

## Saba\_cross

October 16, 2022

```
[10]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingClassifier
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn.metrics import classification_report
from dmba import plotDecisionTree, gainsChart, liftChart
from dmba import classificationSummary, regressionSummary
from sklearn.metrics import recall_score
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

```
[11]: checking_dt=pd.DataFrame(pd.read_csv('cross_sell_dataset.tab', sep='\t'))
```

```
[12]: checking_dt.head()
```

```
[12]:
```

	cross_buy	acad_title	age	calls	complaints	customer_tenure_months	\
0	0	0	60	0	0	221	
1	0	0	55	0	0	227	
2	0	0	61	0	0	221	
3	0	0	70	0	0	222	
4	0	1	61	0	0	227	

	directmails	gender	joint_account	inflows	...	volume_debit	\
0	0	0.0	0.0	0.0	...	0.00	
1	0	0.0	1.0	0.0	...	3.28	
2	0	1.0	0.0	3000.0	...	31963.13	
3	0	0.0	0.0	6000.0	...	54048.40	
4	0	1.0	0.0	0.0	...	1374743.09	

	volume_debit_6months	ext_city_size	ext_house_size	ext_purchase_power	\
0	0.00	7.0	4.0	5.0	
1	3.28	7.0	1.0	7.0	
2	28963.13	8.0	4.0	4.0	
3	48048.40	2.0	1.0	7.0	
4	1341722.91	4.0	1.0	7.0	

	ext_share_new_houses	ext_share_new_cars	ext_car_power	\
0	4.0	4.0	3.0	
1	1.0	3.0	1.0	
2	1.0	7.0	3.0	
3	3.0	5.0	4.0	
4	3.0	6.0	5.0	

	ext_living_duration	giro_mailing
0	9.0	0
1	NaN	0
2	9.0	0
3	9.0	0
4	7.0	0

[5 rows x 35 columns]

```
[13]: checking_dt.shape
```

```
[13]: (100000, 35)
```

```
[14]: checking_dt.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 35 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   cross_buy                             100000 non-null  int64
1   acad_title                             100000 non-null  int64
2   age                                    100000 non-null  int64
3   calls                                 100000 non-null  int64
4   complaints                             100000 non-null  int64
5   customer_tenure_months                 100000 non-null  int64
6   directmails                             100000 non-null  int64
7   gender                                 99998 non-null   float64
8   joint_account                          99998 non-null   float64
9   inflows                                99527 non-null   float64
10  last_acc_opening_days                   100000 non-null  int64
11  logins_desktop                           100000 non-null  int64
12  logins_mobile                           100000 non-null  int64
```

13	marital_status	100000	non-null	object
14	member_get_member_active	100000	non-null	int64
15	member_get_member_passive	100000	non-null	int64
16	nr_products	100000	non-null	int64
17	occupation	48725	non-null	object
18	outflows	99527	non-null	float64
19	prod_loan	100000	non-null	int64
20	prod_mortgages	100000	non-null	int64
21	prod_brokerage	100000	non-null	int64
22	prod_pensionplan	100000	non-null	int64
23	prod_savings	100000	non-null	int64
24	relocations	100000	non-null	int64
25	volume_debit	100000	non-null	float64
26	volume_debit_6months	97002	non-null	float64
27	ext_city_size	97338	non-null	float64
28	ext_house_size	96953	non-null	float64
29	ext_purchase_power	95435	non-null	float64
30	ext_share_new_houses	97338	non-null	float64
31	ext_share_new_cars	84845	non-null	float64
32	ext_car_power	89866	non-null	float64
33	ext_living_duration	90935	non-null	float64
34	giro_mailing	100000	non-null	int64

dtypes: float64(13), int64(20), object(2)

memory usage: 26.7+ MB

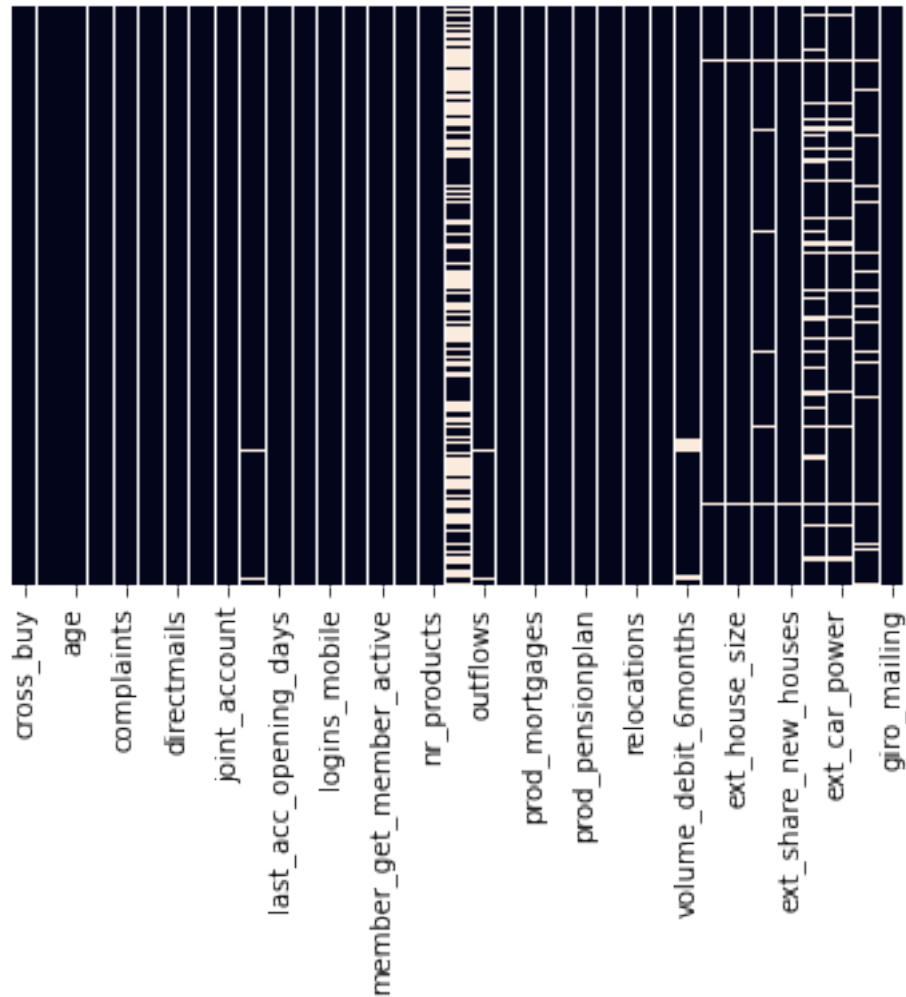
```
[15]: checking_dt.isna().sum()
```

[15]:	cross_buy	0
	acad_title	0
	age	0
	calls	0
	complaints	0
	customer_tenure_months	0
	directmails	0
	gender	2
	joint_account	2
	inflows	473
	last_acc_opening_days	0
	logins_desktop	0
	logins_mobile	0
	marital_status	0
	member_get_member_active	0
	member_get_member_passive	0
	nr_products	0
	occupation	51275
	outflows	473
	prod_loan	0

```
prod_mortgages          0
prod_brokerage          0
prod_pensionplan        0
prod_savings            0
relocations             0
volume_debit            0
volume_debit_6months    2998
ext_city_size           2662
ext_house_size          3047
ext_purchase_power      4565
ext_share_new_houses     2662
ext_share_new_cars      15155
ext_car_power           10134
ext_living_duration     9065
giro_mailing            0
dtype: int64
```

```
[16]: #heat map of missing values
      sns.heatmap(checking_dt.isnull(),yticklabels=False,cbar=False)
```

```
[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7fecf8724810>
```



```
[17]: checking_dt.describe()
```

```
[17]:
```

	cross_buy	acad_title	age	calls \
count	100000.000000	100000.000000	100000.000000	100000.000000
mean	0.100000	0.020390	49.892260	0.104600
std	0.300002	0.141331	14.534085	0.564395
min	0.000000	0.000000	18.000000	0.000000
25%	0.000000	0.000000	39.000000	0.000000
50%	0.000000	0.000000	51.000000	0.000000
75%	0.000000	0.000000	60.000000	0.000000
max	1.000000	1.000000	80.000000	58.000000

	complaints	customer_tenure_months	directmails	gender \
count	100000.000000	100000.000000	100000.000000	99998.000000
mean	0.003530	140.181700	0.470660	0.405588
std	0.078598	74.901654	0.915952	0.491008

min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	78.000000	0.000000	0.000000
50%	0.000000	160.000000	0.000000	0.000000
75%	0.000000	201.000000	1.000000	1.000000
max	8.000000	567.000000	9.000000	1.000000

	joint_account	inflows	...	volume_debit	volume_debit_6months	\
count	99998.000000	9.952700e+04	...	1.000000e+05	9.700200e+04	
mean	0.236675	2.818210e+03	...	2.262297e+04	2.252191e+04	
std	0.425043	1.552502e+04	...	1.493077e+05	8.568004e+04	
min	0.000000	0.000000e+00	...	0.000000e+00	0.000000e+00	
25%	0.000000	0.000000e+00	...	1.247500e+00	2.782500e+00	
50%	0.000000	0.000000e+00	...	1.355575e+03	1.404455e+03	
75%	0.000000	9.000000e+02	...	1.857914e+04	1.865452e+04	
max	1.000000	1.300000e+06	...	3.999071e+07	7.705563e+06	

	ext_city_size	ext_house_size	ext_purchase_power	\
count	97338.000000	96953.000000	95435.000000	
mean	4.386961	1.779048	4.594677	
std	2.379942	1.185036	1.997959	
min	1.000000	1.000000	1.000000	
25%	2.000000	1.000000	3.000000	
50%	4.000000	1.000000	5.000000	
75%	7.000000	3.000000	6.000000	
max	8.000000	5.000000	7.000000	

	ext_share_new_houses	ext_share_new_cars	ext_car_power	\
count	97338.000000	84845.000000	89866.000000	
mean	2.638117	4.307337	3.064674	
std	1.353302	1.916396	1.464527	
min	1.000000	1.000000	1.000000	
25%	1.000000	3.000000	2.000000	
50%	3.000000	4.000000	3.000000	
75%	4.000000	6.000000	4.000000	
max	5.000000	7.000000	5.000000	

	ext_living_duration	giro_mailing
count	90935.000000	100000.000000
mean	7.161896	0.105080
std	2.194956	0.306658
min	1.000000	0.000000
25%	6.000000	0.000000
50%	8.000000	0.000000
75%	9.000000	0.000000
max	9.000000	1.000000

[8 rows x 33 columns]

```
[18]: # Correlation
      checking_dt.corr()
```

```
[18]:
```

	cross_buy	acad_title	age	calls	\
cross_buy	1.000000	-0.009882	-0.189307	0.040220	
acad_title	-0.009882	1.000000	0.057615	0.004102	
age	-0.189307	0.057615	1.000000	0.027188	
calls	0.040220	0.004102	0.027188	1.000000	
complaints	0.011324	0.004323	0.013403	0.096050	
customer_tenure_months	-0.125842	0.011414	0.291242	-0.054208	
directmails	0.072362	-0.010713	-0.209959	0.001855	
gender	0.041760	0.069316	-0.107541	-0.016002	
joint_account	-0.062406	-0.074176	0.192318	0.051165	
inflows	0.043726	0.040241	0.019642	0.056537	
last_acc_opening_days	-0.146949	-0.004697	0.204092	-0.105667	
logins_desktop	0.046032	0.015761	0.020374	0.084036	
logins_mobile	0.090828	0.004411	-0.070243	0.061539	
member_get_member_active	0.043120	0.001372	-0.024528	0.013942	
member_get_member_passive	0.056280	0.003488	-0.054261	0.025706	
nr_products	0.076436	0.031484	0.038399	0.097643	
outflows	-0.011270	-0.034336	-0.032119	-0.046676	
prod_loan	0.027460	-0.028452	-0.070034	0.031063	
prod_mortgages	-0.009592	-0.014775	-0.011224	0.101411	
prod_brokerage	0.101928	0.049662	0.009591	0.059143	
prod_pensionplan	-0.005006	-0.000246	0.033538	0.005654	
prod_savings	0.019189	0.032476	0.085457	-0.030931	
relocations	0.051068	-0.006044	-0.124478	0.034239	
volume_debit	0.004752	0.033654	0.071497	0.025303	
volume_debit_6months	0.009107	0.063094	0.129426	0.051731	
ext_city_size	0.003590	0.056620	-0.006993	0.009223	
ext_house_size	0.019381	0.004447	-0.059520	0.012980	
ext_purchase_power	0.015075	0.052988	0.011680	0.004424	
ext_share_new_houses	0.004484	-0.013002	-0.025952	-0.004475	
ext_share_new_cars	-0.006054	0.029723	0.077255	0.007583	
ext_car_power	-0.002218	0.034030	0.035650	0.008019	
ext_living_duration	-0.033288	-0.019744	0.196554	-0.008904	
giro_mailing	0.130787	-0.012288	-0.313721	0.027957	

	complaints	customer_tenure_months	directmails	\
cross_buy	0.011324	-0.125842	0.072362	
acad_title	0.004323	0.011414	-0.010713	
age	0.013403	0.291242	-0.209959	
calls	0.096050	-0.054208	0.001855	
complaints	1.000000	-0.008546	-0.004048	
customer_tenure_months	-0.008546	1.000000	-0.131963	
directmails	-0.004048	-0.131963	1.000000	
gender	-0.004968	-0.002996	0.041327	

joint_account	0.015702	-0.042698	-0.010052
inflows	0.023050	0.022929	0.026365
last_acc_opening_days	-0.025699	0.763507	-0.192201
logins_desktop	0.023835	-0.004164	-0.012080
logins_mobile	0.018044	-0.070072	0.035730
member_get_member_active	0.014075	-0.016697	0.015492
member_get_member_passive	0.017633	-0.094129	0.005597
nr_products	0.030911	0.082864	0.079356
outflows	-0.023151	-0.035689	-0.043571
prod_loan	-0.000004	-0.268161	0.162420
prod_mortgages	0.037286	-0.120971	-0.015122
prod_brokerage	0.019865	0.046196	0.064405
prod_pensionplan	0.003544	0.012568	0.006056
prod_savings	-0.008715	0.371350	-0.032924
relocations	0.006176	-0.069396	0.082247
volume_debit	0.012073	0.050782	0.017487
volume_debit_6months	0.025577	0.081041	0.035098
ext_city_size	0.006214	-0.015300	0.020206
ext_house_size	0.005924	-0.061752	0.033382
ext_purchase_power	0.009849	-0.003221	0.011723
ext_share_new_houses	-0.003605	-0.011169	-0.001411
ext_share_new_cars	0.005436	0.041144	-0.012223
ext_car_power	0.006597	0.011970	-0.005831
ext_living_duration	-0.005177	0.147168	-0.053855
giro_mailing	-0.000039	-0.177364	0.270552

	gender	joint_account	inflows	...	\
cross_buy	0.041760	-0.062406	0.043726	...	
acad_title	0.069316	-0.074176	0.040241	...	
age	-0.107541	0.192318	0.019642	...	
calls	-0.016002	0.051165	0.056537	...	
complaints	-0.004968	0.015702	0.023050	...	
customer_tenure_months	-0.002996	-0.042698	0.022929	...	
directmails	0.041327	-0.010052	0.026365	...	
gender	1.000000	-0.459960	0.028738	...	
joint_account	-0.459960	1.000000	-0.007882	...	
inflows	0.028738	-0.007882	1.000000	...	
last_acc_opening_days	-0.013485	-0.060886	-0.038986	...	
logins_desktop	0.049443	-0.003702	0.123411	...	
logins_mobile	0.084330	-0.031938	0.106936	...	
member_get_member_active	0.020597	-0.012256	0.029229	...	
member_get_member_passive	0.017415	-0.029128	0.035607	...	
nr_products	0.032865	0.078398	0.115144	...	
outflows	-0.015884	0.003594	-0.320495	...	
prod_loan	0.032143	0.082855	-0.047325	...	
prod_mortgages	-0.147388	0.346461	-0.030526	...	
prod_brokerage	0.141553	-0.067355	0.146753	...	



prod_pensionplan	-0.012519	0.004465	0.001435	...
prod_savings	0.054232	-0.191463	0.107790	...
relocations	0.014575	-0.031810	0.010644	...
volume_debit	0.012378	-0.004712	0.190881	...
volume_debit_6months	0.017588	-0.005617	0.232633	...
ext_city_size	0.005032	-0.052038	0.009528	...
ext_house_size	0.030996	-0.117709	-0.009599	...
ext_purchase_power	-0.002775	0.023079	0.036708	...
ext_share_new_houses	0.000886	0.015665	0.004767	...
ext_share_new_cars	-0.020855	0.019138	0.019496	...
ext_car_power	0.003049	-0.008803	0.022106	...
ext_living_duration	-0.026423	0.052400	-0.002667	...
giro_mailing	0.054532	-0.089840	0.044425	...

	volume_debit	volume_debit_6months	ext_city_size \
cross_buy	0.004752	0.009107	0.003590
acad_title	0.033654	0.063094	0.056620
age	0.071497	0.129426	-0.006993
calls	0.025303	0.051731	0.009223
complaints	0.012073	0.025577	0.006214
customer_tenure_months	0.050782	0.081041	-0.015300
directmails	0.017487	0.035098	0.020206
gender	0.012378	0.017588	0.005032
joint_account	-0.004712	-0.005617	-0.052038
inflows	0.190881	0.232633	0.009528
last_acc_opening_days	-0.005420	-0.019670	-0.021383
logins_desktop	0.076987	0.124372	0.000187
logins_mobile	0.026915	0.045893	0.008981
member_get_member_active	0.014987	0.029838	0.002801
member_get_member_passive	0.000352	0.002767	0.007130
nr_products	0.109444	0.190212	0.018215
outflows	-0.158221	-0.424953	-0.004442
prod_loan	-0.049536	-0.083790	-0.023308
prod_mortgages	-0.034506	-0.060009	0.004798
prod_brokerage	0.140670	0.247727	0.027899
prod_pensionplan	0.021139	0.039274	-0.005896
prod_savings	0.083256	0.141969	0.007125
relocations	-0.009145	-0.015994	0.021371
volume_debit	1.000000	0.612161	0.013689
volume_debit_6months	0.612161	1.000000	0.017154
ext_city_size	0.013689	0.017154	1.000000
ext_house_size	-0.007614	-0.010971	0.451141
ext_purchase_power	0.030468	0.050879	0.098991
ext_share_new_houses	-0.007203	-0.012238	-0.239034
ext_share_new_cars	0.026716	0.046391	0.073007
ext_car_power	0.024850	0.042948	0.065945
ext_living_duration	0.014172	0.033426	-0.088390

giro_mailing	-0.004722	-0.008093	0.016330
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	ext_house_size	ext_purchase_power \
cross_buy	0.019381	0.015075
acad_title	0.004447	0.052988
age	-0.059520	0.011680
calls	0.012980	0.004424
complaints	0.005924	0.009849
customer_tenure_months	-0.061752	-0.003221
directmails	0.033382	0.011723
gender	0.030996	-0.002775
joint_account	-0.117709	0.023079
inflows	-0.009599	0.036708
last_acc_opening_days	-0.049470	-0.025504
logins_desktop	0.006230	0.019049
logins_mobile	0.019784	0.011753
member_get_member_active	0.004710	0.003044
member_get_member_passive	0.011572	0.002823
nr_products	-0.025351	0.065181
outflows	0.014802	-0.028468
prod_loan	0.022999	-0.038335
prod_mortgages	-0.062665	0.038343
prod_brokerage	0.009465	0.066249
prod_pensionplan	-0.002977	-0.003345
prod_savings	-0.005448	0.027171
relocations	0.068742	-0.015441
volume_debit	-0.007614	0.030468
volume_debit_6months	-0.010971	0.050879
ext_city_size	0.451141	0.098991
ext_house_size	1.000000	-0.187804
ext_purchase_power	-0.187804	1.000000
ext_share_new_houses	-0.119239	-0.012093
ext_share_new_cars	-0.058746	0.161210
ext_car_power	-0.015200	0.180932
ext_living_duration	-0.141131	-0.021162
giro_mailing	0.037636	0.008221

	ext_share_new_houses	ext_share_new_cars \
cross_buy	0.004484	-0.006054
acad_title	-0.013002	0.029723
age	-0.025952	0.077255
calls	-0.004475	0.007583
complaints	-0.003605	0.005436
customer_tenure_months	-0.011169	0.041144
directmails	-0.001411	-0.012223
gender	0.000886	-0.020855
joint_account	0.015665	0.019138

inflows	0.004767	0.019496
last_acc_opening_days	-0.004915	0.021040
logins_desktop	0.001205	0.007124
logins_mobile	-0.000421	0.002445
member_get_member_active	-0.002535	-0.001395
member_get_member_passive	-0.000270	-0.001042
nr_products	0.001934	0.030629
outflows	0.000181	-0.016452
prod_loan	0.002571	-0.043396
prod_mortgages	0.023283	0.004463
prod_brokerage	-0.005131	0.029828
prod_pensionplan	-0.005805	0.003933
prod_savings	-0.014495	0.037408
relocations	0.001984	-0.009040
volume_debit	-0.007203	0.026716
volume_debit_6months	-0.012238	0.046391
ext_city_size	-0.239034	0.073007
ext_house_size	-0.119239	-0.058746
ext_purchase_power	-0.012093	0.161210
ext_share_new_houses	1.000000	-0.070569
ext_share_new_cars	-0.070569	1.000000
ext_car_power	-0.037692	0.146037
ext_living_duration	-0.013951	0.035083
giro_mailing	-0.002204	-0.013015

	ext_car_power	ext_living_duration	giro_mailing
cross_buy	-0.002218	-0.033288	0.130787
acad_title	0.034030	-0.019744	-0.012288
age	0.035650	0.196554	-0.313721
calls	0.008019	-0.008904	0.027957
complaints	0.006597	-0.005177	-0.000039
customer_tenure_months	0.011970	0.147168	-0.177364
directmails	-0.005831	-0.053855	0.270552
gender	0.003049	-0.026423	0.054532
joint_account	-0.008803	0.052400	-0.089840
inflows	0.022106	-0.002667	0.044425
last_acc_opening_days	0.000514	0.113907	-0.209515
logins_desktop	0.010031	0.000953	-0.020129
logins_mobile	0.001145	-0.022142	0.118943
member_get_member_active	0.003921	-0.003746	0.021948
member_get_member_passive	0.003156	-0.007500	0.073406
nr_products	0.023779	-0.004710	0.077915
outflows	-0.021374	-0.006269	-0.013284
prod_loan	-0.021233	-0.056570	0.013612
prod_mortgages	-0.008567	-0.040746	-0.043861
prod_brokerage	0.032512	0.001098	0.129173
prod_pensionplan	0.002607	0.012055	-0.010247

prod_savings	0.025131	0.060480	0.042411
relocations	-0.000892	-0.069009	0.110319
volume_debit	0.024850	0.014172	-0.004722
volume_debit_6months	0.042948	0.033426	-0.008093
ext_city_size	0.065945	-0.088390	0.016330
ext_house_size	-0.015200	-0.141131	0.037636
ext_purchase_power	0.180932	-0.021162	0.008221
ext_share_new_houses	-0.037692	-0.013951	-0.002204
ext_share_new_cars	0.146037	0.035083	-0.013015
ext_car_power	1.000000	0.014130	0.001550
ext_living_duration	0.014130	1.000000	-0.042524
giro_mailing	0.001550	-0.042524	1.000000

[33 rows x 33 columns]

```
[19]: #columns
checking_dt.columns
```

```
[19]: Index(['cross_buy', 'acad_title', 'age', 'calls', 'complaints',
        'customer_tenure_months', 'directmails', 'gender', 'joint_account',
        'inflows', 'last_acc_opening_days', 'logins_desktop', 'logins_mobile',
        'marital_status', 'member_get_member_active',
        'member_get_member_passive', 'nr_products', 'occupation', 'outflows',
        'prod_loan', 'prod_mortgages', 'prod_brokerage', 'prod_pensionplan',
        'prod_savings', 'relocations', 'volume_debit', 'volume_debit_6months',
        'ext_city_size', 'ext_house_size', 'ext_purchase_power',
        'ext_share_new_houses', 'ext_share_new_cars', 'ext_car_power',
        'ext_living_duration', 'giro_mailing'],
        dtype='object')
```

```
[20]: checking_dt['acad_title'].value_counts()
```

```
[20]: 0    97961
      1     2039
      Name: acad_title, dtype: int64
```

```
[21]: checking_dt['complaints'].value_counts()
```

```
[21]: 0    99719
      1     240
      2      25
      3       9
      4       3
      5       2
      6       1
      8       1
      Name: complaints, dtype: int64
```

```
[22]: checking_dt['directmails'].value_counts()
```

```
[22]: 0    71126
      1    17318
      2     7621
      3     2480
      4      744
      5     331
      6     248
      7     112
      8      17
      9       3
      Name: directmails, dtype: int64
```

```
[23]: checking_dt['gender'].value_counts()
```

```
[23]: 0.0    59440
      1.0    40558
      Name: gender, dtype: int64
```

```
[24]: checking_dt['joint_account'].value_counts()
```

```
[24]: 0.0    76331
      1.0    23667
      Name: joint_account, dtype: int64
```

```
[25]: checking_dt['marital_status'].value_counts()
```

```
[25]: married      53394
      single      33889
      unmarried   4559
      divorced    3617
      widowed     1938
      cohabiting  1435
      separated   1168
      Name: marital_status, dtype: int64
```

```
[26]: checking_dt['member_get_member_active'].value_counts()
```

```
[26]: 0    99708
      1     292
      Name: member_get_member_active, dtype: int64
```

```
[27]: checking_dt['member_get_member_passive'].value_counts()
```

```
[27]: 0    99611
      1     389
```

Name: member\_get\_member\_passive, dtype: int64

```
[28]: checking_dt['nr_products'].value_counts()
```

```
[28]: 1      68926
      2      23129
      3       5259
      4       1747
      5        554
      6        237
      7         77
      8         35
      9         16
     11          7
     10          6
     12          3
     15          2
     14          1
     17          1
      Name: nr_products, dtype: int64
```

```
[29]: checking_dt['occupation'].value_counts()
```

```
[29]: white-collar worker    29272
      self-employed         4059
      public servant         3942
      blue-collar worker    3880
      pensioner/retiree     3480
      freelancer            984
      housewife             877
      unemployed            791
      university student    499
      private means         348
      student               290
      apprentice            166
      soldier               137
      Name: occupation, dtype: int64
```

```
[30]: checking_dt['prod_loan'].value_counts()
```

```
[30]: 0      88379
      1     11070
      2       540
      3        10
      4         1
      Name: prod_loan, dtype: int64
```

```
[31]: checking_dt['prod_mortgages'].value_counts()
```

```
[31]: 0      90636
      1       5271
      2       2881
      3        856
      4        246
      5         69
      6         24
      7          9
      8          3
      9          2
     10          1
     13          1
     12          1
      Name: prod_mortgages, dtype: int64
```

```
[32]: checking_dt['prod_brokerage'].value_counts()
```

```
[32]: 0      82282
      1     16352
      2      1155
      3       152
      4        42
      5        13
      8         2
      7         1
     10         1
      Name: prod_brokerage, dtype: int64
```

```
[33]: checking_dt['prod_pensionplan'].value_counts()
```

```
[33]: 0      99703
      1       233
      2        41
      3        12
      4         6
      5         3
      7         1
     11         1
      Name: prod_pensionplan, dtype: int64
```

```
[34]: checking_dt['prod_savings'].value_counts()
```

```
[34]: 1      74872
      0     17983
      2      5765
```

```
3      979
4      254
5      129
6       13
7        2
8        1
10       1
11       1
Name: prod_savings, dtype: int64
```

```
[35]: checking_dt['relocations'].value_counts()
```

```
[35]: 0      95942
      1      3919
      2       126
      3        13
      Name: relocations, dtype: int64
```

```
[36]: checking_dt['ext_city_size'].value_counts()
```

```
[36]: 4.0      18260
      8.0      17987
      3.0      14970
      1.0      13046
      2.0      11425
      5.0       8274
      7.0       7650
      6.0       5726
      Name: ext_city_size, dtype: int64
```

```
[37]: checking_dt['ext_house_size'].value_counts()
```

```
[37]: 1.0      61854
      3.0      12451
      2.0      10427
      4.0       8682
      5.0       3539
      Name: ext_house_size, dtype: int64
```

```
[38]: checking_dt['ext_purchase_power'].value_counts()
```

```
[38]: 7.0      22197
      6.0      16750
      5.0      14529
      4.0      12370
      3.0      10802
      1.0       9491
```



```
2.0      9296
Name: ext_purchase_power, dtype: int64
```

```
[39]: checking_dt['ext_share_new_houses'].value_counts()
```

```
[39]: 1.0      27920
      4.0      20199
      3.0      19860
      2.0      19434
      5.0       9925
      Name: ext_share_new_houses, dtype: int64
```

```
[40]: checking_dt['ext_car_power'].value_counts()
```

```
[40]: 5.0      21521
      1.0      18040
      2.0      18014
      4.0      16864
      3.0      15427
      Name: ext_car_power, dtype: int64
```

```
[41]: checking_dt['ext_living_duration'].value_counts()
```

```
[41]: 9.0      39927
      7.0      17325
      8.0       8529
      4.0       5746
      5.0       5512
      6.0       5372
      3.0       4270
      2.0       2577
      1.0       1677
      Name: ext_living_duration, dtype: int64
```

```
[42]: checking_dt['giro_mailing'].value_counts()
```

```
[42]: 0      89492
      1      10508
      Name: giro_mailing, dtype: int64
```

```
[43]: checking_dt['cross_buy'].value_counts()
```

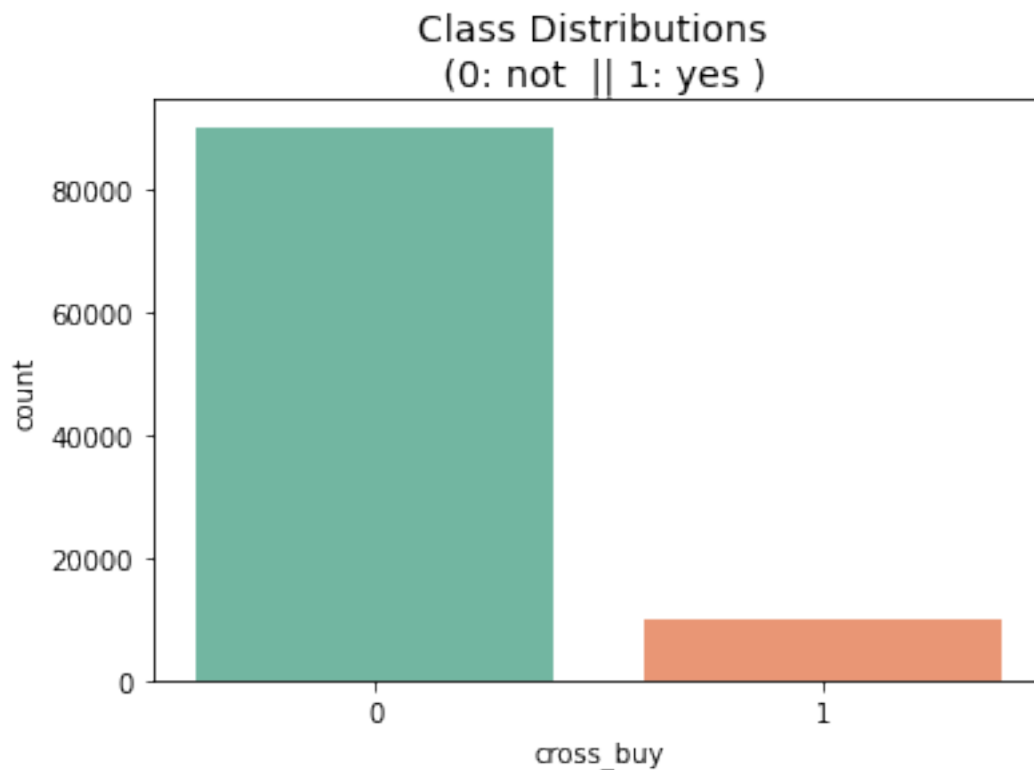
```
[43]: 0      90000
      1      10000
      Name: cross_buy, dtype: int64
```

```
[44]: # The classes are unbalanced
print('no', round(checking_dt['cross_buy'].value_counts()[0]/len(checking_dt) *
↳100,2), '% of the dataset')
print('yes', round(checking_dt['cross_buy'].value_counts()[1]/len(checking_dt)
↳* 100,2), '% of the dataset')
```

no 90.0 % of the dataset  
yes 10.0 % of the dataset

```
[45]: # Visualization of imbalanced data
sns.countplot(checking_dt['cross_buy'], palette = "Set2")
plt.title('Class Distributions \n (0: not || 1: yes )', fontsize=14)
```

```
[45]: Text(0.5, 1.0, 'Class Distributions \n (0: not || 1: yes )')
```

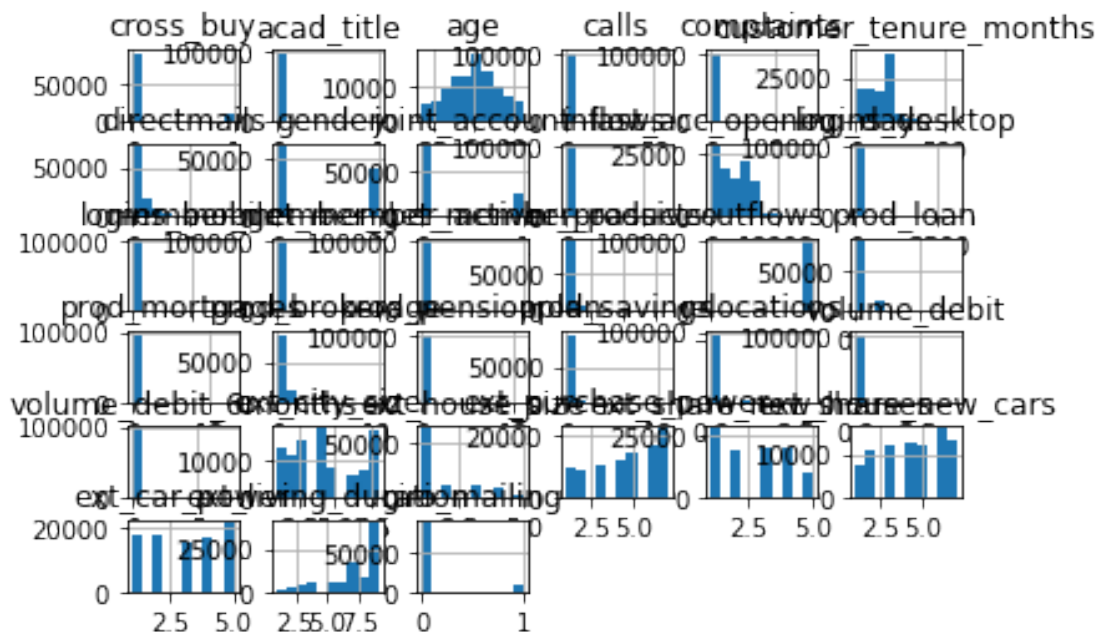


```
[45]:
```

## Exploratory Data Analysis

### Visualization of Numerical Variables

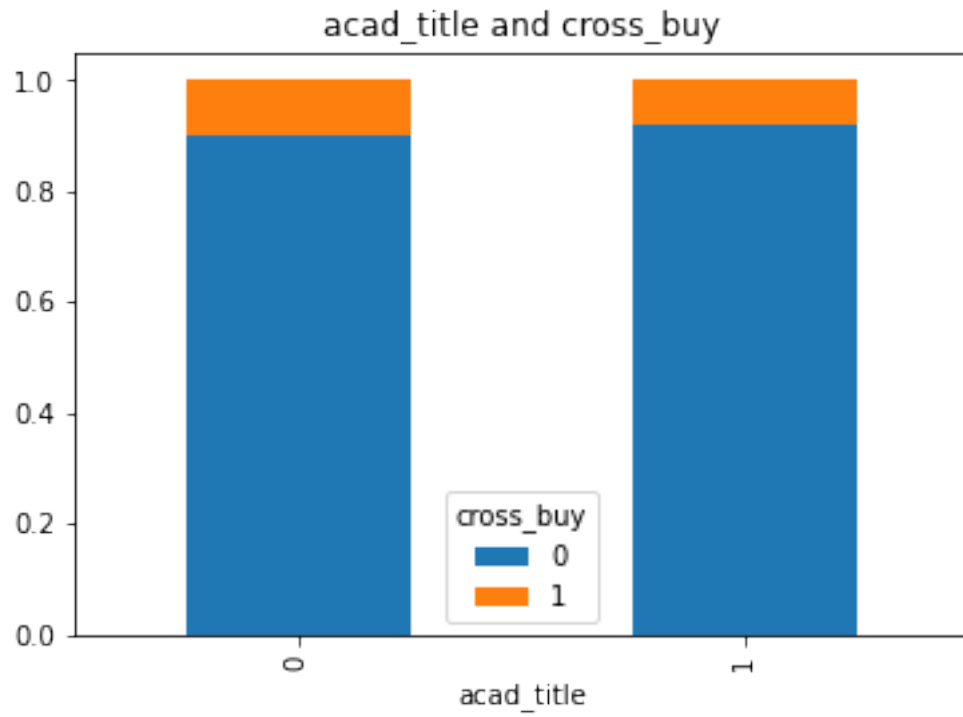
```
[46]: hist = checking_dt.hist()
```



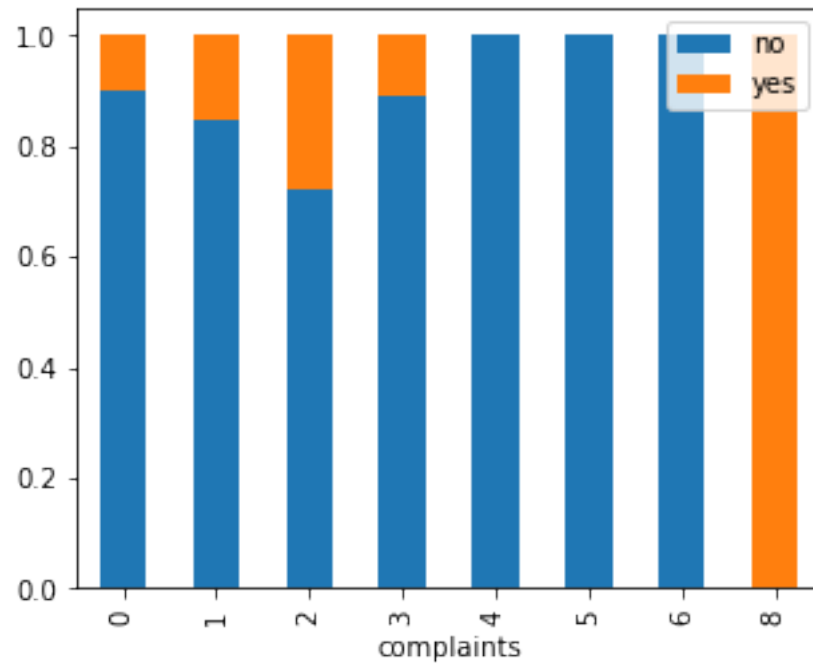
Visualizing the relationship of categorical and the response variable

```
[50]: #Analysing acad_title and cross_buy
crosstab_01=pd.crosstab(checking_dt['acad_title'],checking_dt['cross_buy'])
crosstab_norm1=crosstab_01.div(crosstab_01.sum(1),axis=0)
crosstab_norm1.plot(kind='bar',stacked=True,title="acad_title and cross_buy")
```

```
[50]: <matplotlib.axes._subplots.AxesSubplot at 0x7fecf49b7990>
```



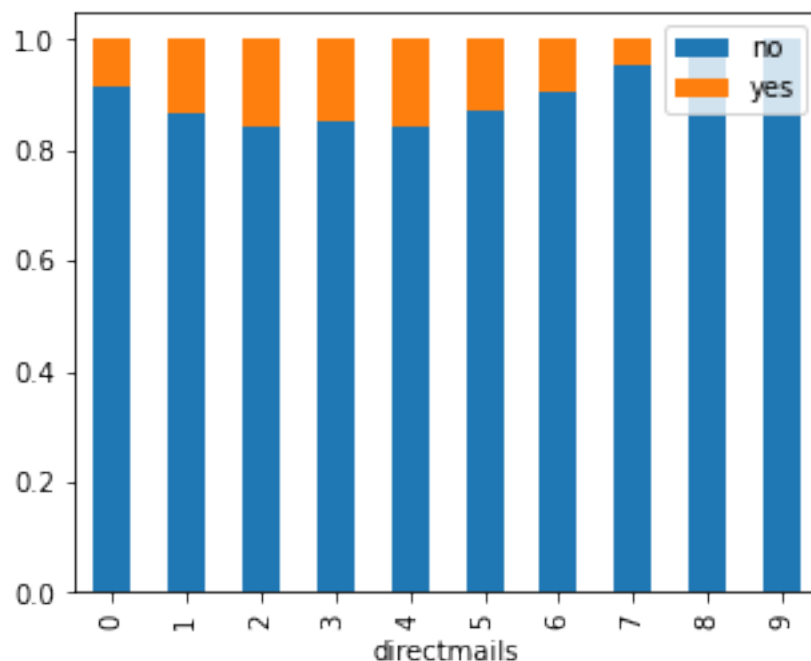
```
[51]: #Analysing complaints and cross_buy  
ax=pd.crosstab(checking_dt.complaints,  
               checking_dt.cross_buy,  
               normalize='index')  
ax.columns=['no','yes']  
ax.plot(kind='bar',stacked=True,figsize=(5,4))  
  
plt.show()  
print(ax)
```



	no	yes
complaints		
0	0.900180	0.099820
1	0.845833	0.154167
2	0.720000	0.280000
3	0.888889	0.111111
4	1.000000	0.000000
5	1.000000	0.000000
6	1.000000	0.000000
8	0.000000	1.000000

```
[52]: #Analysing directmails and cross_buy
ax=pd.crosstab(checking_dt.directmails,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

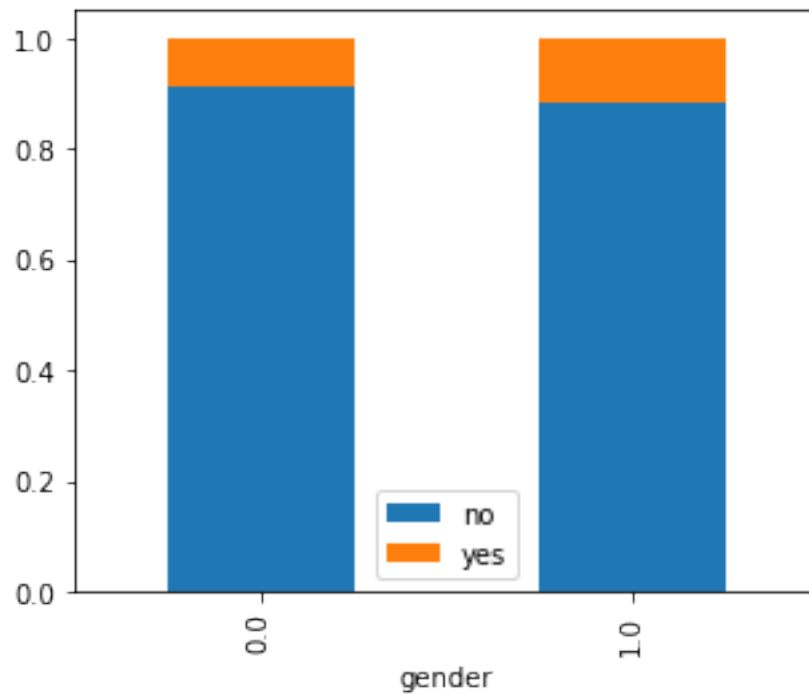
plt.show()
print(ax)
```



	no	yes
directmails		
0	0.916838	0.083162
1	0.865285	0.134715
2	0.843721	0.156279
3	0.850806	0.149194
4	0.840054	0.159946
5	0.870091	0.129909
6	0.903226	0.096774
7	0.955357	0.044643
8	1.000000	0.000000
9	1.000000	0.000000

```
[53]: #Analysing gender and cross_buy
ax=pd.crosstab(checking_dt.gender,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

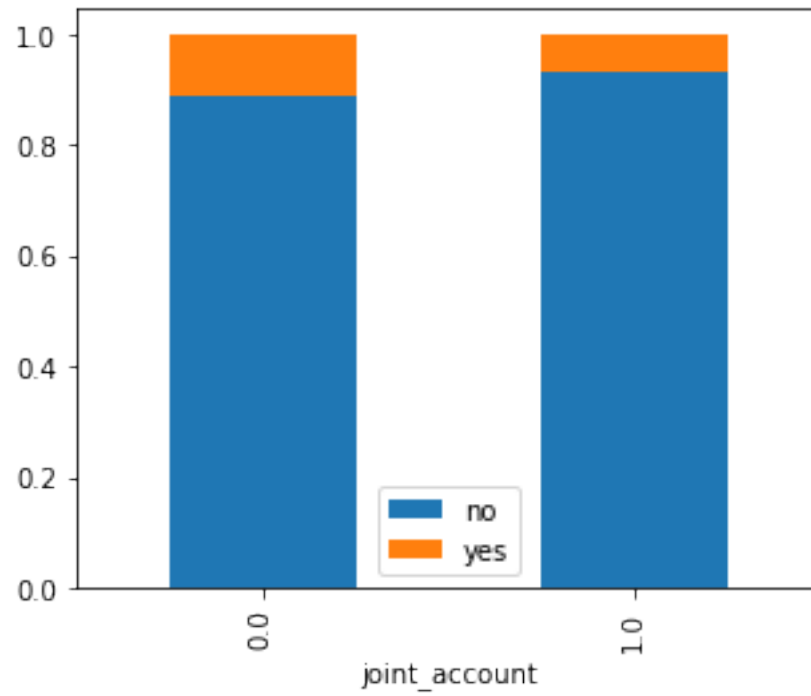
plt.show()
print(ax)
```



	no	yes
gender		
0.0	0.910347	0.089653
1.0	0.884832	0.115168

```
[54]: #Analysing joint_account and cross_buy
ax=pd.crosstab(checking_dt.joint_account,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

plt.show()
print(ax)
```

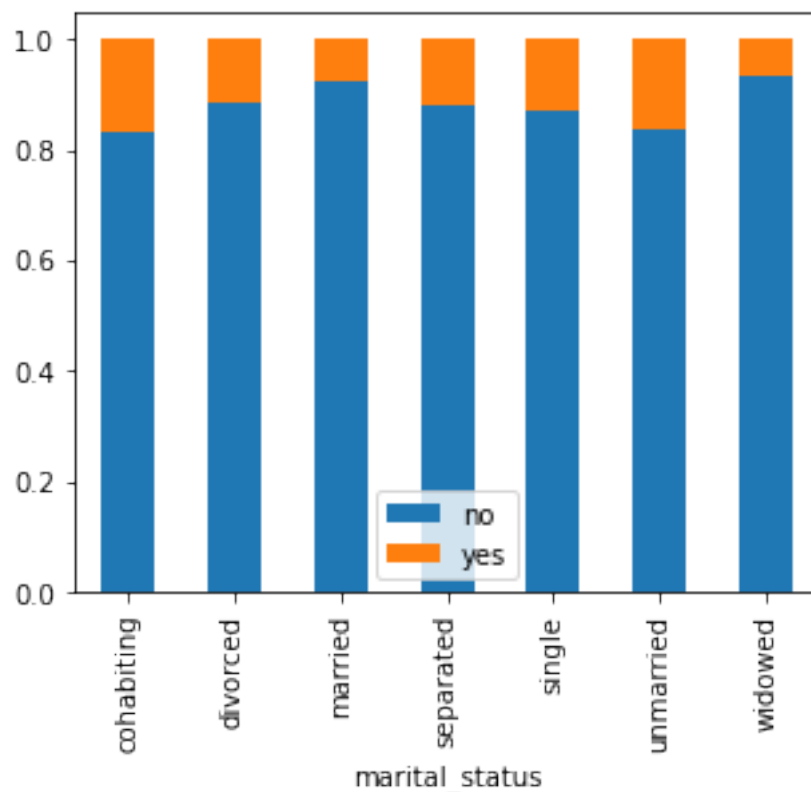


	no	yes
joint_account		
0.0	0.889573	0.110427
1.0	0.933621	0.066379

```
[55]: #Analysing marital_status and cross_buy
ax=pd.crosstab(checking_dt.marital_status,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no', 'yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

plt.show()
print(ax)
```

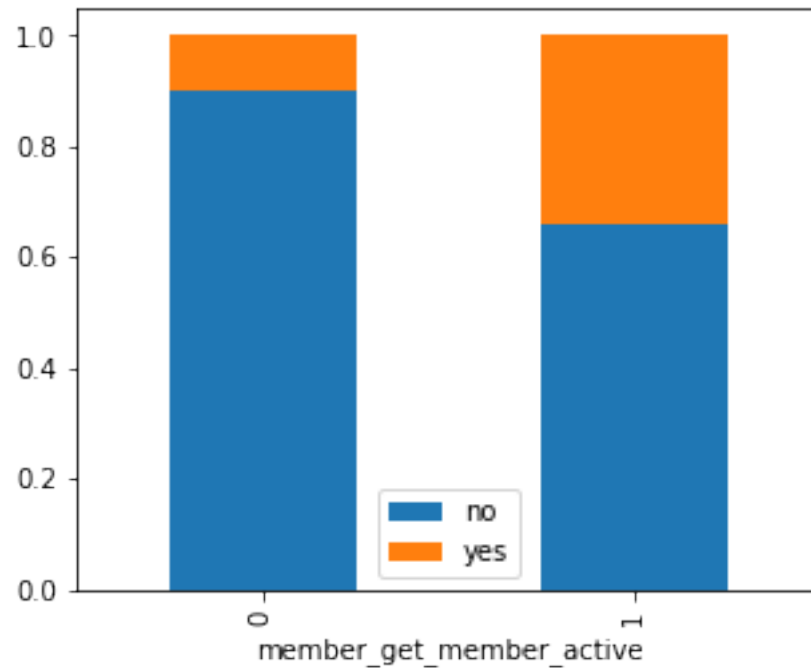




	no	yes
marital_status		
cohabiting	0.832056	0.167944
divorced	0.883605	0.116395
married	0.924748	0.075252
separated	0.880993	0.119007
single	0.872614	0.127386
unmarried	0.838342	0.161658
widowed	0.934469	0.065531

```
[56]: #Analysing member_get_member_active and cross_buy
ax=pd.crosstab(checking_dt.member_get_member_active,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

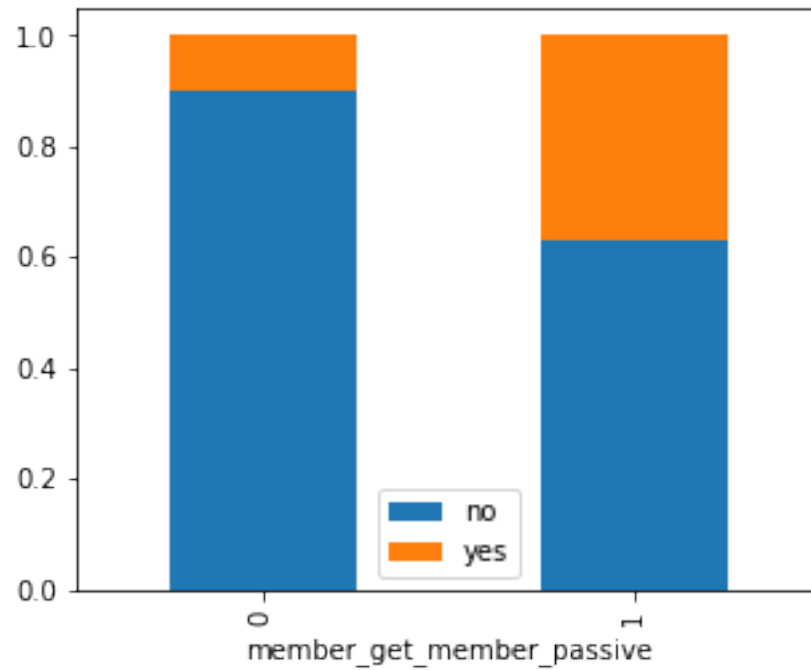
plt.show()
print(ax)
```



	no	yes
member_get_member_active		
0	0.900700	0.099300
1	0.660959	0.339041

```
[57]: #Analysing member_get_member_passive and cross_buy
ax=pd.crosstab(checking_dt.member_get_member_passive,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

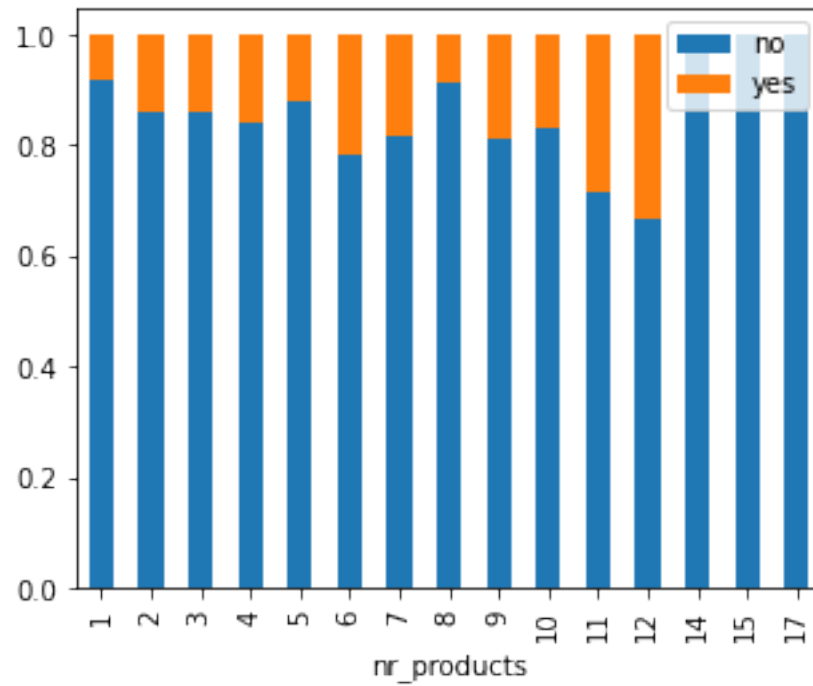
plt.show()
print(ax)
```



	no	yes
member_get_member_passive		
0	0.901055	0.098945
1	0.629820	0.370180

```
[58]: #Analysing nr_products and cross_buy
ax=pd.crosstab(checking_dt.nr_products,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

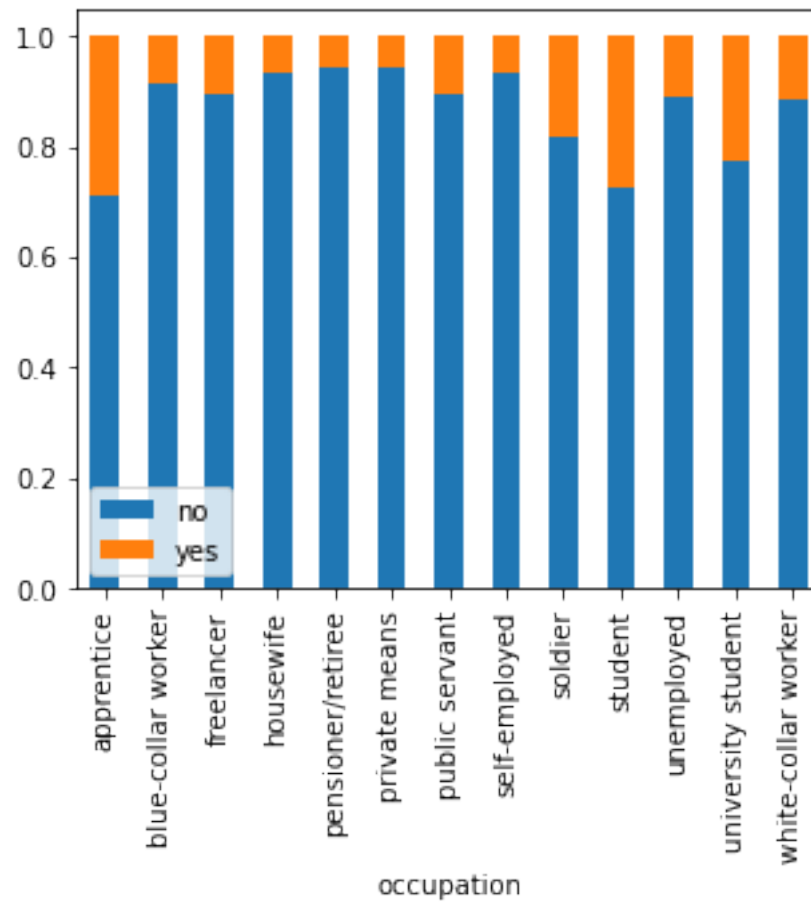
plt.show()
print(ax)
```



nr_products	no	yes
1	0.917767	0.082233
2	0.862164	0.137836
3	0.862521	0.137479
4	0.840870	0.159130
5	0.879061	0.120939
6	0.780591	0.219409
7	0.818182	0.181818
8	0.914286	0.085714
9	0.812500	0.187500
10	0.833333	0.166667
11	0.714286	0.285714
12	0.666667	0.333333
14	1.000000	0.000000
15	1.000000	0.000000
17	1.000000	0.000000

```
[59]: #Analysing occupation and cross_buy
ax=pd.crosstab(checking_dt.occupation,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))
```

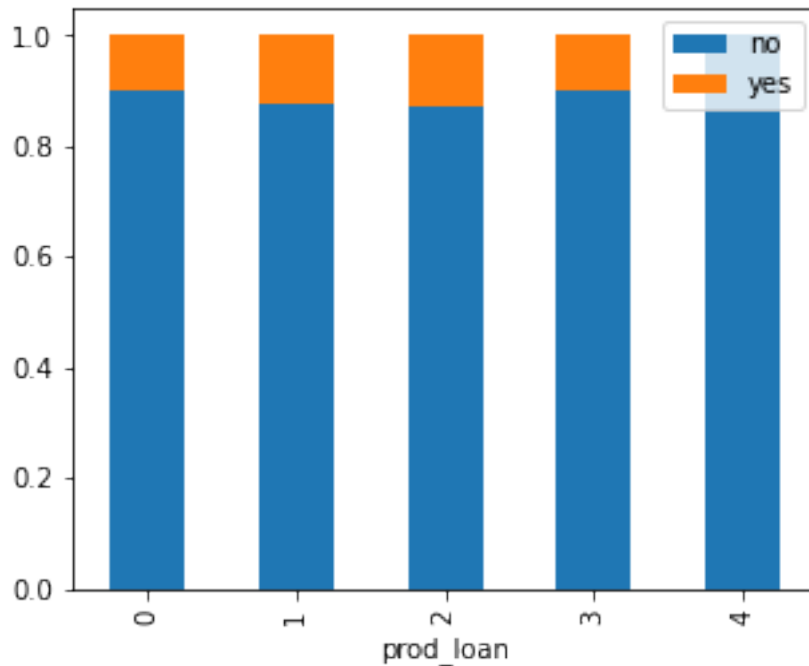
```
plt.show()
print(ax)
```



	no	yes
occupation		
apprentice	0.710843	0.289157
blue-collar worker	0.915206	0.084794
freelancer	0.893293	0.106707
housewife	0.931585	0.068415
pensioner/retiree	0.941667	0.058333
private means	0.942529	0.057471
public servant	0.896499	0.103501
self-employed	0.932742	0.067258
soldier	0.817518	0.182482
student	0.724138	0.275862
unemployed	0.891277	0.108723
university student	0.775551	0.224449
white-collar worker	0.883472	0.116528

```
[60]: #Analysing prod_loan and cross_buy
ax=pd.crosstab(checking_dt.prod_loan,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

plt.show()
print(ax)
```



	no	yes
prod_loan		
0	0.903031	0.096969
1	0.877236	0.122764
2	0.870370	0.129630
3	0.900000	0.100000
4	1.000000	0.000000

```
[61]: #Analysing prod_mortgages and cross_buy
ax=pd.crosstab(checking_dt.prod_mortgages,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))
```

```
plt.show()
print(ax)
```

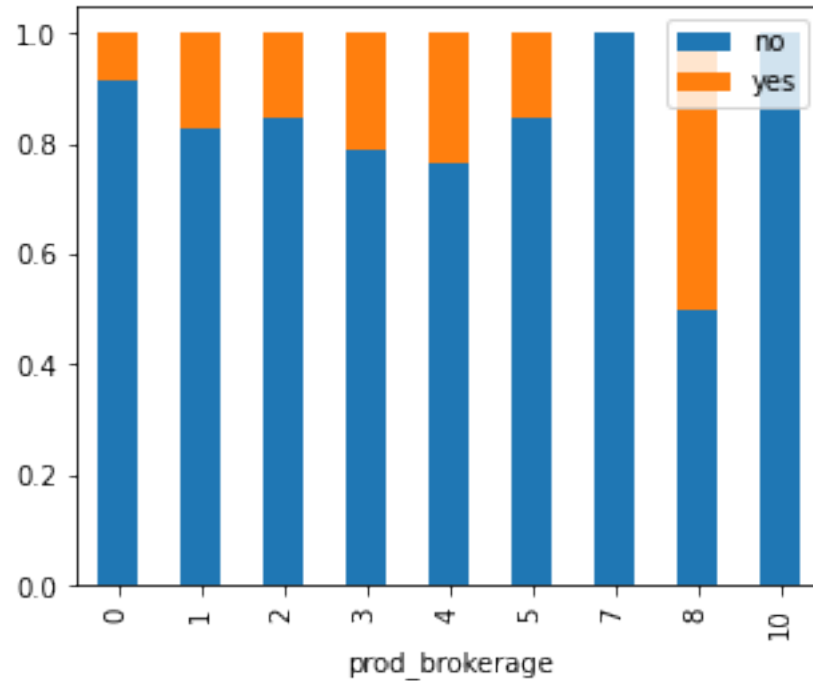


	no	yes
prod_mortgages		
0	0.899047	0.100953
1	0.905141	0.094859
2	0.919125	0.080875
3	0.899533	0.100467
4	0.906504	0.093496
5	0.942029	0.057971
6	0.916667	0.083333
7	0.888889	0.111111
8	1.000000	0.000000
9	0.500000	0.500000
10	1.000000	0.000000
12	1.000000	0.000000
13	1.000000	0.000000

```
[62]: #Analysing prod_brokerage and cross_buy
ax=pd.crosstab(checking_dt.prod_brokerage,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no', 'yes']
```

```
ax.plot(kind='bar',stacked=True,figsize=(5,4))

plt.show()
print(ax)
```

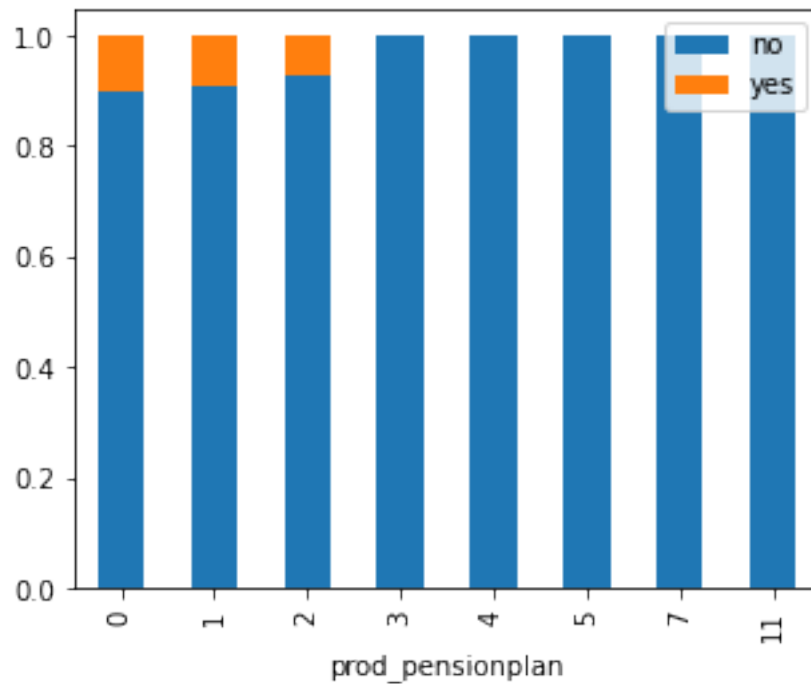


	no	yes
prod_brokerage		
0	0.915109	0.084891
1	0.829195	0.170805
2	0.846753	0.153247
3	0.789474	0.210526
4	0.761905	0.238095
5	0.846154	0.153846
7	1.000000	0.000000
8	0.500000	0.500000
10	1.000000	0.000000

```
[63]: #Analysing prod_pensionplan and cross_buy
ax=pd.crosstab(checking_dt.prod_pensionplan,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))
```



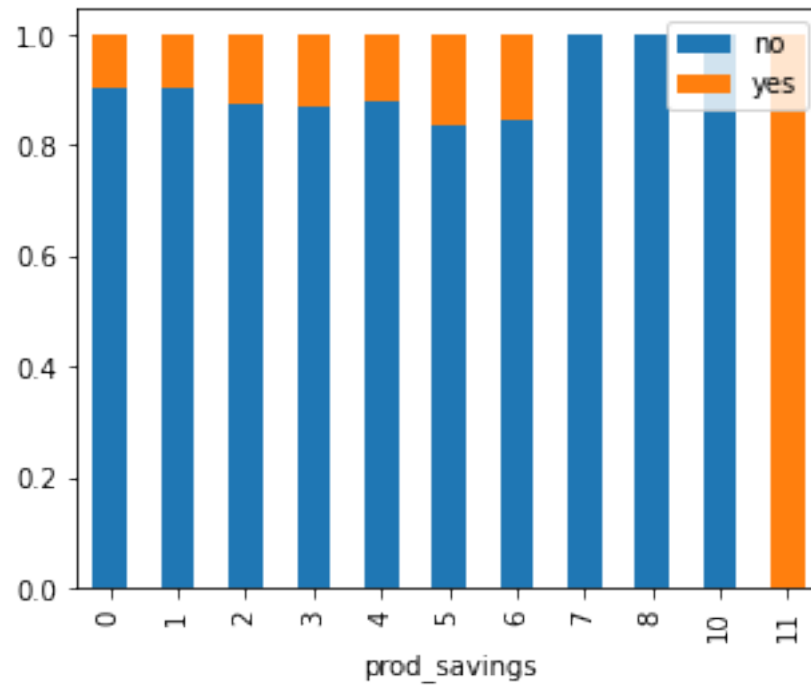
```
plt.show()
print(ax)
```



	no	yes
prod_pensionplan		
0	0.899943	0.100057
1	0.909871	0.090129
2	0.926829	0.073171
3	1.000000	0.000000
4	1.000000	0.000000
5	1.000000	0.000000
7	1.000000	0.000000
11	1.000000	0.000000

```
[64]: #Analysing prod_savings and cross_buy
ax=pd.crosstab(checking_dt.prod_savings,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no', 'yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

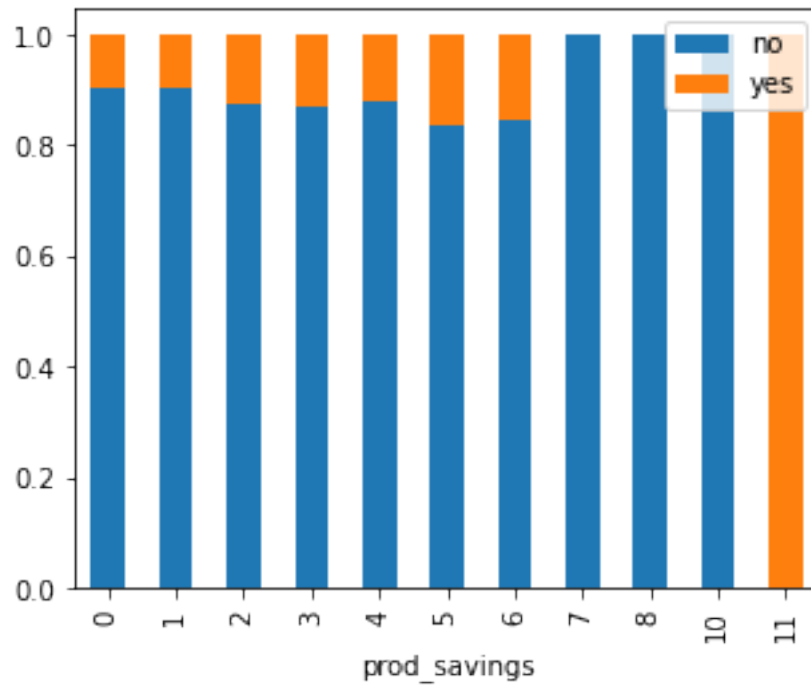
plt.show()
print(ax)
```



	no	yes
prod_savings		
0	0.903742	0.096258
1	0.901552	0.098448
2	0.875976	0.124024
3	0.869254	0.130746
4	0.877953	0.122047
5	0.837209	0.162791
6	0.846154	0.153846
7	1.000000	0.000000
8	1.000000	0.000000
10	1.000000	0.000000
11	0.000000	1.000000

```
[65]: #Analysing prod_savings and cross_buy
ax=pd.crosstab(checking_dt.prod_savings,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

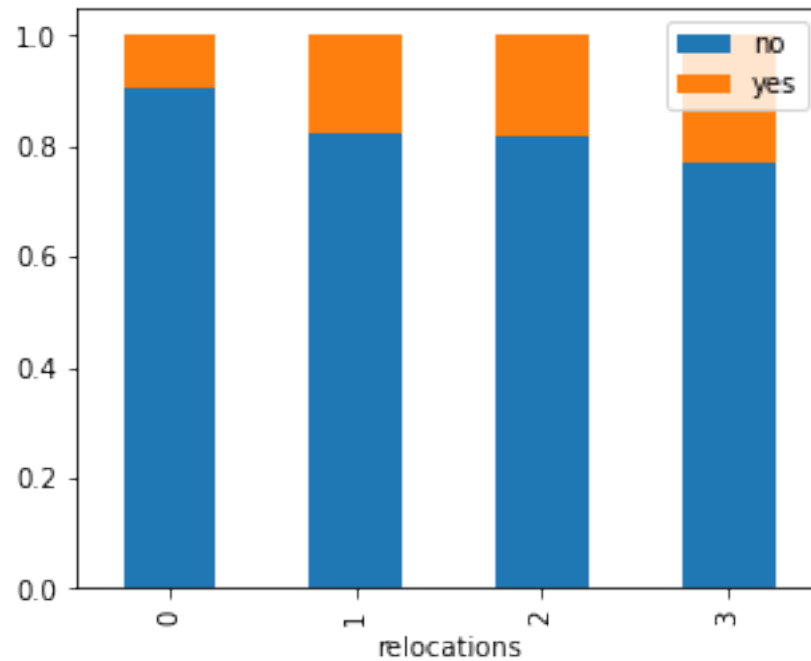
plt.show()
print(ax)
```



	no	yes
prod_savings		
0	0.903742	0.096258
1	0.901552	0.098448
2	0.875976	0.124024
3	0.869254	0.130746
4	0.877953	0.122047
5	0.837209	0.162791
6	0.846154	0.153846
7	1.000000	0.000000
8	1.000000	0.000000
10	1.000000	0.000000
11	0.000000	1.000000

```
[66]: #Analysing relocations and cross_buy
ax=pd.crosstab(checking_dt.relocations,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no', 'yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

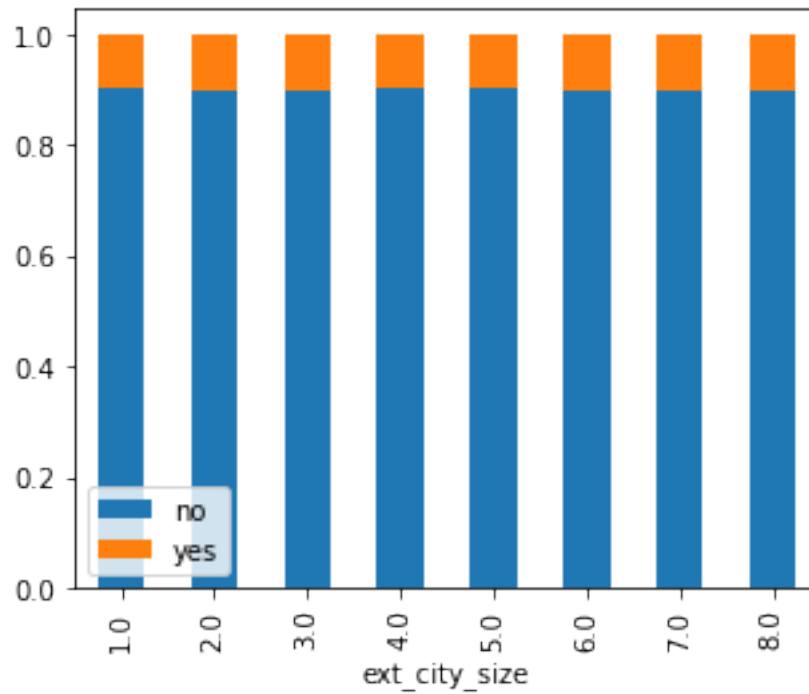
plt.show()
print(ax)
```



	no	yes
relocations		
0	0.903192	0.096808
1	0.824955	0.175045
2	0.817460	0.182540
3	0.769231	0.230769

```
[67]: #Analysing ext_city_size and cross_buy
ax=pd.crosstab(checking_dt.ext_city_size,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

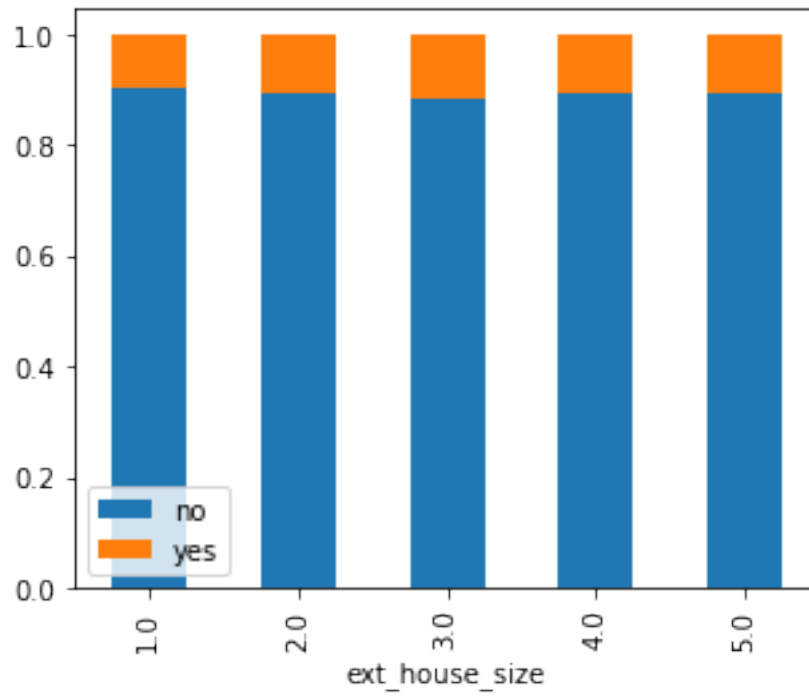
plt.show()
print(ax)
```



	no	yes
ext_city_size		
1.0	0.900736	0.099264
2.0	0.900481	0.099519
3.0	0.897595	0.102405
4.0	0.905422	0.094578
5.0	0.900774	0.099226
6.0	0.899930	0.100070
7.0	0.897255	0.102745
8.0	0.897482	0.102518

```
[68]: #Analysing ext_house_size and cross_buy
ax=pd.crosstab(checking_dt.ext_house_size,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

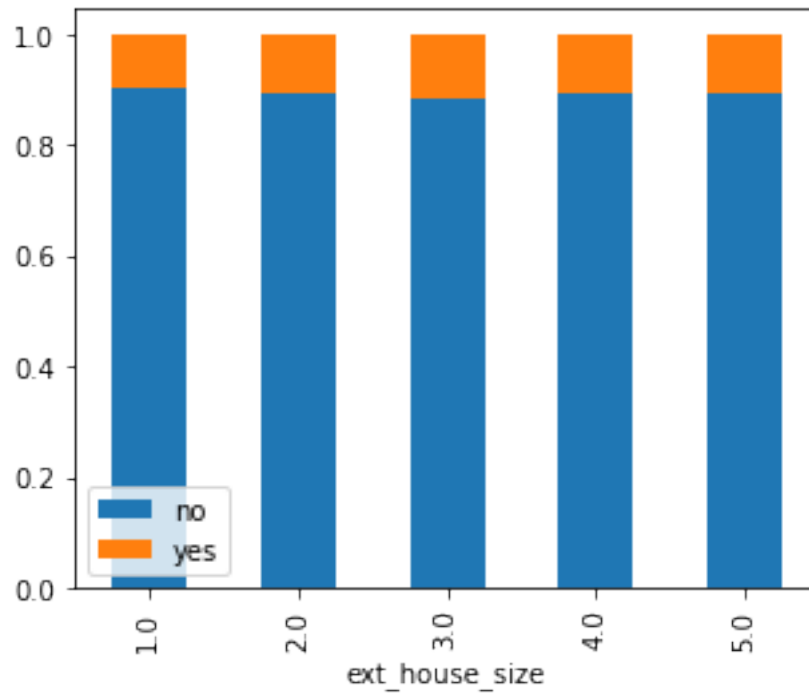
plt.show()
print(ax)
```



	no	yes
ext_house_size		
1.0	0.905406	0.094594
2.0	0.894984	0.105016
3.0	0.885069	0.114931
4.0	0.893803	0.106197
5.0	0.895733	0.104267

```
[69]: #Analysing ext_house_size and cross_buy
ax=pd.crosstab(checking_dt.ext_house_size,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no', 'yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

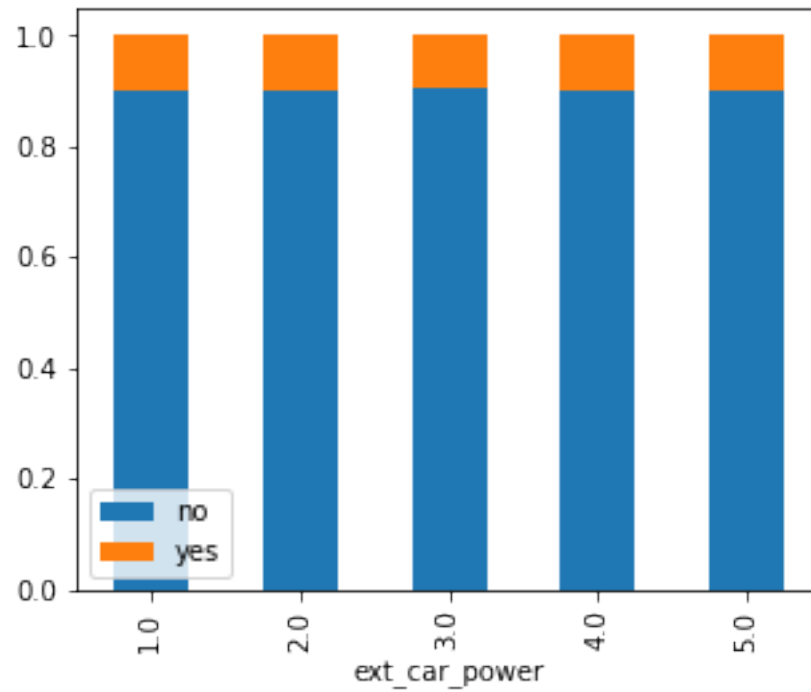
plt.show()
print(ax)
```



	no	yes
ext_house_size		
1.0	0.905406	0.094594
2.0	0.894984	0.105016
3.0	0.885069	0.114931
4.0	0.893803	0.106197
5.0	0.895733	0.104267

```
[70]: #Analysing ext_car_power and cross_buy
ax=pd.crosstab(checking_dt.ext_car_power,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no', 'yes']
ax.plot(kind='bar', stacked=True, figsize=(5,4))

plt.show()
print(ax)
```

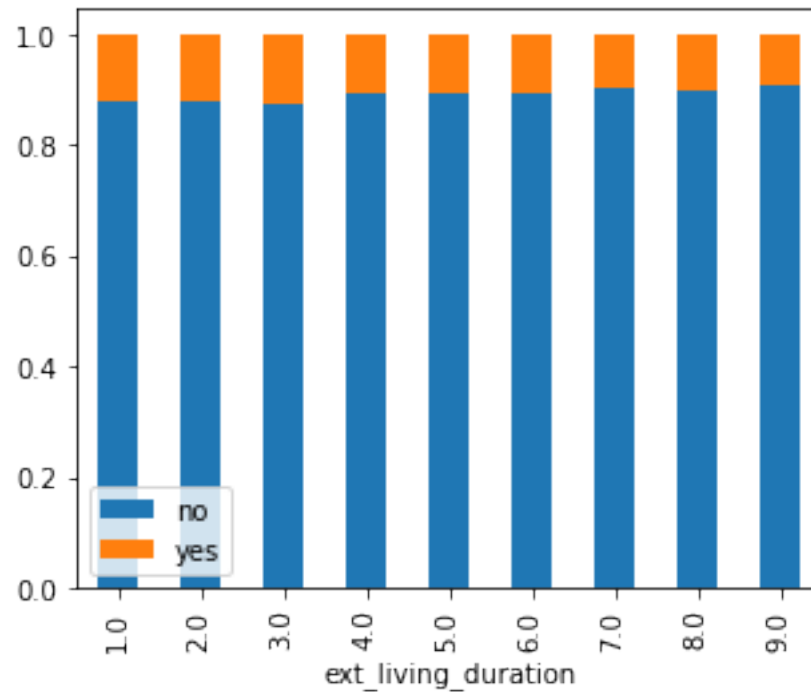


	no	yes
ext_car_power		
1.0	0.899390	0.100610
2.0	0.899689	0.100311
3.0	0.903935	0.096065
4.0	0.900024	0.099976
5.0	0.901492	0.098508

```
[71]: #Analysing ext_living_duration and cross_buy
ax=pd.crosstab(checking_dt.ext_living_duration,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no','yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

plt.show()
print(ax)
```

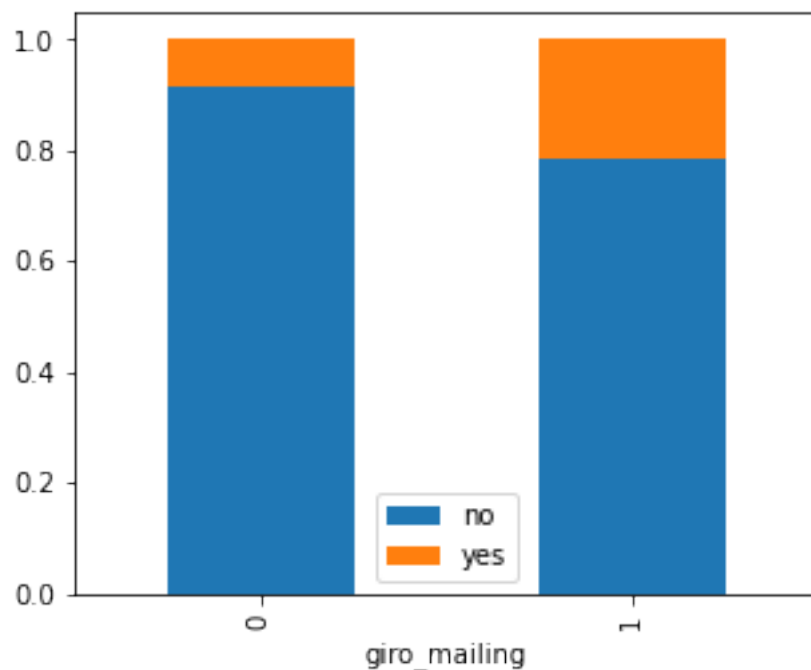




	no	yes
ext_living_duration		
1.0	0.878951	0.121049
2.0	0.879317	0.120683
3.0	0.874239	0.125761
4.0	0.891229	0.108771
5.0	0.892054	0.107946
6.0	0.893150	0.106850
7.0	0.902222	0.097778
8.0	0.899168	0.100832
9.0	0.910186	0.089814

```
[72]: #Analysing giro_mailing and cross_buy
ax=pd.crosstab(checking_dt.giro_mailing,
               checking_dt.cross_buy,
               normalize='index')
ax.columns=['no', 'yes']
ax.plot(kind='bar',stacked=True,figsize=(5,4))

plt.show()
print(ax)
```



	no	yes
giro_mailing		
0	0.913445	0.086555
1	0.785497	0.214503

Checking skewness

```
[73]: checking_dt.skew()
```

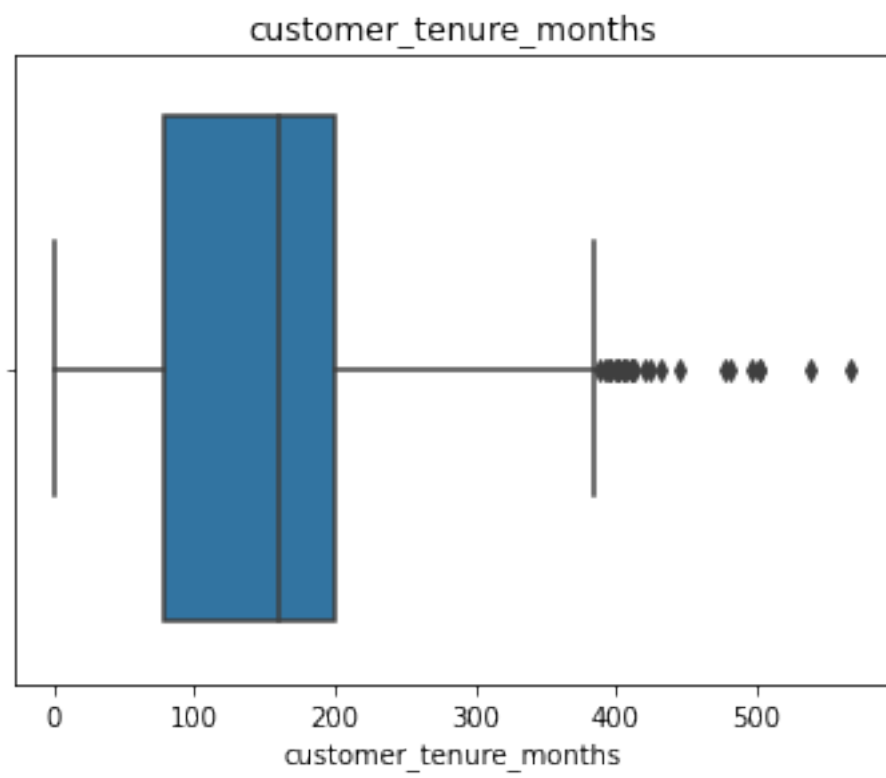
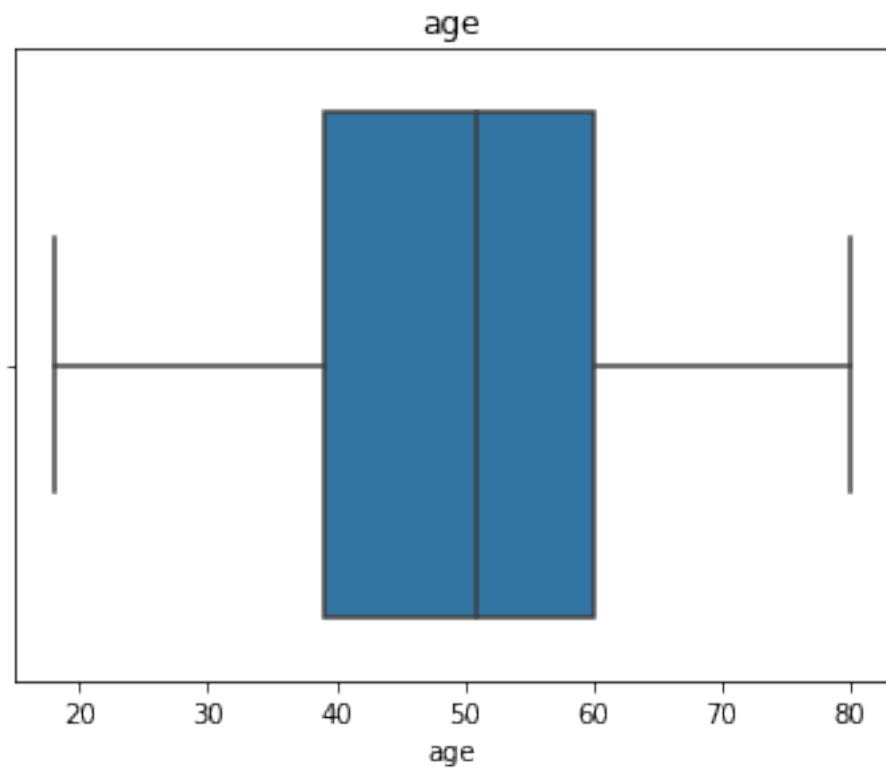
```
[73]: cross_buy          2.666707
      acad_title         6.787182
      age               -0.061094
      calls             21.114449
      complaints        38.029591
      customer_tenure_months -0.198338
      directmails        2.709763
      gender             0.384571
      joint_account       1.239077
      inflows            27.071333
      last_acc_opening_days  0.187719
      logins_desktop      25.147134
      logins_mobile       14.612906
      member_get_member_active 18.424952
      member_get_member_passive 15.939916
      nr_products         2.952820
      outflows           -48.451305
```

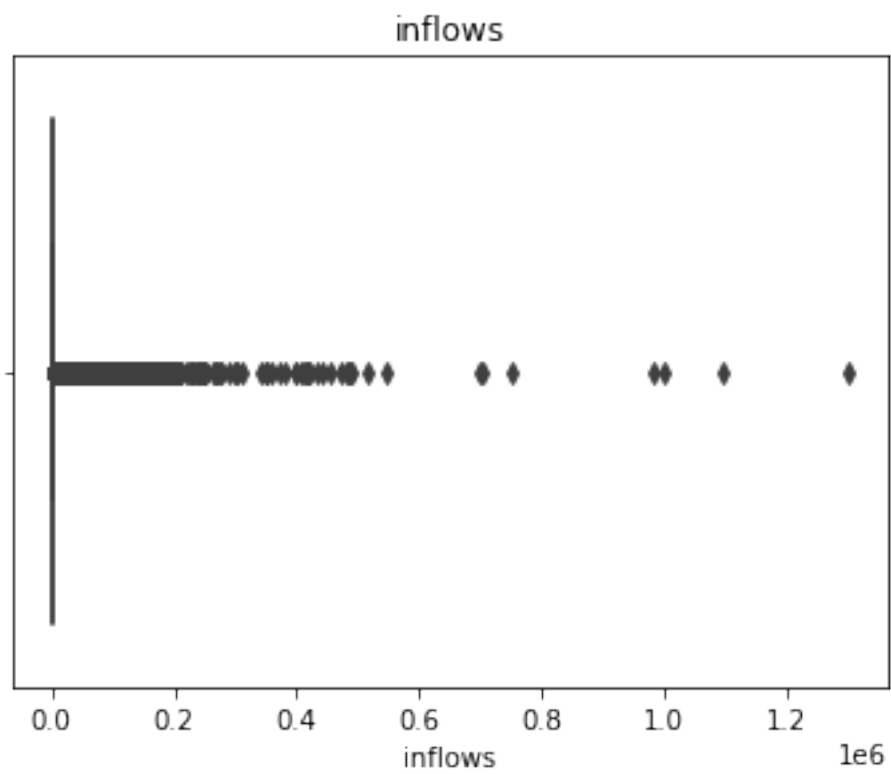
prod_loan	2.747877
prod_mortgages	4.765646
prod_brokerage	2.723816
prod_pensionplan	42.633866
prod_savings	1.302325
relocations	5.179200
volume_debit	196.292726
volume_debit_6months	34.933565
ext_city_size	0.234372
ext_house_size	1.282385
ext_purchase_power	-0.385338
ext_share_new_houses	0.227788
ext_share_new_cars	-0.176475
ext_car_power	-0.037989
ext_living_duration	-1.089300
giro_mailing	2.575689
dtype:	float64

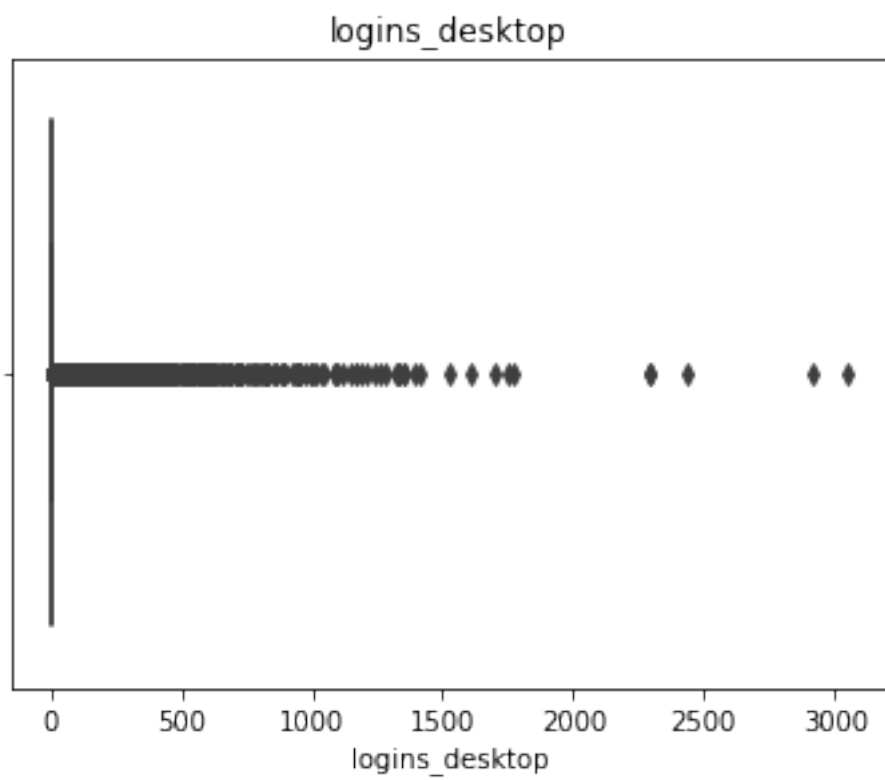
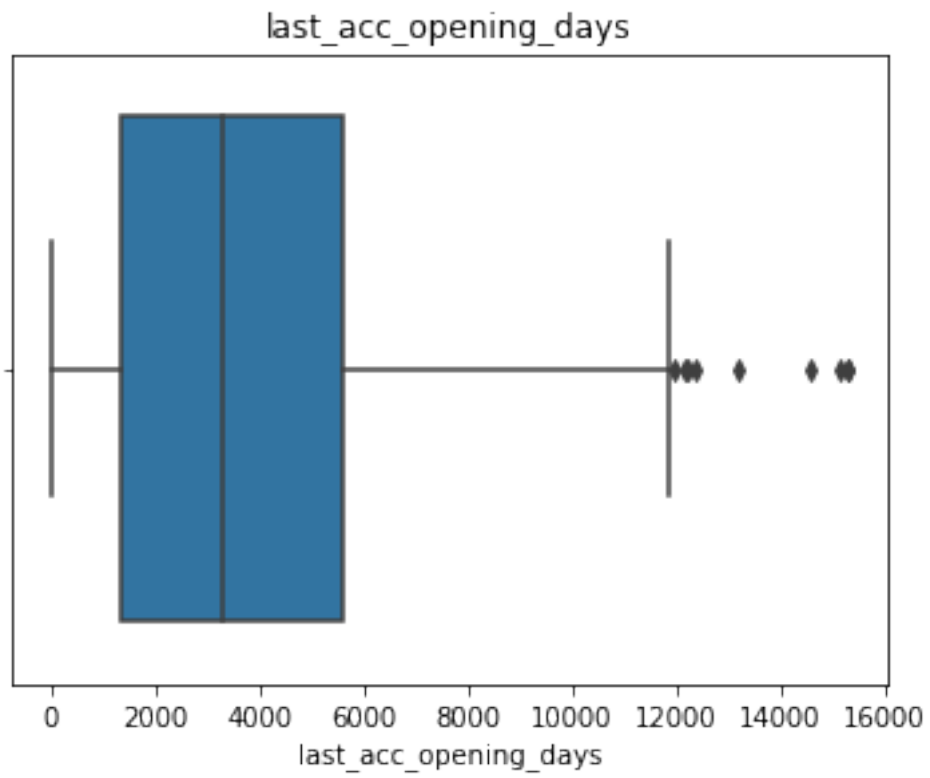
Visualizing Outliers

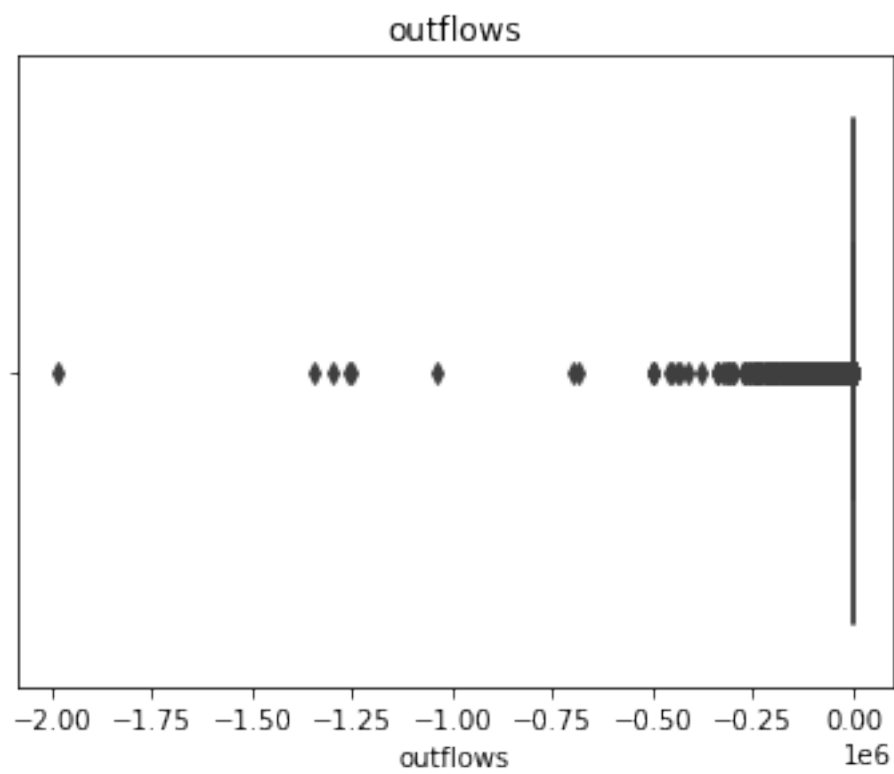
```
[74]: # Visualizing each variables outlier
col=checking_dt[['age','customer_tenure_months','inflows',
                 'last_acc_opening_days','logins_desktop',
                 'outflows','volume_debit','volume_debit_6months']]

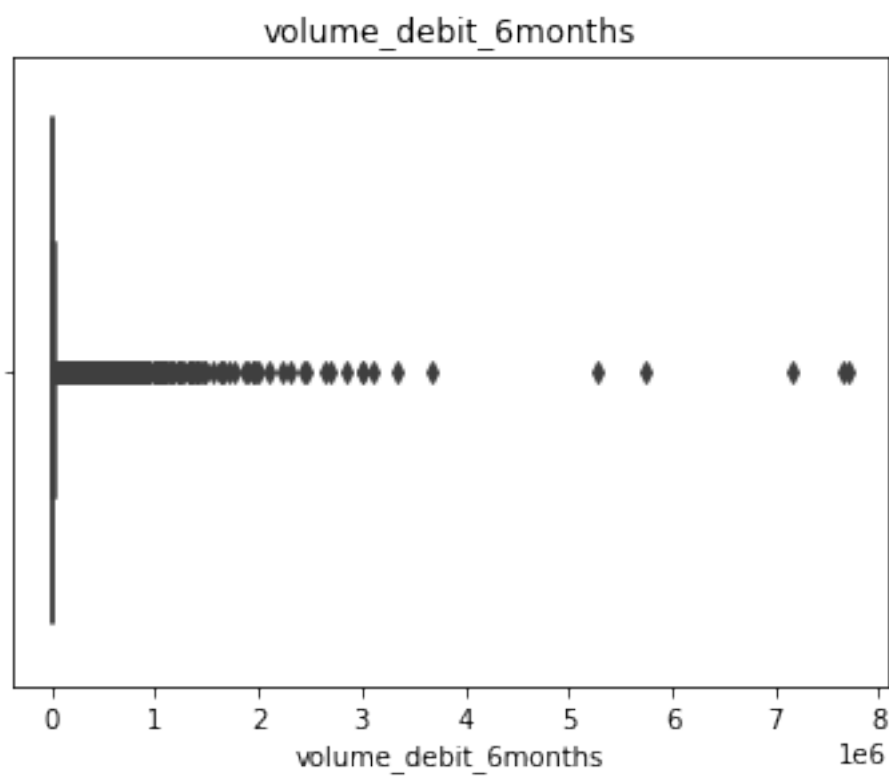
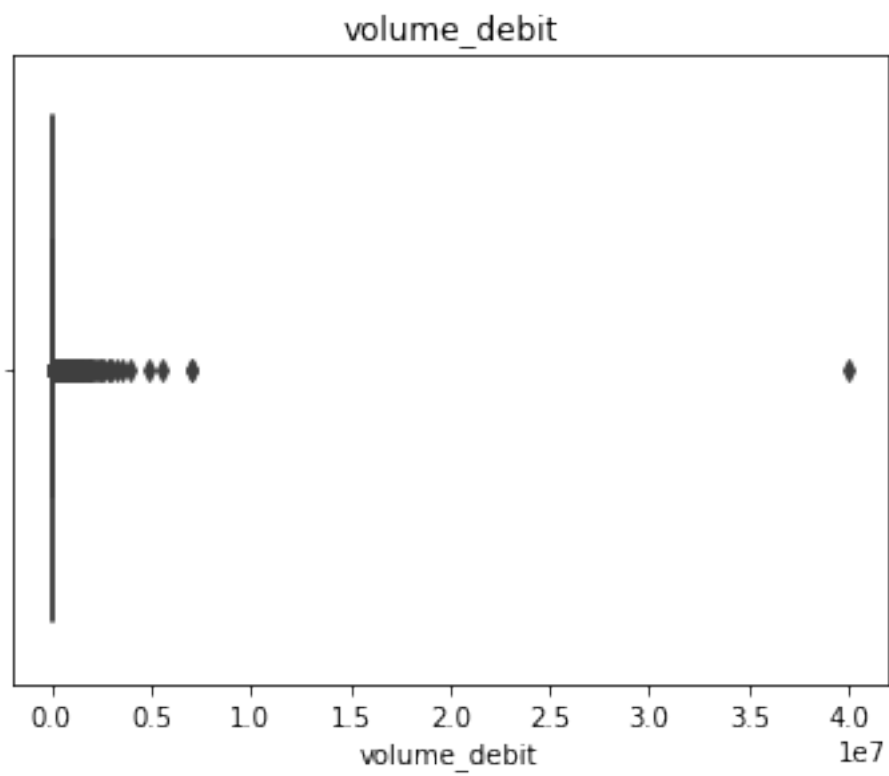
for i in col:
    n=1
    plt.figure(figsize=(20,20))
    plt.subplot(4,3,1)
    sns.boxplot(checking_dt[i])
    plt.title(i)
    plt.show()
    n=n+1
```













### Dropping unrelated columns

## Removing Outliers

## Handling missing values

```
#imputation with most frequent  
checking_dt[['gender',  
             'joint_account',  
             'ext_city_size',  
             'ext_house_size',  
             'ext_house_size',  
             'ext_purchase_power',  
             'ext_share_new_houses',  
             'ext_share_new_cars',  
             'ext_car_power',  
             'ext_living_duration']] = pd.DataFrame(mode_imputer.  
↳ fit_transform(checking_dt[['gender',  
                               ↳ 'joint_account',  
                               ↳ 'ext_city_size',  
                               ↳ 'ext_house_size',
```

```

↳      'ext_house_size',
↳      'ext_purchase_power',
↳      'ext_share_new_houses',
↳      'ext_share_new_cars',
↳      'ext_car_power',
↳      'ext_living_duration']])))

```

```
[78]: checking_dt.isna().sum()
```

```

[78]: cross_buy          0
      acad_title        0
      age              0
      calls            0
      complaints       0
      customer_tenure_months 0
      directmails      0
      gender           0
      joint_account    0
      inflows          0
      last_acc_opening_days 0
      logins_desktop   0
      logins_mobile    0
      marital_status   0
      member_get_member_active 0
      member_get_member_passive 0
      nr_products      0
      outflows         0
      prod_loan        0
      prod_mortgages   0
      prod_brokerage   0
      prod_pensionplan 0
      prod_savings     0
      relocations      0
      volume_debit     0
      volume_debit_6months 0
      ext_city_size    0
      ext_house_size   0
      ext_purchase_power 0
      ext_share_new_houses 0
      ext_share_new_cars 0
      ext_car_power    0

```

```

ext_living_duration      0
giro_mailing              0
dtype: int64

```

```

[79]: # creating dummy variables
checking_dt = pd.get_dummies(checking_dt,
                             columns = ['complaints',
                                         'directmails',
                                         'marital_status',
                                         'nr_products',
                                         'prod_loan',
                                         'prod_pensionplan',
                                         'prod_savings',
                                         'relocations',
                                         'prod_brokerage'],
                             drop_first = True)

```

```

[80]: checking_dt.head()

```

```

[80]:   cross_buy  acad_title  age  calls  customer_tenure_months  gender  \
0          0          0   60     0                221      0.0
1          0          0   55     0                227      0.0
2          0          0   61     0                221      1.0
3          0          0   70     0                222      0.0
4          0          1   61     0                227      1.0

   joint_account  inflows  last_acc_opening_days  logins_desktop  ...  \
0          0.0      0.0                1786                0  ...
1          1.0      0.0                6911                0  ...
2          0.0    3000.0                6728                0  ...
3          0.0    6000.0                6762                0  ...
4          0.0      0.0                6302                30  ...

   relocations_2  relocations_3  prod_brokerage_1  prod_brokerage_2  \
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

   prod_brokerage_3  prod_brokerage_4  prod_brokerage_5  prod_brokerage_7  \
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

```

	prod_brokerage_8	prod_brokerage_10
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

[5 rows x 93 columns]

```
[81]: # creating ordinal variables
from sklearn.preprocessing import OrdinalEncoder
enc = OrdinalEncoder()
enc.fit(checking_dt[["ext_city_size",
                    "ext_house_size",
                    "ext_purchase_power",
                    "ext_share_new_houses",
                    "ext_share_new_cars",
                    "ext_car_power",
                    "ext_living_duration",]])
checking_dt[["ext_city_size",
             "ext_house_size",
             "ext_purchase_power",
             "ext_share_new_houses",
             "ext_share_new_cars",
             "ext_car_power",
             "ext_living_duration",]] = enc.transform(checking_dt[["ext_city_size",
                                                                    "ext_house_size",
                                                                    "ext_purchase_power",
                                                                    ↪"ext_share_new_houses",
                                                                    ↪"ext_share_new_cars",
                                                                    ↪"ext_car_power",
                                                                    ↪"ext_living_duration"]])
```

```
[82]: checking_dt.shape
```

```
[82]: (100000, 93)
```

Dimentionality reduction

```
[82]:
```

## Data Spliting

```
[83]: # Subsetting the predictors and response variables
X = checking_dt.drop(['cross_buy'],axis = 1)
y = checking_dt['cross_buy']
```

```

#NearMiss under_sampling
from imblearn.under_sampling import NearMiss
nm = NearMiss()
X_res, y_res = nm.fit_resample(X, y)

X_train, X_test, y_train, y_test = train_test_split(X_res, y_res,
                                                    test_size=0.4,
                                                    random_state=1)

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)

```

```

(12000, 92)
(8000, 92)
(12000,)
(8000,)

```

```

[84]: # MinMaxScaler
from sklearn.preprocessing import MinMaxScaler
norm = MinMaxScaler().fit(X_train)
train_X = norm.transform(X_train)
test_X = norm.transform(X_test)

```

## Logistic Regression

```

[85]: model = LogisticRegression(class_weight = 'balanced')
grid={ "C":np.logspace(-3,3,7),
       "penalty":["l1","l2"]}# l1 lasso l2 ridge
logreg_cv=GridSearchCV(model,grid,cv=10)
logreg_cv.fit(X_train, y_train)
print("tuned hpyerparameters :(best parameters) ",logreg_cv.best_params_)
print("accuracy :",logreg_cv.best_score_)
log_pred = logreg_cv.predict(X_test)

#Evaluation
print(classification_report(y_test,log_pred))
print("accuracy: ", metrics.accuracy_score(y_test, log_pred))
print("Recall:", recall_score(y_test,log_pred))

#Classification Error(Misclassification Rate)
print("Error_rate: ", 1 - metrics.accuracy_score(y_test, log_pred))

# Plot the cumulative gains chart of the expected spending
gains_df = pd.DataFrame({'actual': y_test,

```

```

                                'prob': log_pred})
gains_df = gains_df.sort_values(by=['prob'], ascending=False).
    ↳reset_index(drop=True)
gainsChart(gains_df.actual)
plt.show()

```

tuned hpyerparameters :(best parameters) {'C': 1.0, 'penalty': 'l2'}  
accuracy : 0.8952499999999999

	precision	recall	f1-score	support
0	0.84	0.98	0.91	4031
1	0.97	0.82	0.89	3969
accuracy			0.90	8000
macro avg	0.91	0.90	0.90	8000
weighted avg	0.91	0.90	0.90	8000

accuracy: 0.89675  
Recall: 0.8150667674477198  
Error\_rate: 0.10324999999999995

