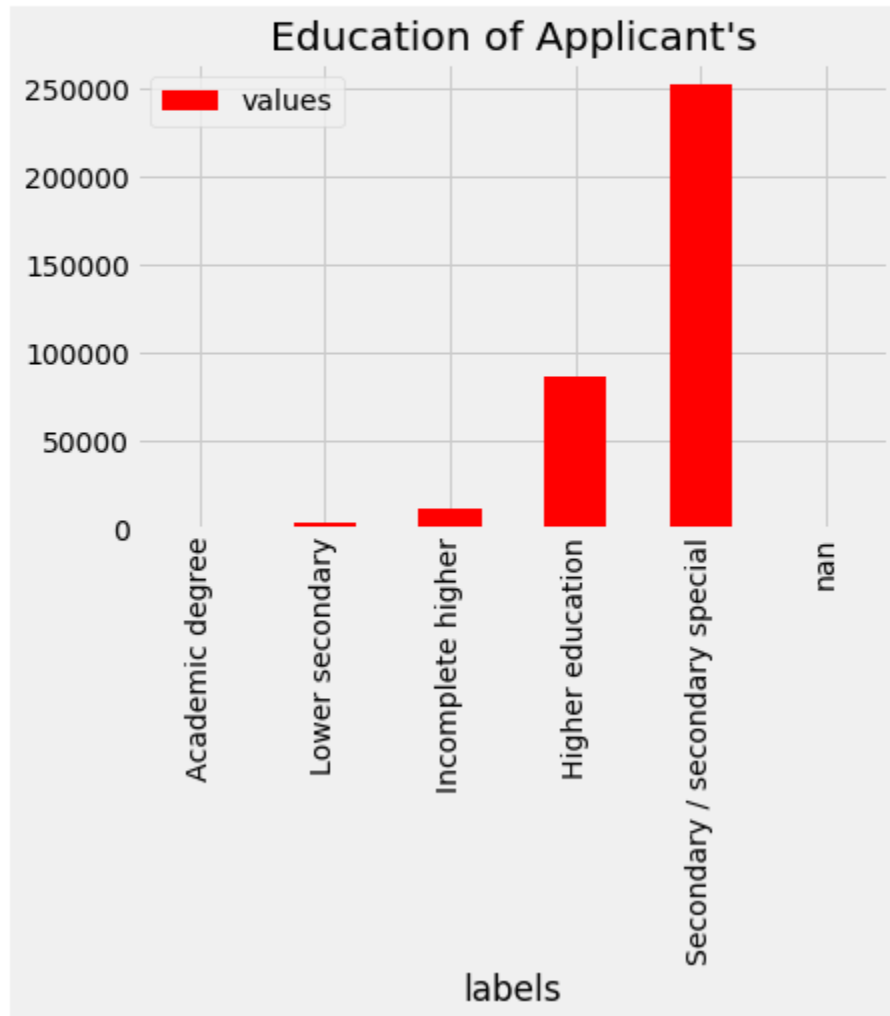




Applicant's Education:

	labels	values
0	Academic degree	205.0
3	Lower secondary	4291.0
2	Incomplete higher	12000.0
1	Higher education	87378.0
4	Secondary / secondary special	252377.0
5	nan	NaN

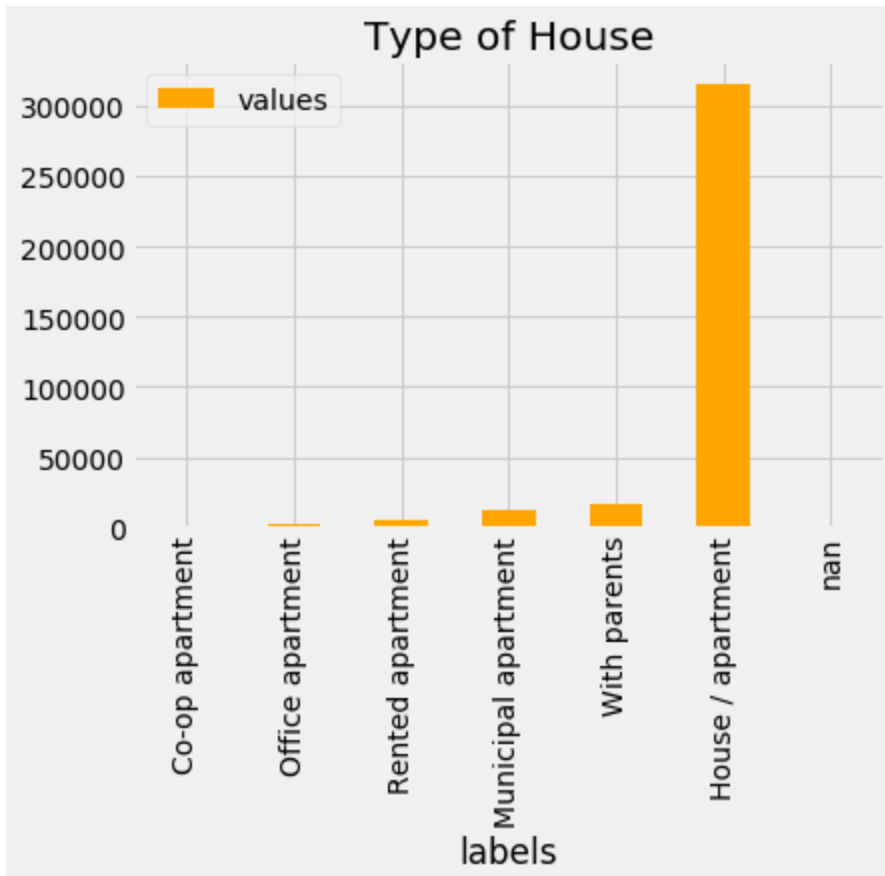
<matplotlib.axes.\_subplots.AxesSubplot at 0x21807469208>



Type of House :

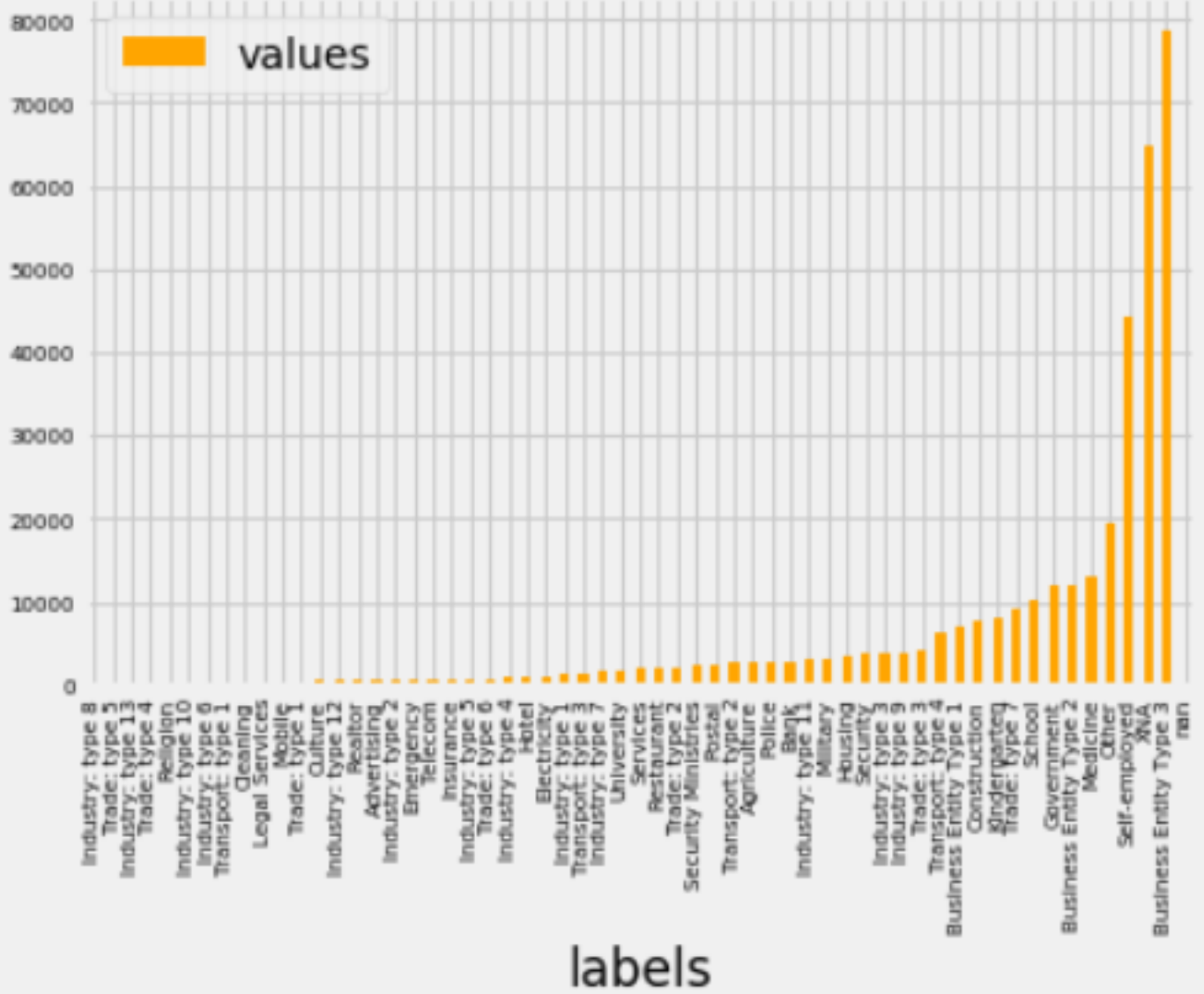
	labels	values
0	Co-op apartment	1245.0
3	Office apartment	3024.0
4	Rented apartment	5599.0
2	Municipal apartment	12799.0
5	With parents	17074.0
1	House / apartment	316510.0
6	nan	NaN

<matplotlib.axes.\_subplots.AxesSubplot at 0x218089eaac8>



Type Of Organization :

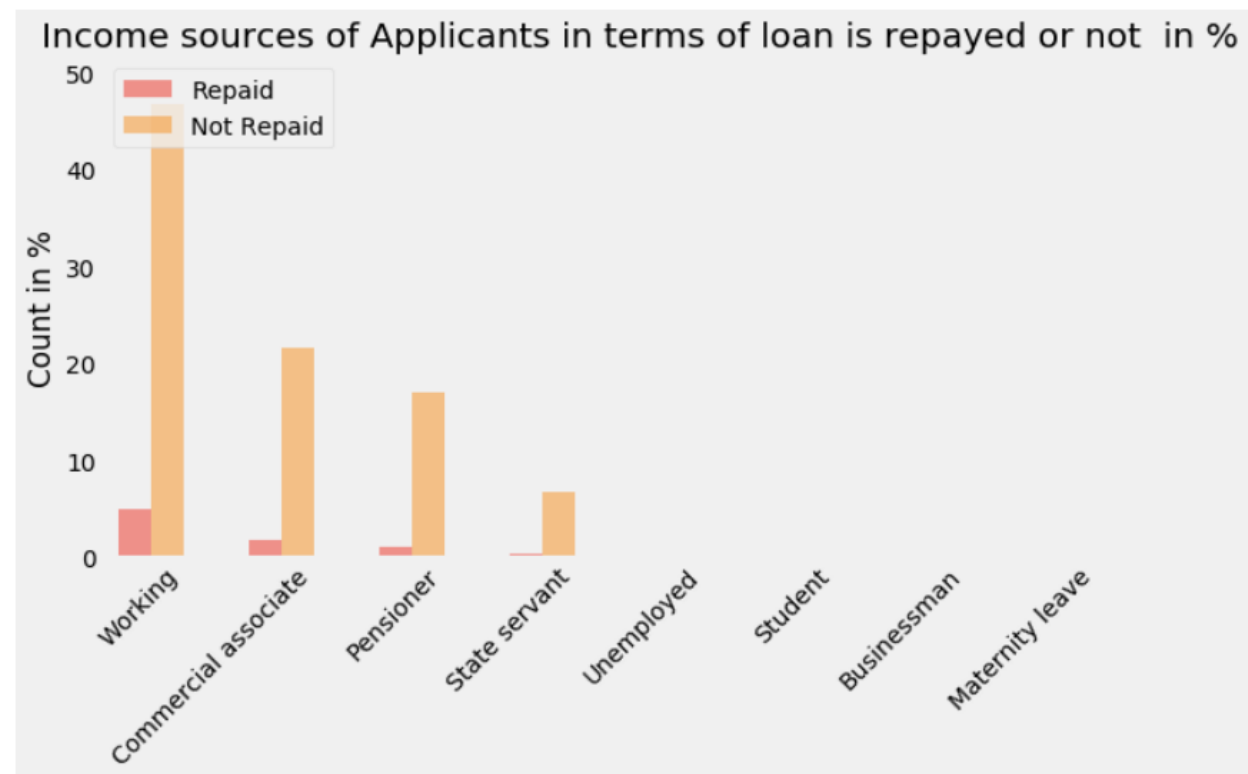
# Type of ORGANIZATION



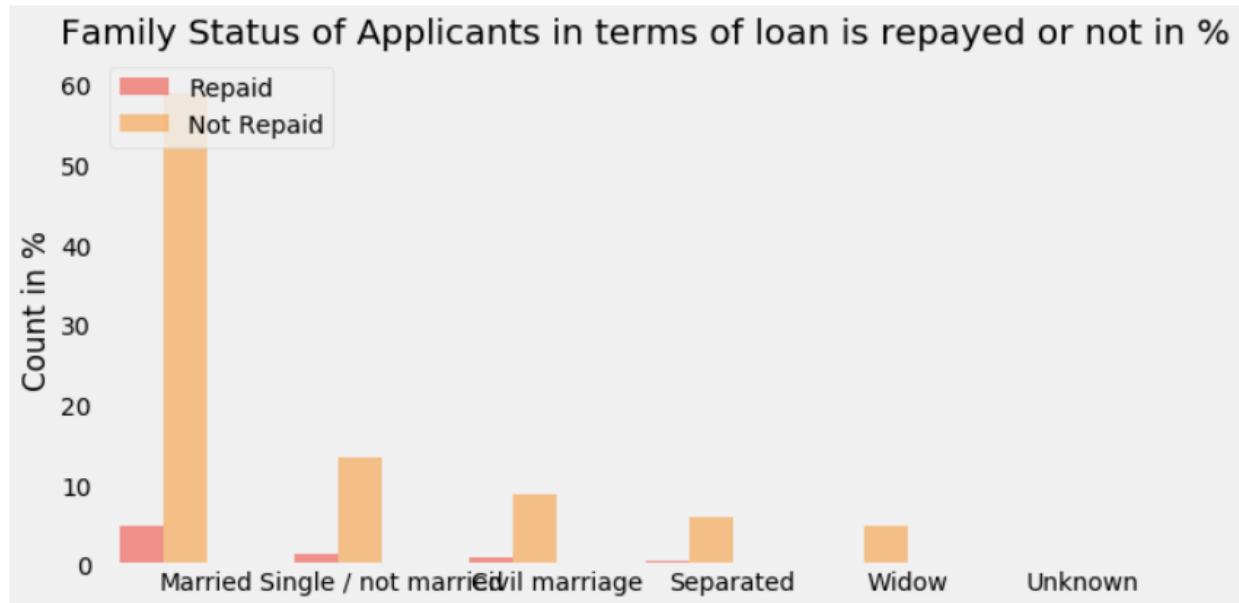
	labels	values
25	Industry: type 8	27.0
49	Trade: type 5	58.0
18	Industry: type 13	73.0
48	Trade: type 4	78.0
37	Religion	97.0
15	Industry: type 10	133.0
23	Industry: type 6	139.0
52	Transport: type 1	236.0
6	Cleaning	303.0
29	Legal Services	358.0
32	Mobile	362.0
45	Trade: type 1	412.0
8	Culture	440.0
17	Industry: type 12	446.0
36	Realtor	468.0
0	Advertising	500.0
19	Industry: type 2	535.0
10	Emergency	651.0
44	Telecom	672.0
27	Insurance	677.0
22	Industry: type 5	696.0
50	Trade: type 6	753.0
21	Industry: type 4	1044.0
12	Hotel	1100.0
9	Electricity	1106.0
14	Industry: type 1	1217.0
54	Transport: type 3	1361.0
24	Industry: type 7	1524.0
56	University	1548.0
43	Services	1877.0
38	Restaurant	2095.0
46	Trade: type 2	2142.0
41	Security Ministries	2315.0
35	Postal	2451.0
53	Transport: type 2	2652.0
1	Agriculture	2746.0
34	Police	2782.0
2	Bank	2881.0
16	Industry: type 11	3120.0
31	Military	3164.0
13	Housing	3393.0
40	Security	3719.0
20	Industry: type 3	3766.0
26	Industry: type 9	3867.0
47	Trade: type 3	4070.0
55	Transport: type 4	6282.0
3	Business Entity Type 1	6870.0
7	Construction	7760.0
28	Kindergarten	7917.0
51	Trade: type 7	9134.0
39	School	10180.0
11	Government	11912.0
4	Business Entity Type 2	12032.0
30	Medicine	12908.0
33	Other	19390.0
42	Self-employed	44332.0
57	XNA	64648.0
5	Business Entity Type 3	78832.0

Repaid Or not Based on Previous Data :

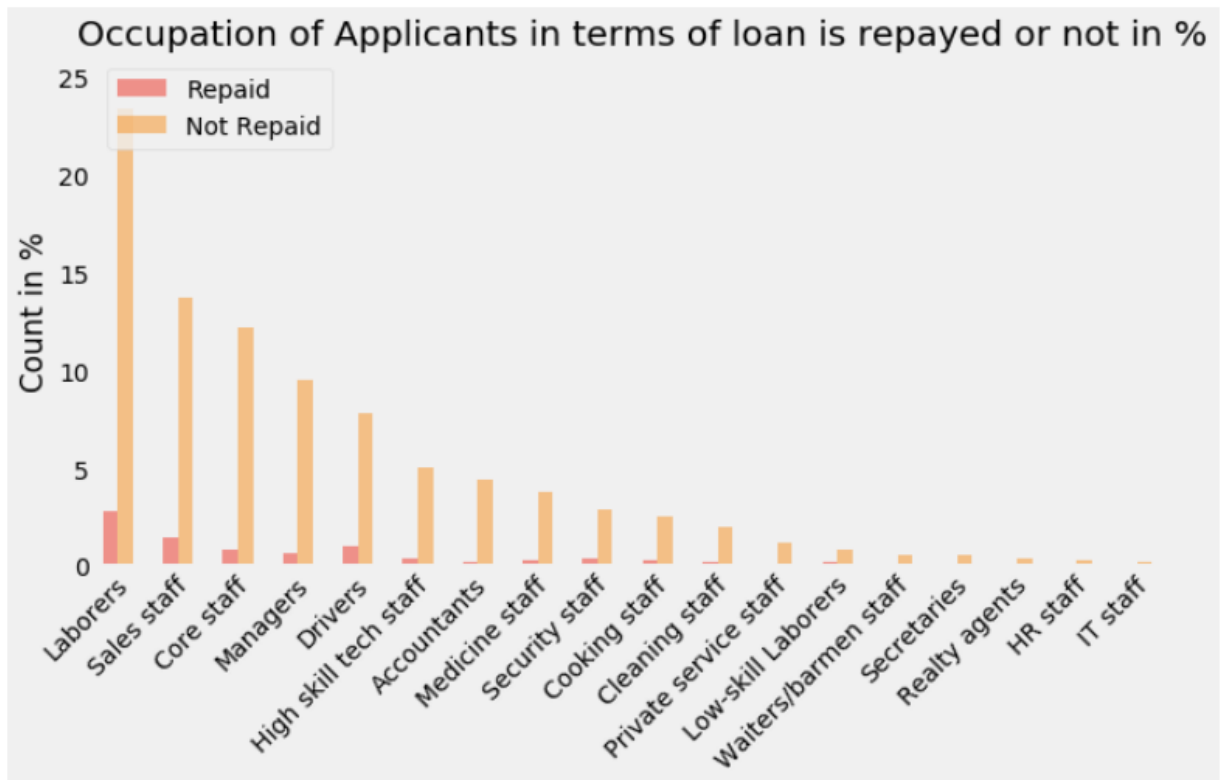
	business_name	success	failure
0	Working	4.950717	46.681257
1	Commercial associate	1.743027	21.546221
2	Pensioner	0.969721	17.033537
3	State servant	0.406164	6.651469
4	Unemployed	0.002602	0.004553
5	Student	0.000000	0.005853
6	Businessman	0.000000	0.003252
7	Maternity leave	0.000650	0.000976



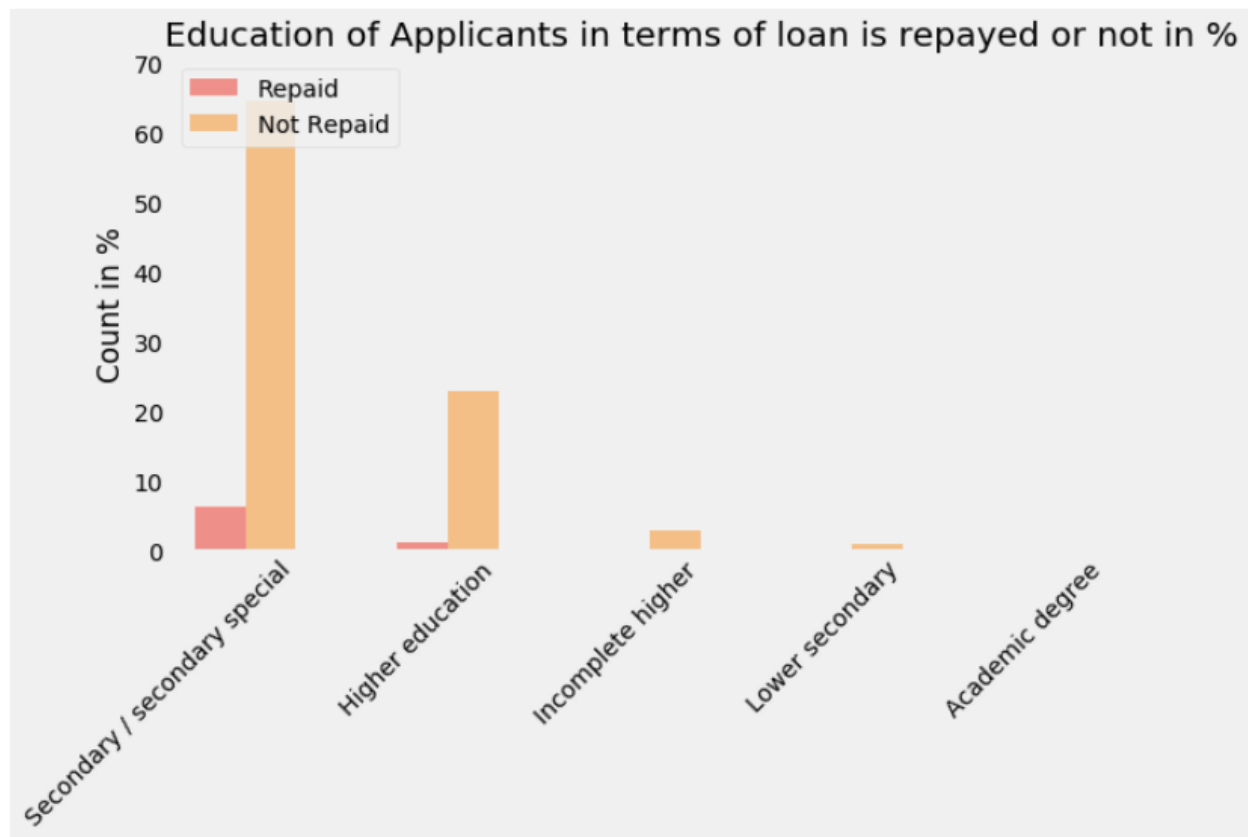
	business_name	success	failure
0	Married	4.829096	59.048945
1	Single / not married	1.449379	13.328629
2	Civil marriage	0.962892	8.719688
3	Separated	0.526810	5.902228
4	Widow	0.304705	4.926978
5	Unknown	0.000000	0.000650



	business_name	success	failure
0	Laborers	2.765252	23.374384
1	Sales staff	1.464570	13.741000
2	Core staff	0.823228	12.235695
3	Managers	0.629026	9.493653
4	Drivers	0.998011	7.813566
5	High skill tech staff	0.332039	5.058261
6	Accountants	0.224517	4.423551
7	Medicine staff	0.270936	3.772736
8	Security staff	0.341986	2.841512
9	Cooking staff	0.294146	2.522262
10	Cleaning staff	0.211728	1.992232
11	Private service staff	0.082891	1.173266
12	Low-skill Laborers	0.170045	0.821334
13	Waiters/barmen staff	0.071997	0.566502
14	Secretaries	0.043577	0.574555
15	Realty agents	0.027946	0.327776
16	HR staff	0.017052	0.249621
17	IT staff	0.016105	0.233043



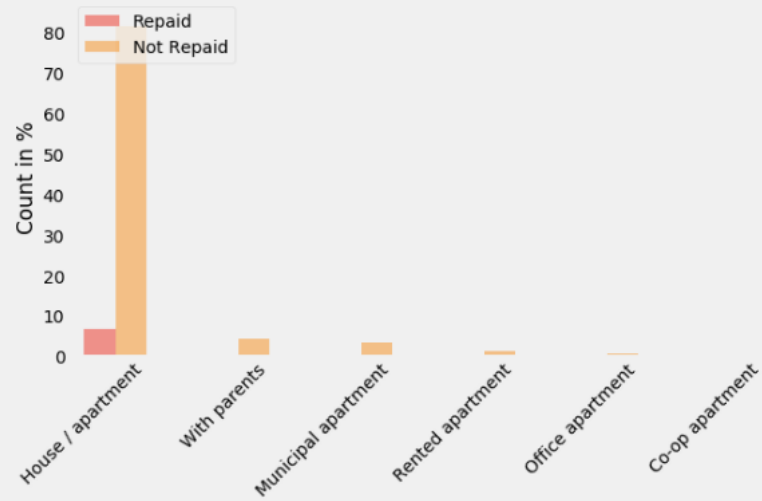
	business_name	success	failure
0	Secondary / secondary special	6.349041	64.669882
1	Higher education	1.303693	23.041127
2	Incomplete higher	0.283567	3.058427
3	Lower secondary	0.135605	1.105326
4	Academic degree	0.000976	0.052356





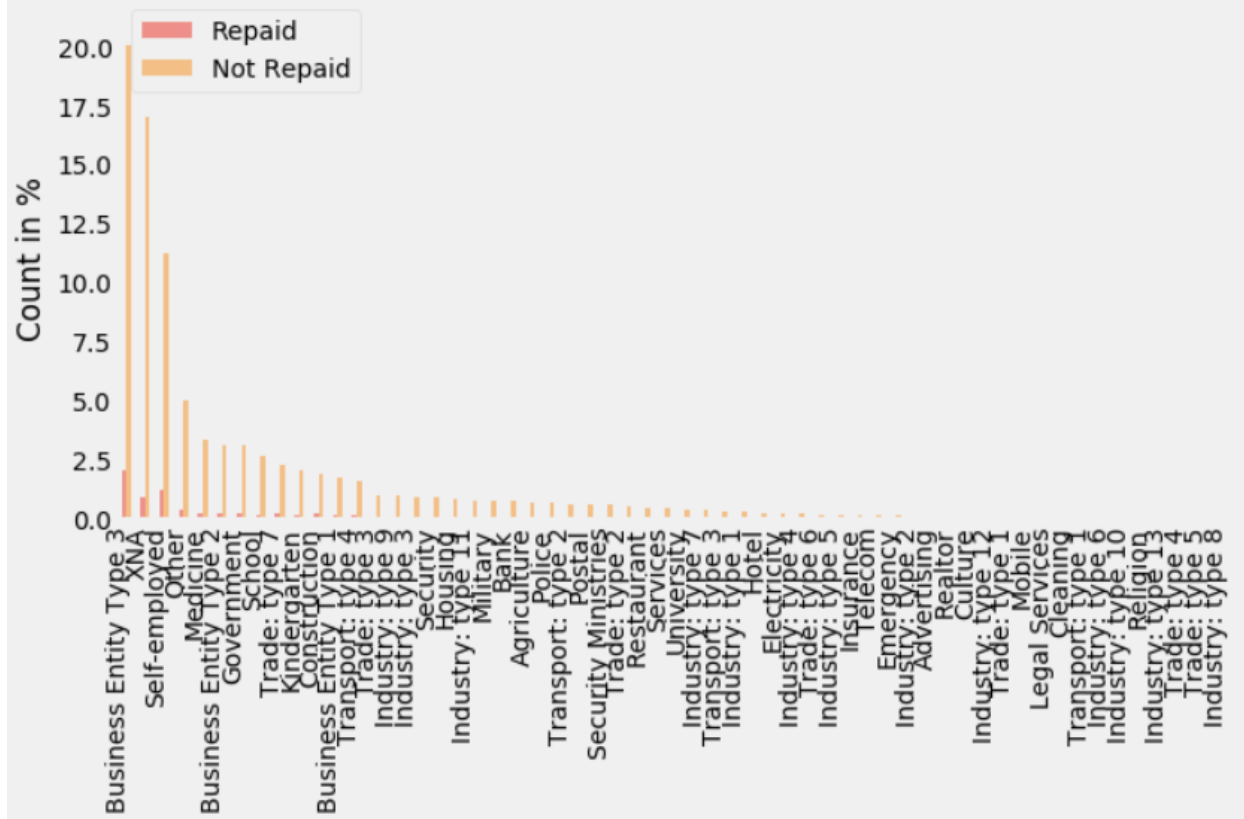
	business_name	success	failure
0	House / apartment	6.917476	81.816911
1	With parents	0.564533	4.261311
2	Municipal apartment	0.310558	3.326060
3	Rented apartment	0.195440	1.391820
4	Office apartment	0.055933	0.795094
5	Co-op apartment	0.028942	0.335923

For which types of house higher applicants applied for loan in terms of loan is repayed or not in %



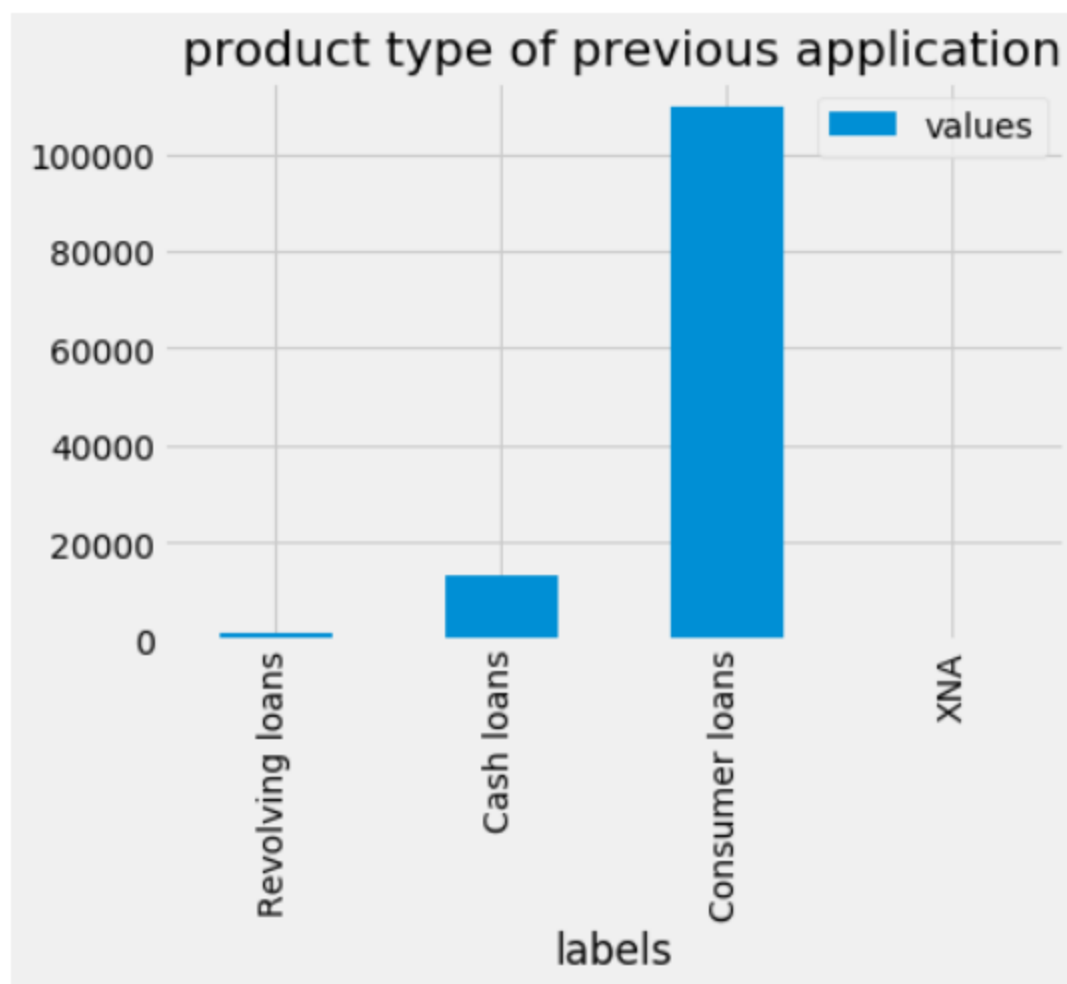
	business_name	success	failure
0	Business Entity Type 3	2.056187	20.054242
1	XNA	0.972323	17.034838
2	Self-employed	1.270849	11.220412
3	Other	0.414619	5.010552
4	Medicine	0.239666	3.400204
5	Business Entity Type 2	0.292672	3.139075
6	Government	0.236089	3.147204
7	School	0.171051	2.720878
8	Trade: type 7	0.240642	2.305934
9	Kindergarten	0.157393	2.079926
10	Construction	0.255275	1.930337
11	Business Entity Type 1	0.158368	1.787578
12	Transport: type 4	0.162921	1.592463
13	Trade: type 3	0.117394	1.018175
14	Industry: type 9	0.073168	1.022077
15	Industry: type 3	0.113167	0.952811
16	Security	0.105362	0.950535
17	Housing	0.076420	0.885497
18	Industry: type 11	0.076095	0.803223
19	Military	0.043901	0.812654
20	Bank	0.042275	0.772980
21	Agriculture	0.083574	0.714446
22	Police	0.038047	0.723226
23	Transport: type 2	0.055933	0.660789
24	Postal	0.059185	0.642253
25	Security Ministries	0.031218	0.610710
26	Trade: type 2	0.043250	0.574614
27	Restaurant	0.068941	0.519981
28	Services	0.033820	0.478357
29	University	0.021137	0.410392
30	Industry: type 7	0.034145	0.390880
31	Transport: type 3	0.060811	0.325192
32	Industry: type 1	0.037397	0.300477
33	Hotel	0.020162	0.293973
34	Electricity	0.020487	0.288445
35	Industry: type 4	0.028942	0.256251
36	Trade: type 6	0.009431	0.195765
37	Industry: type 5	0.013333	0.181457
38	Insurance	0.011057	0.183083
39	Telecom	0.014308	0.173327
40	Emergency	0.013008	0.169100
41	Industry: type 2	0.010731	0.138206
42	Advertising	0.011382	0.128125
43	Realtor	0.013658	0.115118
44	Culture	0.006829	0.116419
45	Industry: type 12	0.004553	0.115443
46	Trade: type 1	0.010081	0.103086
47	Mobile	0.009431	0.093655
48	Legal Services	0.007805	0.091379
49	Cleaning	0.009431	0.075119
50	Transport: type 1	0.002927	0.062437
51	Industry: type 6	0.002602	0.033820
52	Industry: type 10	0.002276	0.033170
53	Religion	0.001626	0.026015
54	Industry: type 13	0.002927	0.018861
55	Trade: type 4	0.000650	0.020162
56	Trade: type 5	0.000976	0.014959
57	Industry: type 8	0.000976	0.006829

# Types of Organizations in terms of loan is repayed or not in %



	labels	values
2	Revolving loans	1691.0
0	Cash loans	13257.0
1	Consumer loans	109781.0
3	XNA	NaN

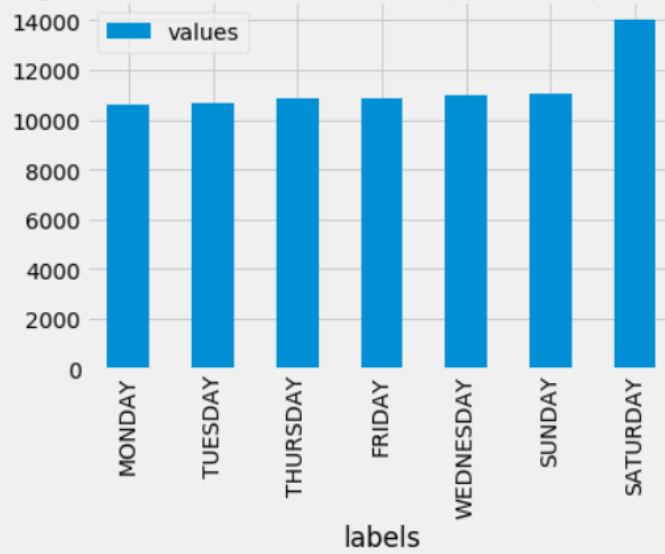
1]: <matplotlib.axes.\_subplots.AxesSubplot at 0x218070a7ec8>



```
labels values
1 MONDAY 10595
5 TUESDAY 10678
4 THURSDAY 10838
0 FRIDAY 10896
6 WEDNESDAY 10966
3 SUNDAY 11076
2 SATURDAY 14060
```

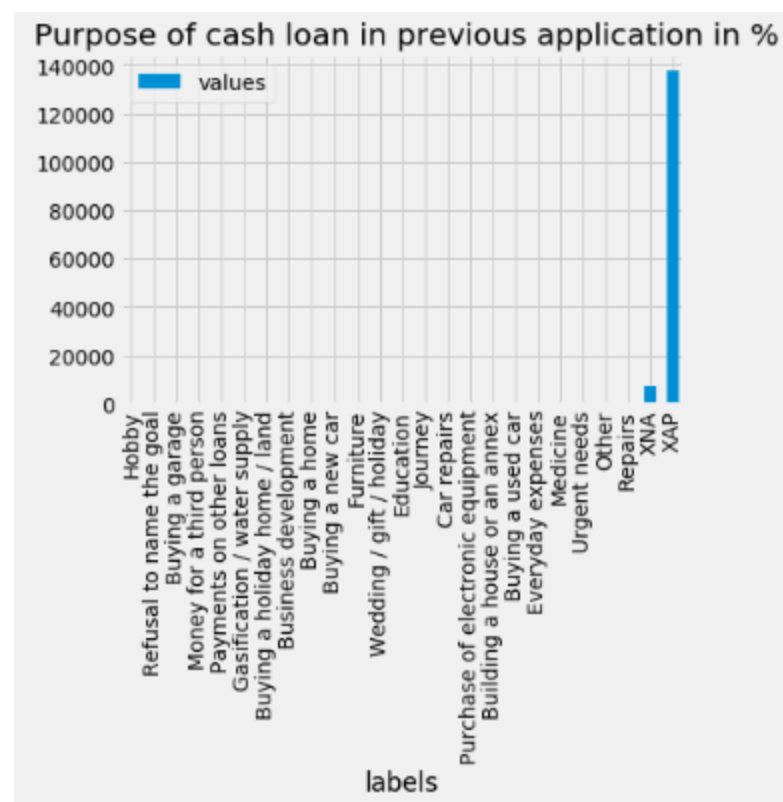
<matplotlib.axes.\_subplots.AxesSubplot at 0x2180a314688>

On which day highest number of clients applied in prevoies application in %



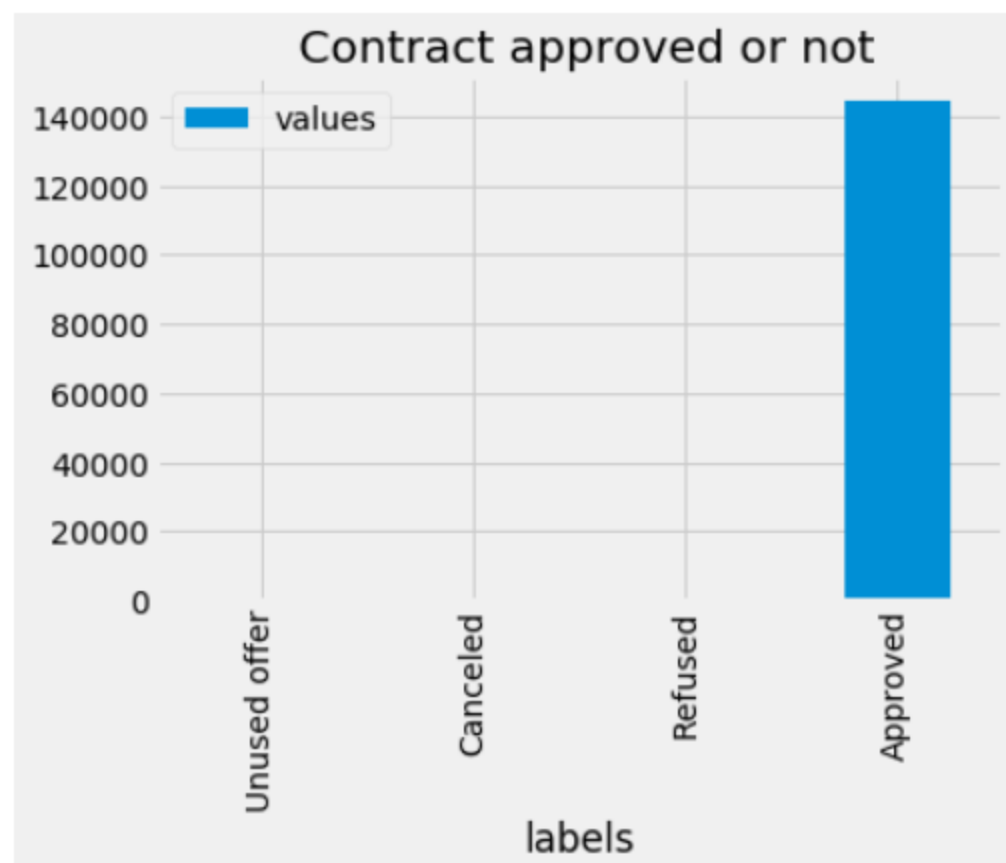
	labels	values
12	Hobby	1
19	Refusal to name the goal	1
2	Buying a garage	2
15	Money for a third person	2
17	Payments on other loans	9
11	Gasification / water supply	11
3	Buying a holiday home / land	12
1	Business development	13
4	Buying a home	17
5	Buying a new car	20
10	Furniture	30
22	Wedding / gift / holiday	35
8	Education	40
13	Journey	42
7	Car repairs	43
18	Purchase of electronic equipment	43
0	Building a house or an annex	63
6	Buying a used car	68
9	Everyday expenses	74
14	Medicine	86
21	Urgent needs	323
16	Other	456
20	Repairs	757
24	XNA	7365
23	XAP	138032

<matplotlib.axes.\_subplots.AxesSubplot at 0x21809625648>



```
labels values
3 Unused offer 175
1 Canceled 255
2 Refused 499
0 Approved 144615
```

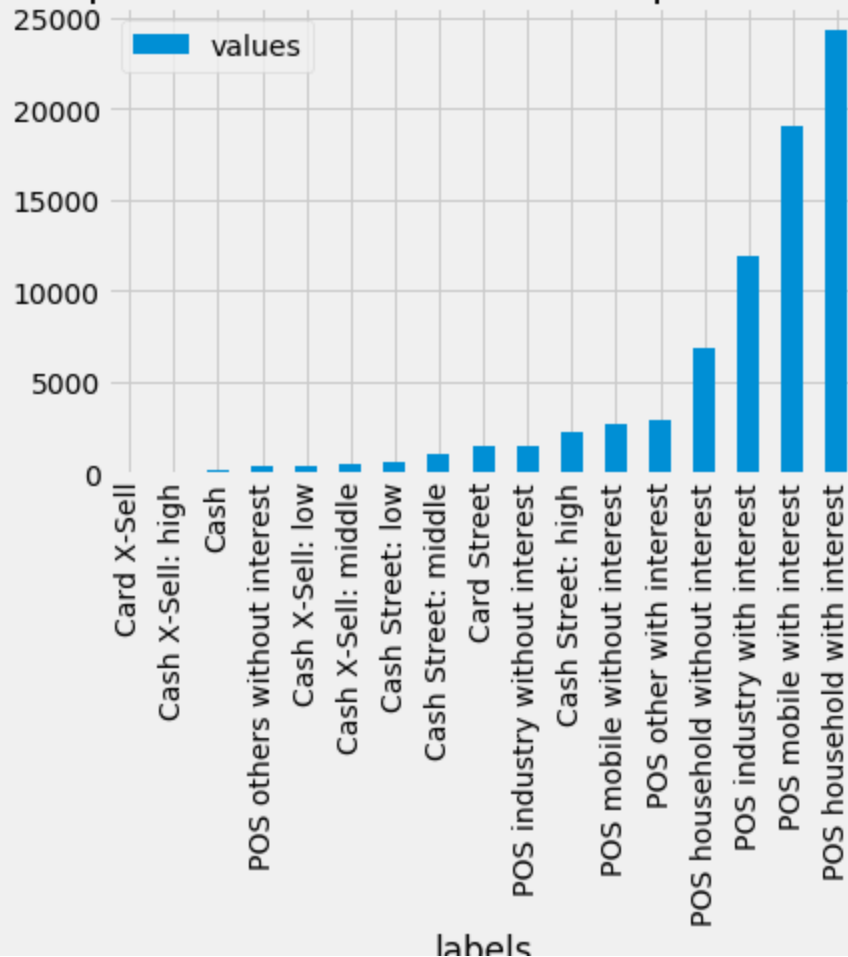
<matplotlib.axes.\_subplots.AxesSubplot at 0x2187062c1c8>



	labels	values
1	Card X-Sell	104
6	Cash X-Sell: high	112
2	Cash	234
16	POS others without interest	361
7	Cash X-Sell: low	375
8	Cash X-Sell: middle	540
4	Cash Street: low	630
5	Cash Street: middle	1053
0	Card Street	1527
12	POS industry without interest	1534
3	Cash Street: high	2225
14	POS mobile without interest	2678
15	POS other with interest	2879
10	POS household without interest	6887
11	POS industry with interest	11931
13	POS mobile with interest	19062
9	POS household with interest	24355

<matplotlib.axes.\_subplots.AxesSubplot at 0x21808c17448>

### Detailed product combination of the previous application

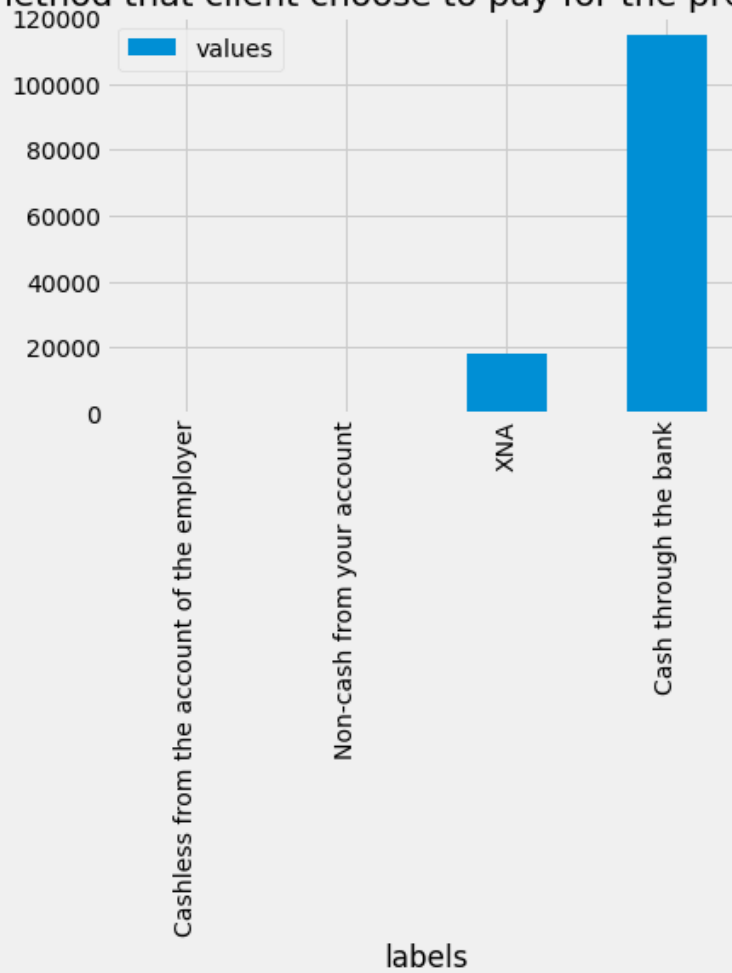




```

                                labels values
1  Cashless from the account of the employer    52
2                Non-cash from your account   567
3                                XNA   18194
0                Cash through the bank  114980
<matplotlib.axes._subplots.AxesSubplot at 0x21809ca1108>
```

Payment method that client choose to pay for the previous application



	labels	values
1	Car dealer	22
3	Contact center	491
2	Channel of corporate sales	500
0	AP+ (Cash loan)	1590
6	Regional / Local	11383
5	Credit and cash offices	12685
7	Stone	23451
4	Country-wide	56174

<matplotlib.axes.\_subplots.AxesSubplot at 0x2180f08e7c8>

