

Topic 1. Exploratory data analysis with Pandas

[mlcourse.ai](#) – Open Machine Learning Course

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1 Demonstration of main Pandas methods

Well... There are dozens of cool tutorials on Pandas and visual data analysis. If you are already familiar with these topics, you can wait for the 3rd article in the series, where we get into machine learning.

Pandas is a Python library that provides extensive means for data analysis. Data scientists often work with data stored in table formats like `.csv`, `.tsv`, or `.xlsx`. Pandas makes it very convenient to load, process, and analyze such tabular data using SQL-like queries. In conjunction with Matplotlib and Seaborn, Pandas provides a wide range of opportunities for visual analysis of tabular data.

The main data structures in Pandas are implemented with **Series** and **DataFrame** classes. The former is a one-dimensional indexed array of some fixed data type. The latter is a two-dimensional data structure - a table - where each column contains data of the same type. You can see it as a dictionary of Series instances. DataFrames are great for representing real data: rows correspond to instances (examples, observations, etc.), and columns correspond to features of these instances.

```
In [1]: import numpy as np
import pandas as pd
# we don't like warnings
# you can comment the following 2 lines if you'd like to
import warnings
warnings.filterwarnings('ignore')
```

We'll demonstrate the main methods in action by analyzing a [dataset](#) on the churn rate of telecom operator clients. Let's read the data (using `read_csv`), and take a look at the first 5 lines using the `head` method:

```
In [2]: df = pd.read_csv('../data/telecom_churn.csv')
df.head()
```

```
Out[2]:
```

	State	Account length	Area code	International plan	Voice mail plan	\
0	KS	128	415	No	Yes	
1	OH	107	415	No	Yes	
2	NJ	137	415	No	No	
3	OH	84	408	Yes	No	
4	OK	75	415	Yes	No	

	Number vmail messages	Total day minutes	Total day calls	\
0	25	265.1	110	
1	26	161.6	123	
2	0	243.4	114	
3	0	299.4	71	
4	0	166.7	113	

	Total day charge	Total eve minutes	Total eve calls	Total eve charge	\
0	45.07	197.4	99	16.78	
1	27.47	195.5	103	16.62	
2	41.38	121.2	110	10.30	
3	50.90	61.9	88	5.26	
4	28.34	148.3	122	12.61	

	Total night minutes	Total night calls	Total night charge	\
0	244.7	91	11.01	
1	254.4	103	11.45	
2	162.6	104	7.32	
3	196.9	89	8.86	
4	186.9	121	8.41	

	Total intl minutes	Total intl calls	Total intl charge	\
0	10.0	3	2.70	
1	13.7	3	3.70	
2	12.2	5	3.29	
3	6.6	7	1.78	
4	10.1	3	2.73	

	Customer service calls	Churn
0	1	False
1	1	False
2	0	False
3	2	False
4	3	False

About printing DataFrames in Jupyter notebooks

In Jupyter notebooks, Pandas DataFrames are printed as these pretty tables seen above while `print(df.head())` is less nicely formatted. By default, Pandas displays 20 columns and 60 rows, so, if your DataFrame is bigger, use the `set_option` function as shown in the example below:

```
pd.set_option('display.max_columns', 100)
pd.set_option('display.max_rows', 100)
```

Recall that each row corresponds to one client, an **instance**, and columns are **features** of this instance.

Let's have a look at data dimensionality, feature names, and feature types.

```
In [3]: print(df.shape)
```

```
(3333, 20)
```

From the output, we can see that the table contains 3333 rows and 20 columns.

Now let's try printing out column names using columns:

```
In [4]: print(df.columns)
```

```
Index(['State', 'Account length', 'Area code', 'International plan',
      'Voice mail plan', 'Number vmail messages', 'Total day minutes',
      'Total day calls', 'Total day charge', 'Total eve minutes',
      'Total eve calls', 'Total eve charge', 'Total night minutes',
      'Total night calls', 'Total night charge', 'Total intl minutes',
      'Total intl calls', 'Total intl charge', 'Customer service calls',
      'Churn'],
      dtype='object')
```

We can use the `info()` method to output some general information about the dataframe:

```
In [5]: print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 20 columns):
State                3333 non-null object
Account length       3333 non-null int64
Area code            3333 non-null int64
International plan    3333 non-null object
Voice mail plan       3333 non-null object
Number vmail messages 3333 non-null int64
Total day minutes     3333 non-null float64
Total day calls       3333 non-null int64
Total day charge      3333 non-null float64
Total eve minutes     3333 non-null float64
Total eve calls       3333 non-null int64
Total eve charge      3333 non-null float64
Total night minutes   3333 non-null float64
Total night calls     3333 non-null int64
Total night charge    3333 non-null float64
```

```

Total intl minutes      3333 non-null float64
Total intl calls        3333 non-null int64
Total intl charge       3333 non-null float64
Customer service calls  3333 non-null int64
Churn                   3333 non-null bool
dtypes: bool(1), float64(8), int64(8), object(3)
memory usage: 498.1+ KB
None

```

bool, int64, float64 and object are the data types of our features. We see that one feature is logical (bool), 3 features are of type object, and 16 features are numeric. With this same method, we can easily see if there are any missing values. Here, there are none because each column contains 3333 observations, the same number of rows we saw before with shape.

We can **change the column type** with the astype method. Let's apply this method to the Churn feature to convert it into int64:

```
In [6]: df['Churn'] = df['Churn'].astype('int64')
```

The describe method shows basic statistical characteristics of each numerical feature (int64 and float64 types): number of non-missing values, mean, standard deviation, range, median, 0.25 and 0.75 quartiles.

```
In [7]: df.describe()
```

```

Out[7]:
   Account length  Area code  Number vmail messages  Total day minutes \
count    3333.000000    3333.000000             3333.000000    3333.000000
mean      101.064806     437.182418               8.099010     179.775098
std       39.822106      42.371290              13.688365      54.467389
min        1.000000     408.000000               0.000000       0.000000
25%       74.000000     408.000000               0.000000     143.700000
50%      101.000000     415.000000               0.000000     179.400000
75%      127.000000     510.000000              20.000000     216.400000
max      243.000000     510.000000              51.000000     350.800000

   Total day calls  Total day charge  Total eve minutes  Total eve calls \
count    3333.000000    3333.000000    3333.000000    3333.000000
mean     100.435644      30.562307     200.980348     100.114311
std       20.069084       9.259435      50.713844      19.922625
min         0.000000       0.000000       0.000000       0.000000
25%        87.000000      24.430000     166.600000      87.000000
50%       101.000000      30.500000     201.400000     100.000000
75%       114.000000      36.790000     235.300000     114.000000
max       165.000000      59.640000     363.700000     170.000000

   Total eve charge  Total night minutes  Total night calls \
count    3333.000000    3333.000000    3333.000000
mean       17.083540      200.872037      100.107711
std         4.310668       50.573847       19.568609

```

min	0.000000	23.200000	33.000000
25%	14.160000	167.000000	87.000000
50%	17.120000	201.200000	100.000000
75%	20.000000	235.300000	113.000000
max	30.910000	395.000000	175.000000

	Total night charge	Total intl minutes	Total intl calls \
count	3333.000000	3333.000000	3333.000000
mean	9.039325	10.237294	4.479448
std	2.275873	2.791840	2.461214
min	1.040000	0.000000	0.000000
25%	7.520000	8.500000	3.000000
50%	9.050000	10.300000	4.000000
75%	10.590000	12.100000	6.000000
max	17.770000	20.000000	20.000000

	Total intl charge	Customer service calls	Churn
count	3333.000000	3333.000000	3333.000000
mean	2.764581	1.562856	0.144914
std	0.753773	1.315491	0.352067
min	0.000000	0.000000	0.000000
25%	2.300000	1.000000	0.000000
50%	2.780000	1.000000	0.000000
75%	3.270000	2.000000	0.000000
max	5.400000	9.000000	1.000000

In order to see statistics on non-numerical features, one has to explicitly indicate data types of interest in the `include` parameter.

```
In [8]: df.describe(include=['object', 'bool'])
```

```
Out[8]:
```

	State	International	plan	Voice	mail	plan
count	3333			3333		3333
unique	51			2		2
top	WV			No		No
freq	106			3010		2411

For categorical (type `object`) and boolean (type `bool`) features we can use the `value_counts` method. Let's have a look at the distribution of `Churn`:

```
In [9]: df['Churn'].value_counts()
```

```
Out[9]: 0    2850
        1     483
        Name: Churn, dtype: int64
```

2850 users out of 3333 are *loyal*; their `Churn` value is 0. To calculate fractions, pass `normalize=True` to the `value_counts` function.

```
In [10]: df['Churn'].value_counts(normalize=True)
```

```
Out[10]: 0    0.855086
         1    0.144914
         Name: Churn, dtype: float64
```

1.1 Sorting

A DataFrame can be sorted by the value of one of the variables (i.e columns). For example, we can sort by *Total day charge* (use `ascending=False` to sort in descending order):

```
In [11]: df.sort_values(by='Total day charge', ascending=False).head()
```

```
Out[11]:
```

	State	Account length	Area code	International plan	Voice mail plan	\
365	CO	154	415	No	No	
985	NY	64	415	Yes	No	
2594	OH	115	510	Yes	No	
156	OH	83	415	No	No	
605	MO	112	415	No	No	

	Number vmail messages	Total day minutes	Total day calls	\
365	0	350.8	75	
985	0	346.8	55	
2594	0	345.3	81	
156	0	337.4	120	
605	0	335.5	77	

	Total day charge	Total eve minutes	Total eve calls	Total eve charge	\
365	59.64	216.5	94	18.40	
985	58.96	249.5	79	21.21	
2594	58.70	203.4	106	17.29	
156	57.36	227.4	116	19.33	
605	57.04	212.5	109	18.06	

	Total night minutes	Total night calls	Total night charge	\
365	253.9	100	11.43	
985	275.4	102	12.39	
2594	217.5	107	9.79	
156	153.9	114	6.93	
605	265.0	132	11.93	

	Total intl minutes	Total intl calls	Total intl charge	\
365	10.1	9	2.73	
985	13.3	9	3.59	
2594	11.8	8	3.19	
156	15.8	7	4.27	
605	12.7	8	3.43	

	Customer service calls	Churn
365	1	1

985	1	1
2594	1	1
156	0	1
605	2	1

We can also sort by multiple columns:

```
In [12]: df.sort_values(by=['Churn', 'Total day charge'],
                        ascending=[True, False]).head()
```

```
Out[12]:
```

	State	Account length	Area code	International plan	Voice mail plan	\
688	MN	13	510	No	Yes	
2259	NC	210	415	No	Yes	
534	LA	67	510	No	No	
575	SD	114	415	No	Yes	
2858	AL	141	510	No	Yes	

	Number vmail messages	Total day minutes	Total day calls	\
688	21	315.6	105	
2259	31	313.8	87	
534	0	310.4	97	
575	36	309.9	90	
2858	28	308.0	123	

	Total day charge	Total eve minutes	Total eve calls	Total eve charge	\
688	53.65	208.9	71	17.76	
2259	53.35	147.7	103	12.55	
534	52.77	66.5	123	5.65	
575	52.68	200.3	89	17.03	
2858	52.36	247.8	128	21.06	

	Total night minutes	Total night calls	Total night charge	\
688	260.1	123	11.70	
2259	192.7	97	8.67	
534	246.5	99	11.09	
575	183.5	105	8.26	
2858	152.9	103	6.88	

	Total intl minutes	Total intl calls	Total intl charge	\
688	12.1	3	3.27	
2259	10.1	7	2.73	
534	9.2	10	2.48	
575	14.2	2	3.83	
2858	7.4	3	2.00	

	Customer service calls	Churn
688	3	0
2259	3	0

534	4	0
575	1	0
2858	1	0

1.2 Indexing and retrieving data

A DataFrame can be indexed in a few different ways.

To get a single column, you can use a `DataFrame['Name']` construction. Let's use this to answer a question about that column alone: **what is the proportion of churned users in our dataframe?**

```
In [13]: df['Churn'].mean()
```

```
Out[13]: 0.14491449144914492
```

14.5% is actually quite bad for a company; such a churn rate can make the company go bankrupt.

Boolean indexing with one column is also very convenient. The syntax is `df[P(df['Name'])]`, where `P` is some logical condition that is checked for each element of the `Name` column. The result of such indexing is the DataFrame consisting only of rows that satisfy the `P` condition on the `Name` column.

Let's use it to answer the question:

What are average values of numerical features for churned users?

```
In [14]: df[df['Churn'] == 1].mean()
```

```
Out[14]: Account length      102.664596
Area code      437.817805
Number vmail messages      5.115942
Total day minutes      206.914079
Total day calls      101.335404
Total day charge      35.175921
Total eve minutes      212.410145
Total eve calls      100.561077
Total eve charge      18.054969
Total night minutes      205.231677
Total night calls      100.399586
Total night charge      9.235528
Total intl minutes      10.700000
Total intl calls      4.163561
Total intl charge      2.889545
Customer service calls      2.229814
Churn      1.000000
dtype: float64
```

How much time (on average) do churned users spend on the phone during daytime?

```
In [15]: df[df['Churn'] == 1]['Total day minutes'].mean()
```

```
Out[15]: 206.91407867494814
```


What is the maximum length of international calls among loyal users (`Churn == 0`) who do not have an international plan?

```
In [16]: df[(df['Churn'] == 0) & (df['International plan'] == 'No')]
          ['Total intl minutes'].max()
```

```
Out[16]: 18.9
```

DataFrames can be indexed by column name (label) or row name (index) or by the serial number of a row. The `loc` method is used for **indexing by name**, while `iloc()` is used for **indexing by number**.

In the first case below, we say “give us the values of the rows with index from 0 to 5 (inclusive) and columns labeled from State to Area code (inclusive)”. In the second case, we say “give us the values of the first five rows in the first three columns” (as in a typical Python slice: the maximal value is not included).

```
In [17]: df.loc[0:5, 'State':'Area code']
```

```
Out[17]:
```

	State	Account length	Area code
0	KS	128	415
1	OH	107	415
2	NJ	137	415
3	OH	84	408
4	OK	75	415
5	AL	118	510

```
In [18]: df.iloc[0:5, 0:3]
```

```
Out[18]:
```

	State	Account length	Area code
0	KS	128	415
1	OH	107	415
2	NJ	137	415
3	OH	84	408
4	OK	75	415

If we need the first or the last line of the data frame, we can use the `df[:1]` or `df[-1:]` construct:

```
In [19]: df[-1:]
```

```
Out[19]:
```

	State	Account length	Area code	International plan	Voice mail plan \
3332	TN	74	415	No	Yes

	Number vmail messages	Total day minutes	Total day calls \
3332	25	234.4	113

	Total day charge	Total eve minutes	Total eve calls	Total eve charge \
3332	39.85	265.9	82	22.6

	Total night minutes	Total night calls	Total night charge \
3332	241.4	77	10.86

	Total intl minutes	Total intl calls	Total intl charge \
3332	13.7	4	3.7

	Customer service calls	Churn
3332	0	0

1.3 Applying Functions to Cells, Columns and Rows

To apply functions to each column, use `apply()`:

```
In [20]: df.apply(np.max)
```

```
Out[20]: State                WY
Account length              243
Area code                   510
International plan          Yes
Voice mail plan             Yes
Number vmail messages       51
Total day minutes           350.8
Total day calls              165
Total day charge             59.64
Total eve minutes            363.7
Total eve calls              170
Total eve charge             30.91
Total night minutes          395
Total night calls            175
Total night charge           17.77
Total intl minutes           20
Total intl calls             20
Total intl charge            5.4
Customer service calls       9
Churn                        1
dtype: object
```

The `apply` method can also be used to apply a function to each row. To do this, specify `axis=1`. Lambda functions are very convenient in such scenarios. For example, if we need to select all states starting with *W*, we can do it like this:

```
In [21]: df[df['State'].apply(lambda state: state[0] == 'W')].head()
```

```
Out[21]:   State  Account length  Area code  International plan  Voice mail plan \
9      WV              141        415                Yes        Yes
26     WY              57        408                No         Yes
44     WI              64        510                No         No
49     WY              97        415                No         Yes
54     WY              87        415                No         No
```

	Number vmail messages	Total day minutes	Total day calls	\
9	37	258.6	84	
26	39	213.0	115	
44	0	154.0	67	
49	24	133.2	135	
54	0	151.0	83	

	Total day charge	Total eve minutes	Total eve calls	Total eve charge	\
9	43.96	222.0	111	18.87	
26	36.21	191.1	112	16.24	
44	26.18	225.8	118	19.19	
49	22.64	217.2	58	18.46	
54	25.67	219.7	116	18.67	

	Total night minutes	Total night calls	Total night charge	\
9	326.4	97	14.69	
26	182.7	115	8.22	
44	265.3	86	11.94	
49	70.6	79	3.18	
54	203.9	127	9.18	

	Total intl minutes	Total intl calls	Total intl charge	\
9	11.2	5	3.02	
26	9.5	3	2.57	
44	3.5	3	0.95	
49	11.0	3	2.97	
54	9.7	3	2.62	

	Customer service calls	Churn
9	0	0
26	0	0
44	1	0
49	1	0
54	5	1

The map method can be used to **replace values in a column** by passing a dictionary of the form {old_value: new_value} as its argument:

```
In [22]: d = {'No' : False, 'Yes' : True}
df['International plan'] = df['International plan'].map(d)
df.head()
```

```
Out[22]: State Account length Area code International plan Voice mail plan \
0 KS 128 415 False Yes
1 OH 107 415 False Yes
2 NJ 137 415 False No
3 OH 84 408 True No
```

4	OK	75	415	True	No
---	----	----	-----	------	----

	Number vmail messages	Total day minutes	Total day calls	\
0	25	265.1	110	
1	26	161.6	123	
2	0	243.4	114	
3	0	299.4	71	
4	0	166.7	113	

	Total day charge	Total eve minutes	Total eve calls	Total eve charge	\
0	45.07	197.4	99	16.78	
1	27.47	195.5	103	16.62	
2	41.38	121.2	110	10.30	
3	50.90	61.9	88	5.26	
4	28.34	148.3	122	12.61	

	Total night minutes	Total night calls	Total night charge	\
0	244.7	91	11.01	
1	254.4	103	11.45	
2	162.6	104	7.32	
3	196.9	89	8.86	
4	186.9	121	8.41	

	Total intl minutes	Total intl calls	Total intl charge	\
0	10.0	3	2.70	
1	13.7	3	3.70	
2	12.2	5	3.29	
3	6.6	7	1.78	
4	10.1	3	2.73	

	Customer service calls	Churn
0	1	0
1	1	0
2	0	0
3	2	0
4	3	0

The same thing can be done with the replace method:

```
In [23]: df = df.replace({'Voice mail plan': d})
df.head()
```

```
Out[23]:
```

	State	Account length	Area code	International plan	Voice mail plan	\
0	KS	128	415	False	True	
1	OH	107	415	False	True	
2	NJ	137	415	False	False	
3	OH	84	408	True	False	
4	OK	75	415	True	False	

	Number vmail messages	Total day minutes	Total day calls	\
0	25	265.1	110	
1	26	161.6	123	
2	0	243.4	114	
3	0	299.4	71	
4	0	166.7	113	

	Total day charge	Total eve minutes	Total eve calls	Total eve charge	\
0	45.07	197.4	99	16.78	
1	27.47	195.5	103	16.62	
2	41.38	121.2	110	10.30	
3	50.90	61.9	88	5.26	
4	28.34	148.3	122	12.61	

	Total night minutes	Total night calls	Total night charge	\
0	244.7	91	11.01	
1	254.4	103	11.45	
2	162.6	104	7.32	
3	196.9	89	8.86	
4	186.9	121	8.41	

	Total intl minutes	Total intl calls	Total intl charge	\
0	10.0	3	2.70	
1	13.7	3	3.70	
2	12.2	5	3.29	
3	6.6	7	1.78	
4	10.1	3	2.73	

	Customer service calls	Churn
0	1	0
1	1	0
2	0	0
3	2	0
4	3	0

1.4 Grouping

In general, grouping data in Pandas works as follows:

```
df.groupby(by=grouping_columns)[columns_to_show].function()
```

1. First, the groupby method divides the grouping_columns by their values. They become a new index in the resulting dataframe.
2. Then, columns of interest are selected (columns_to_show). If columns_to_show is not included, all non groupby clauses will be included.
3. Finally, one or several functions are applied to the obtained groups per selected columns.

Here is an example where we group the data according to the values of the Churn variable and display statistics of three columns in each group:

```
In [24]: columns_to_show = ['Total day minutes', 'Total eve minutes',
                           'Total night minutes']
```

```
df.groupby(['Churn'])[columns_to_show].describe(percentiles=[])
```

```
Out[24]:
```

Total day minutes						
	count	mean	std	min	50%	max
Churn						
0	2850.0	175.175754	50.181655	0.0	177.2	315.6
1	483.0	206.914079	68.997792	0.0	217.6	350.8

```
Out[24]:
```

Total eve minutes						
	count	mean	std	min	50%	max
Churn						
0	2850.0	199.043298	50.292175	0.0	199.6	361.8
1	483.0	212.410145	51.728910	70.9	211.3	363.7

```
Out[24]:
```

Total night minutes						
	count	mean	std	min	50%	max
Churn						
0	2850.0	200.133193	51.105032	23.2	200.25	395.0
1	483.0	205.231677	47.132825	47.4	204.80	354.9

Let's do the same thing, but slightly differently by passing a list of functions to agg():

```
In [25]: columns_to_show = ['Total day minutes', 'Total eve minutes',
                           'Total night minutes']
```

```
df.groupby(['Churn'])[columns_to_show].agg([np.mean, np.std, np.min,
                                             np.max])
```

```
Out[25]:
```

Total day minutes					Total eve minutes		
	mean	std	amin	amax		mean	std
Churn							
0	175.175754	50.181655	0.0	315.6		199.043298	50.292175
1	206.914079	68.997792	0.0	350.8		212.410145	51.728910

Total night minutes						
	amin	amax	mean	std	amin	amax
Churn						
0	0.0	361.8	200.133193	51.105032	23.2	395.0
1	70.9	363.7	205.231677	47.132825	47.4	354.9

1.5 Summary tables

Suppose we want to see how the observations in our sample are distributed in the context of two variables - Churn and International plan. To do so, we can build a **contingency table** using the crosstab method:

```
In [26]: pd.crosstab(df['Churn'], df['International plan'])
```

```
Out[26]: International plan  False  True
Churn
0                2664    186
1                346    137
```

```
In [27]: pd.crosstab(df['Churn'], df['Voice mail plan'], normalize=True)
```

```
Out[27]: Voice mail plan      False      True
Churn
0          0.602460  0.252625
1          0.120912  0.024002
```

We can see that most of the users are loyal and do not use additional services (International Plan/Voice mail).

This will resemble **pivot tables** to those familiar with Excel. And, of course, pivot tables are implemented in Pandas: the `pivot_table` method takes the following parameters:

- `values` – a list of variables to calculate statistics for,
- `index` – a list of variables to group data by,
- `aggfunc` – what statistics we need to calculate for groups, ex. `sum`, `mean`, `maximum`, `minimum` or something else.

Let's take a look at the average number of day, evening, and night calls by area code:

```
In [28]: df.pivot_table(['Total day calls', 'Total eve calls', 'Total night calls'],
                        ['Area code'], aggfunc='mean')
```

```
Out[28]:
```

	Total day calls	Total eve calls	Total night calls
Area code			
408	100.496420	99.788783	99.039379
415	100.576435	100.503927	100.398187
510	100.097619	99.671429	100.601190

1.6 DataFrame transformations

Like many other things in Pandas, adding columns to a DataFrame is doable in many ways.

For example, if we want to calculate the total number of calls for all users, let's create the `total_calls` Series and paste it into the DataFrame:

```
In [29]: total_calls = df['Total day calls'] + df['Total eve calls'] + \
          df['Total night calls'] + df['Total intl calls']
df.insert(loc=len(df.columns), column='Total calls', value=total_calls)
# loc parameter is the number of columns after which to insert the Series object
# we set it to len(df.columns) to paste it at the very end of the dataframe
df.head()
```

```
Out[29]:
```

	State	Account length	Area code	International plan	Voice mail plan	\
0	KS	128	415	False	True	
1	OH	107	415	False	True	
2	NJ	137	415	False	False	
3	OH	84	408	True	False	
4	OK	75	415	True	False	

	Number vmail messages	Total day minutes	Total day calls	\
0	25	265.1	110	
1	26	161.6	123	
2	0	243.4	114	
3	0	299.4	71	
4	0	166.7	113	

	Total day charge	Total eve minutes	...	Total eve charge	\
0	45.07	197.4	...	16.78	
1	27.47	195.5	...	16.62	
2	41.38	121.2	...	10.30	
3	50.90	61.9	...	5.26	
4	28.34	148.3	...	12.61	

	Total night minutes	Total night calls	Total night charge	\
0	244.7	91	11.01	
1	254.4	103	11.45	
2	162.6	104	7.32	
3	196.9	89	8.86	
4	186.9	121	8.41	

	Total intl minutes	Total intl calls	Total intl charge	\
0	10.0	3	2.70	
1	13.7	3	3.70	
2	12.2	5	3.29	
3	6.6	7	1.78	
4	10.1	3	2.73	

	Customer service calls	Churn	Total calls
0	1	0	303
1	1	0	332
2	0	0	333
3	2	0	255
4	3	0	359

[5 rows x 21 columns]

It is possible to add a column more easily without creating an intermediate Series instance:

```
In [30]: df['Total charge'] = df['Total day charge'] + df['Total eve charge'] + \
        df['Total night charge'] + df['Total intl charge']

df.head()
```



```

Out[30]: State Account length Area code International plan Voice mail plan \
0 KS 128 415 False True
1 OH 107 415 False True
2 NJ 137 415 False False
3 OH 84 408 True False
4 OK 75 415 True False

Number vmail messages Total day minutes Total day calls \
0 25 265.1 110
1 26 161.6 123
2 0 243.4 114
3 0 299.4 71
4 0 166.7 113

Total day charge Total eve minutes ... Total night minutes \
0 45.07 197.4 ... 244.7
1 27.47 195.5 ... 254.4
2 41.38 121.2 ... 162.6
3 50.90 61.9 ... 196.9
4 28.34 148.3 ... 186.9

Total night calls Total night charge Total intl minutes \
0 91 11.01 10.0
1 103 11.45 13.7
2 104 7.32 12.2
3 89 8.86 6.6
4 121 8.41 10.1

Total intl calls Total intl charge Customer service calls Churn \
0 3 2.70 1 0
1 3 3.70 1 0
2 5 3.29 0 0
3 7 1.78 2 0
4 3 2.73 3 0

Total calls Total charge
0 303 75.56
1 332 59.24
2 333 62.29
3 255 66.80
4 359 52.09

[5 rows x 22 columns]

```

To delete columns or rows, use the drop method, passing the required indexes and the axis parameter (1 if you delete columns, and nothing or 0 if you delete rows). The inplace argument tells whether to change the original DataFrame. With inplace=False, the drop method doesn't change the existing DataFrame and returns a new one with dropped rows or columns. With

inplace=True, it alters the DataFrame.

```
In [31]: # get rid of just created columns
df.drop(['Total charge', 'Total calls'], axis=1, inplace=True)
# and here's how you can delete rows
df.drop([1, 2]).head()
```

```
Out[31]:
```

	State	Account length	Area code	International plan	Voice mail plan	\
0	KS	128	415	False	True	
3	OH	84	408	True	False	
4	OK	75	415	True	False	
5	AL	118	510	True	False	
6	MA	121	510	False	True	

	Number vmail messages	Total day minutes	Total day calls	\
0	25	265.1	110	
3	0	299.4	71	
4	0	166.7	113	
5	0	223.4	98	
6	24	218.2	88	

	Total day charge	Total eve minutes	Total eve calls	Total eve charge	\
0	45.07	197.4	99	16.78	
3	50.90	61.9	88	5.26	
4	28.34	148.3	122	12.61	
5	37.98	220.6	101	18.75	
6	37.09	348.5	108	29.62	

	Total night minutes	Total night calls	Total night charge	\
0	244.7	91	11.01	
3	196.9	89	8.86	
4	186.9	121	8.41	
5	203.9	118	9.18	
6	212.6	118	9.57	

	Total intl minutes	Total intl calls	Total intl charge	\
0	10.0	3	2.70	
3	6.6	7	1.78	
4	10.1	3	2.73	
5	6.3	6	1.70	
6	7.5	7	2.03	

	Customer service calls	Churn
0	1	0
3	2	0
4	3	0
5	0	0
6	3	0

2 First attempt at predicting telecom churn

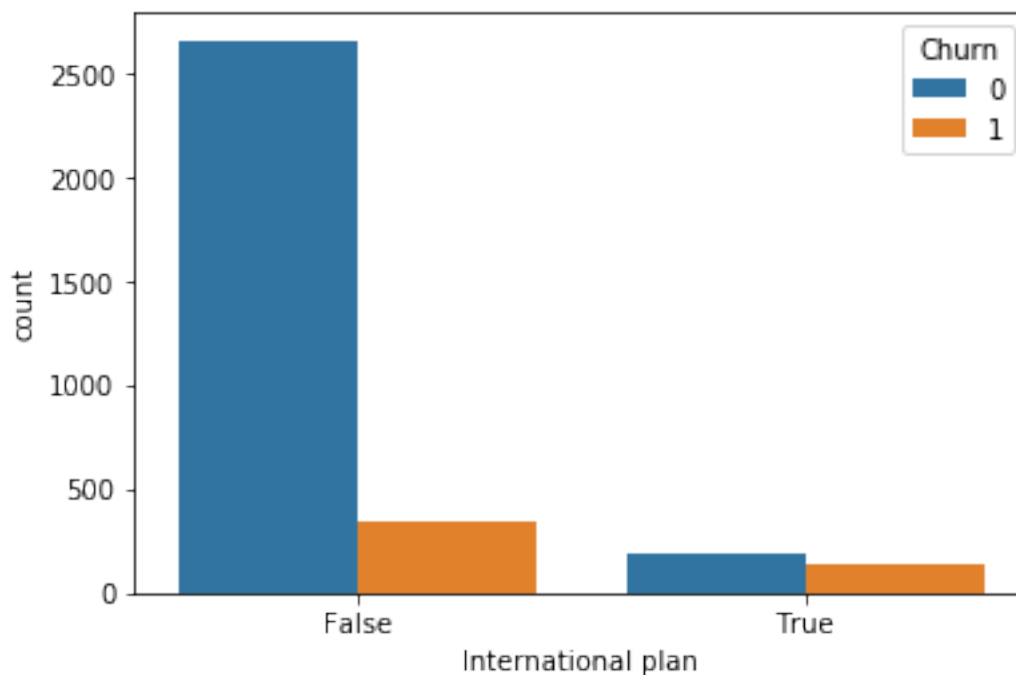
Let's see how churn rate is related to the *International plan* feature. We'll do this using a crosstab contingency table and also through visual analysis with Seaborn (however, visual analysis will be covered more thoroughly in the next article).

```
In [32]: pd.crosstab(df['Churn'], df['International plan'], margins=True)
```

```
Out[32]: International plan  False  True  All
Churn
0          2664    186  2850
1           346    137   483
All         3010    323  3333
```

```
In [33]: # some imports to set up plotting
import matplotlib.pyplot as plt
# pip install seaborn
import seaborn as sns
```

```
In [34]: sns.countplot(x='International plan', hue='Churn', data=df);
```



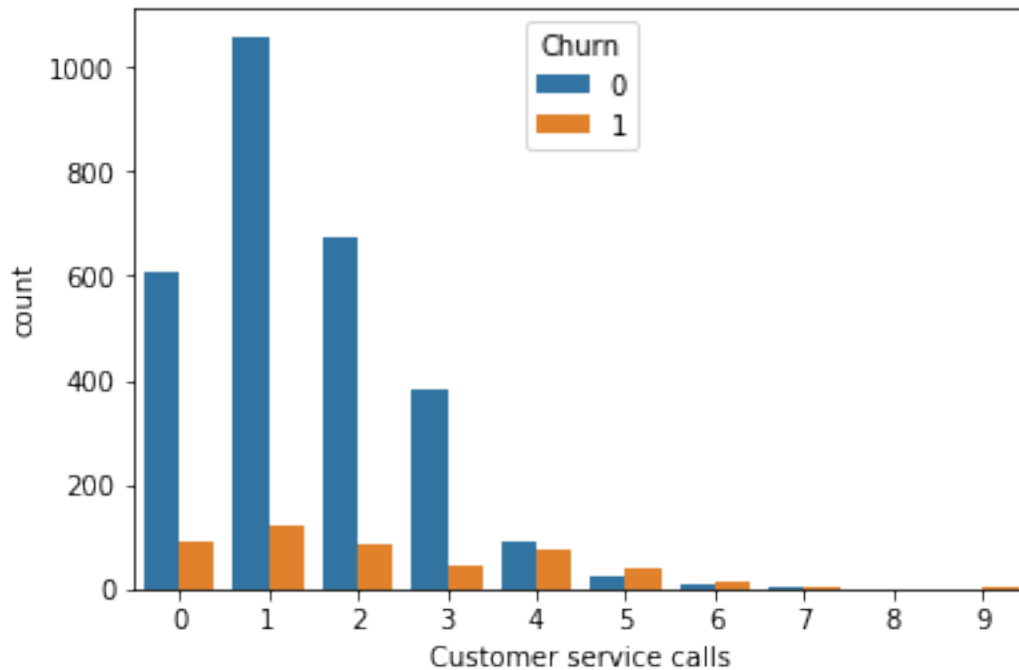
We see that, with *International Plan*, the churn rate is much higher, which is an interesting observation! Perhaps large and poorly controlled expenses with international calls are very conflict-prone and lead to dissatisfaction among the telecom operator's customers.

Next, let's look at another important feature – *Customer service calls*. Let's also make a summary table and a picture.

```
In [35]: pd.crosstab(df['Churn'], df['Customer service calls'], margins=True)
```

```
Out[35]: Customer service calls    0    1    2    3    4    5    6    7    8    9    All
Churn
0          605  1059  672  385   90  26   8   4   1   0  2850
1           92   122   87   44   76  40  14   5   1   2   483
All         697  1181  759  429  166  66  22   9   2   2  3333
```

```
In [36]: sns.countplot(x='Customer service calls', hue='Churn', data=df);
```



Although it's not so obvious from the summary table, it's easy to see from the above plot that the churn rate increases sharply from 4 customer service calls and above.

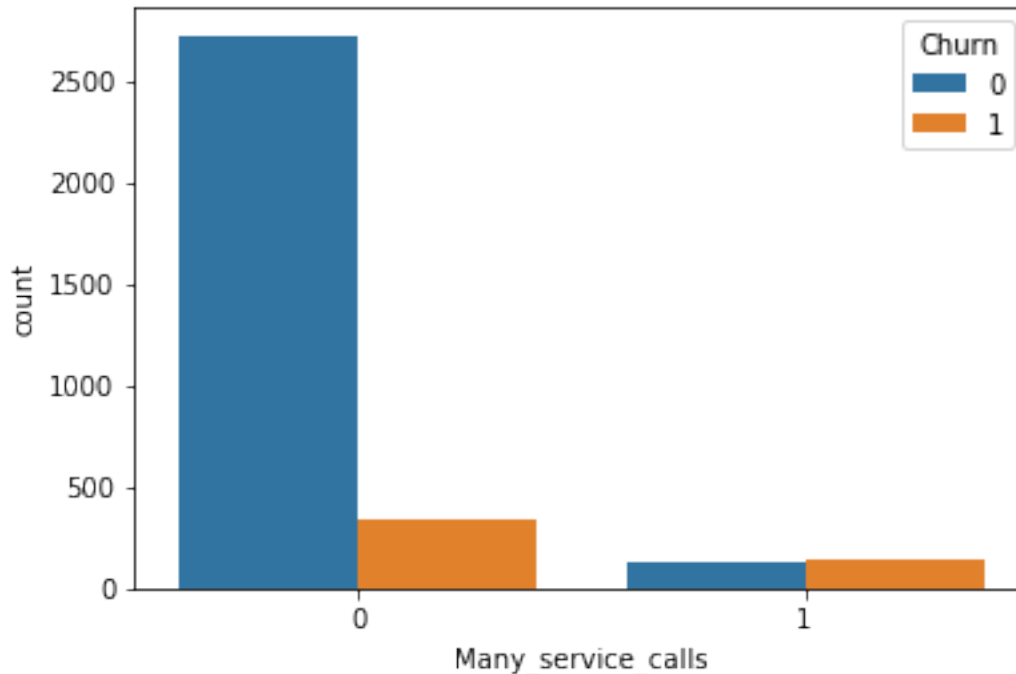
Now let's add a binary feature to our DataFrame – Customer service calls > 3. And once again, let's see how it relates to churn.

```
In [37]: df['Many_service_calls'] = (df['Customer service calls'] > 3).astype('int')
```

```
pd.crosstab(df['Many_service_calls'], df['Churn'], margins=True)
```

```
Out[37]: Churn          0    1    All
Many_service_calls
0          2721  345  3066
1           129  138   267
All         2850  483  3333
```

```
In [38]: sns.countplot(x='Many_service_calls', hue='Churn', data=df);
```



Let's construct another contingency table that relates *Churn* with both *International plan* and freshly created *Many_service_calls*.

```
In [39]: pd.crosstab(df['Many_service_calls'] & df['International plan'] ,
                    df['Churn'])
```

```
Out [39]: Churn      0      1
          row_0
          False  2841  464
          True   9    19
```

Therefore, predicting that a customer is not loyal (*Churn*=1) in the case when the number of calls to the service center is greater than 3 and the *International Plan* is added (and predicting *Churn*=0 otherwise), we might expect an accuracy of 85.8% (we are mistaken only 464 + 9 times). This number, 85.8%, that we got through this very simple reasoning serves as a good starting point (*baseline*) for the further machine learning models that we will build.

As we move on in this course, recall that, before the advent of machine learning, the data analysis process looked something like this. Let's recap what we've covered:

- The share of loyal clients in the sample is 85.5%. The most naive model that always predicts a "loyal customer" on such data will guess right in about 85.5% of all cases. That is, the proportion of correct answers (*accuracy*) of subsequent models should be no less than this number, and will hopefully be significantly higher;
- With the help of a simple forecast that can be expressed by the following formula: "International plan = True & Customer Service calls > 3 => Churn = 1, else Churn = 0", we can expect a guessing rate of 85.8%, which is just above 85.5%. Subsequently, we'll talk about decision trees and figure out how to find such rules **automatically** based only on the input data;

- We got these two baselines without applying machine learning, and they'll serve as the starting point for our subsequent models. If it turns out that with enormous effort, we increase the share of correct answers by 0.5% per se, then possibly we are doing something wrong, and it suffices to confine ourselves to a simple model with two conditions;
- Before training complex models, it is recommended to manipulate the data a bit, make some plots, and check simple assumptions. Moreover, in business applications of machine learning, they usually start with simple solutions and then experiment with more complex ones.

3 Demo assignment

To practice with Pandas and EDA, you can complete [this assignment](#) where you'll be analyzing socio-demographic data.

4 Useful resources

- The same notebook as an interactive web-based [Kaggle Kernel](#)
- ["Merging DataFrames with pandas"](#) - a tutorial by Max Plako within mlcourse.ai (full list of tutorials is [here](#))
- ["Handle different dataset with dask and trying a little dask ML"](#) - a tutorial by Irina Knyazeva within mlcourse.ai
- Main course [site](#), [course repo](#), and YouTube [channel](#)
- Official Pandas [documentation](#)
- Course materials as a [Kaggle Dataset](#)
- Medium ["story"](#) based on this notebook
- If you read Russian: an [article](#) on Habr.com with ~ the same material. And a [lecture](#) on YouTube
- [10 minutes to pandas](#)
- [Pandas cheatsheet PDF](#)
- GitHub repos: [Pandas exercises](#) and ["Effective Pandas"](#)
- [scipy-lectures.org](#) — tutorials on pandas, numpy, matplotlib and scikit-learn