Programming Assignment 1

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Import packages

In [138]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import operator
from sklearn.preprocessing import MinMaxScaler, LabelBinarizer
from sklearn.feature_selection import SelectKBest, chi2, mutual_info_classif
%matplotlib inline
```

Read the data

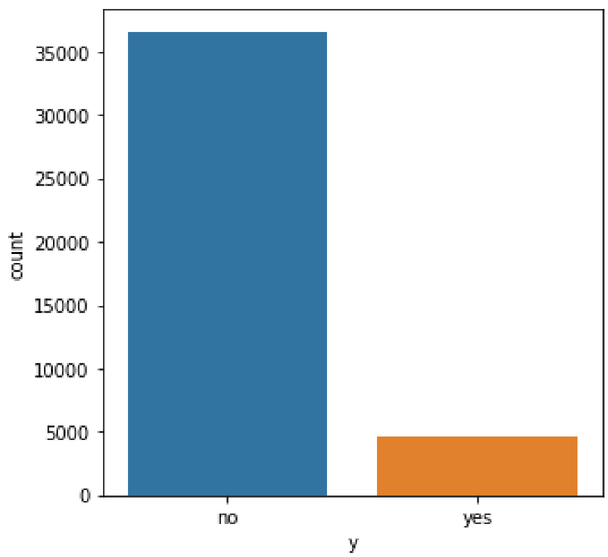
In [139]:
```
bank = pd.read_csv('bank-additional-full.csv', sep=';')
bank.head()
```

Out[139]:
```
   age        job  marital    education  default housing loan    contact  \
0   56  housemaid  married     basic.4y       no      no   no  telephone
1   57   services  married  high.school  unknown      no   no  telephone
2   37   services  married  high.school       no     yes   no  telephone
3   40     admin.  married     basic.6y       no      no   no  telephone
4   56   services  married  high.school       no      no  yes  telephone

  month day_of_week ...  campaign  pdays  previous     poutcome emp.var.rate  \
0   may         mon ...         1    999         0  nonexistent          1.1
1   may         mon ...         1    999         0  nonexistent          1.1
2   may         mon ...         1    999         0  nonexistent          1.1
3   may         mon ...         1    999         0  nonexistent          1.1
4   may         mon ...         1    999         0  nonexistent          1.1

   cons.price.idx  cons.conf.idx  euribor3m  nr.employed   y
0          93.994          -36.4      4.857       5191.0  no
1          93.994          -36.4      4.857       5191.0  no
2          93.994          -36.4      4.857       5191.0  no
3          93.994          -36.4      4.857       5191.0  no
4          93.994          -36.4      4.857       5191.0  no

[5 rows x 21 columns]
```

Data Analysis

Task 1: Plot the distribution of values in the class attribute of the dataset using a bar chart. Please describe what you observe, e.g. whether the data distribution is imbalanced.

```
In [140]: plt.figure(figsize=(5,5))
          sns.countplot("y",data=bank)
          plt.show()
```



As we observe the class distribution from the bar chart above, we can see that the distribution is extremely imbalanced, with `no`(clients who would not consider subscribing the product) taking up the majority, approximately 30000 clients more than `yes`(clients who are subscribers).

Task 2: Read the reference and answer the following questions.

- a) Please summarize the characteristics and differences of chi-square function (https://en.wikipedia.org/wiki/Chi-squared_test) and mutual information functions (https://en.wikipedia.org/wiki/Mutual_information)
- b) Can we simply apply chi-square function and mutual information function on Bank Marketing Dataset for feature selection? Please explain. (hint: the difference between categorical and numerical data)
- c) Employ chi-square or mutual information as appropriate to obtain a measure between values of each feature and the class. Rank features by their measures of chi-square and mutual information. Note: Please make two lists: one for chi-square and the other for mutual information. An attribute only belongs to one list.

a) Both chi-square function and mutual information functions are feature selection techniques that are used to rank features and measure how important each feature is when doing the classification task:

- chi-square:
  - The chi-square test is a statistical test of independence to determine the dependency of two variables.
  - $$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}, O : \text{Observation},\ E : \text{Expectation}$$
    * If the chi-square test score is smaller, then the two features are more likely to be independent, thus it's safe to discard that feature variable without affecting the outcome.
    * If the chi-square test score is high, then the two variables are more likely correlated to each other, which indicates that the feature variable is very important.
  - By calculating the Chi square scores for all the features, we can rank the features by the chi square scores, then choose the top ranked features for model training.
  - chi square test is more appropriate for categorical variables
- mutual information function
  - The goal of MI is to measure mutual dependence between variables, and how strong the relation is between these variables. It is closely associated with the idea of entropy, applied to quantify the amount of information obtained.
  - $$I(X;Y) = \int_Y \int_X p(x,y) \log\left(\frac{p(x,y)}{p(x)\,p(y)}\right) dx\,dy$$
  - thus if X and Y are independent, then their mutual information is zero because

$$p(x,y) = p(x)p(y)$$

$$\log\left(\frac{p(x,y)}{p(x)\,p(y)}\right) = \log 1 = 0$$

  - closely associated with the idea of entropy:

$$\begin{aligned}
I(X;Y) &= \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \\
&= \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)} - \sum_{x,y} p(x,y) \log p(y) \\
&= \sum_{x,y} p(x)p(y|x) \log p(y|x) - \sum_{x,y} \log p(y)p(x,y) \\
&= \sum_{x} p(x) \left(\sum_{y} p(y|x) \log p(y|x)\right) - \sum_{y} \log p(y) \left(\sum_{x} p(x,y)\right) \\
&= -\sum_{x} p(x)\mathrm{H}(Y|X=x) - \sum_{y} p(y) \log p(y) \\
&= -\mathrm{H}(Y|X) + \mathrm{H}(Y) \\
&= \mathrm{H}(Y) - \mathrm{H}(Y|X) \\
&= \mathrm{H}(X) + \mathrm{H}(Y) - \mathrm{H}(X,Y).
\end{aligned}$$

- intuition of the equation: `the amount of uncertainty in Y which is removed by knowing X`
- Unlike chi square test, mutual info function could be applied to both categorical and numerical variables

- b) No.

Test and explain as follows:

```
In [141]: def feature_select(X, y, top_k, score_func):
              selector = SelectKBest(score_func=score_func, k=top_k)
              try:
                  X_selected = selector.fit(X, y)
                  mask = X_selected.get_support()
                  scores = X_selected.scores_
                  res = dict(zip(X.columns[mask], scores[mask]))
                  return sorted(res.items(), key=operator.itemgetter(1),
                                reverse=True)
              except Exception as e:
                  print(e)
```

```
In [142]: categorical_cols = bank.columns[bank.dtypes==object]
          numerical_cols = bank.columns[bank.dtypes!=object]
```

```
In [143]: X = bank.iloc[:,:20]
          y = bank.iloc[:,20]
```

```
In [144]: feature_select(X=X, y=y, top_k=len(X.columns), score_func=chi2)
```

```
could not convert string to float: 'failure'
```

```
In [145]: feature_select(X=X, y=y, top_k=len(X.columns),
                         score_func=mutual_info_classif)
```

```
could not convert string to float: 'failure'
```

Thus we should encode the categorical variables first:

```
In [146]: def convert(df, x):
              df[x] = df[x].astype('category').cat.codes
              return df

          for col in bank.columns[bank.dtypes==object]:
              convert(bank, col)
```

```
In [147]: bank.head()
```

Out[147]:
```
   age  job  marital  education  default  housing  loan  contact  month  \
0   56    3        1          0        0        0     0        1      6
1   57    7        1          3        1        0     0        1      6
2   37    7        1          3        0        2     0        1      6
3   40    0        1          1        0        0     0        1      6
4   56    7        1          3        0        0     2        1      6

   day_of_week ...  campaign  pdays  previous  poutcome  emp.var.rate  \
0            1 ...         1    999         0         1           1.1
1            1 ...         1    999         0         1           1.1
2            1 ...         1    999         0         1           1.1
3            1 ...         1    999         0         1           1.1
4            1 ...         1    999         0         1           1.1

   cons.price.idx  cons.conf.idx  euribor3m  nr.employed  y
0          93.994          -36.4      4.857       5191.0  0
1          93.994          -36.4      4.857       5191.0  0
2          93.994          -36.4      4.857       5191.0  0
3          93.994          -36.4      4.857       5191.0  0
4          93.994          -36.4      4.857       5191.0  0

[5 rows x 21 columns]
```

In [148]:
```
X = bank.iloc[:,:20]
y = bank.iloc[:,20]
```

In [149]:
```
feature_select(X=X, y=y, top_k=len(X.columns),
               score_func=chi2)
```

```
Input X must be non-negative.
```

In [150]:
```
feature_select(X=X, y=y, top_k=len(X.columns),
               score_func=mutual_info_classif)
```

Out[150]:
```
[('duration', 0.07614671423151775),
 ('euribor3m', 0.07327347008256746),
 ('cons.conf.idx', 0.06994188994231076),
 ('cons.price.idx', 0.06767037174509372),
 ('nr.employed', 0.06362196307631929),
 ('emp.var.rate', 0.05779197709582329),
 ('poutcome', 0.03847041057059419),
 ('pdays', 0.036971336336834026),
 ('month', 0.02829677448265744),
 ('previous', 0.02261469360740831),
 ('job', 0.013174539253746786),
 ('contact', 0.013130998323356291),
 ('age', 0.011946569515146166),
 ('campaign', 0.006822691894516009),
```

```
 ('marital', 0.006396233281845021),
 ('default', 0.004979385163925043),
 ('housing', 0.004813778452020578),
 ('education', 0.004016400197124348),
 ('day_of_week', 0.003497944805602282),
 ('loan', 0.0)]
```

Note: after categorical encoding:

- mutual info function is applicable for both categorical and numerical variables;
- for χ^2, we should split the dataset to categorical variables and numerical variables and apply χ^2 on only categorical ones;

- c):

```
In [151]: X_categorical = bank[categorical_cols].iloc[:, :-1]
          X_numerical = bank[numerical_cols]
```

```
In [152]: categorical_list = feature_select(X=X_categorical, y=y,
                                            top_k=len(X_categorical.columns),
                                            score_func=chi2)
          categorical_list
```

```
Out[152]: [('contact', 547.9583093880087),
           ('default', 321.9229031035162),
           ('education', 167.60728300206605),
           ('poutcome', 98.23117431597791),
           ('job', 90.17553267281917),
           ('marital', 27.79559829132918),
           ('day_of_week', 10.231444571849314),
           ('housing', 4.978734333542827),
           ('month', 1.9272840371275475),
           ('loan', 1.587004275347953)]
```

```
In [153]: numerical_list = feature_select(X=X_numerical, y=y,
                                          top_k=len(X_numerical.columns),
                                          score_func=mutual_info_classif)
          numerical_list
```

```
Out[153]: [('duration', 0.07525225098886623),
           ('euribor3m', 0.07316573548893013),
           ('cons.conf.idx', 0.06938219910495858),
           ('cons.price.idx', 0.06827983845588737),
           ('nr.employed', 0.06604616380774075),
           ('emp.var.rate', 0.055734119670813875),
           ('pdays', 0.034706598816409695),
           ('previous', 0.01772265602892253),
           ('age', 0.015810661522751568),
           ('campaign', 0.0034902133516785394)]
```

Task 3: Based on the two ranked lists obtained in Task 2, plot the value distribution of (i) the highest ranked three categorical features, (ii) the lowest ranked three categorical features, (iii) the highest ranked three numerical features, and (iv) the lowest ranked three numerical features. Describe what you observe from these value distributions.

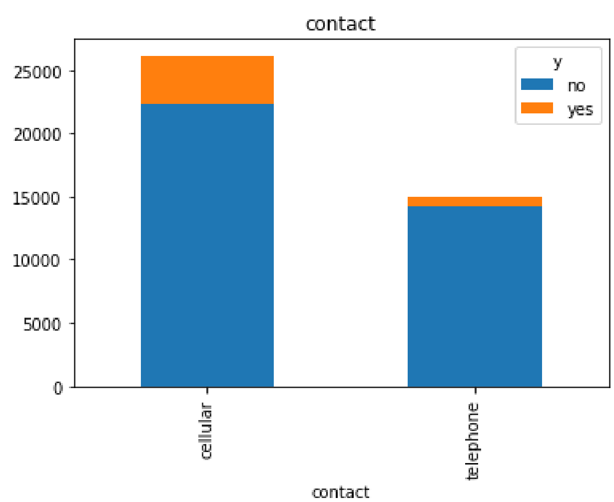
```
In [154]: bank = pd.read_csv('bank-additional-full.csv', sep=';')
```

```
In [155]: def plots(var_list, type_='categorical'):
              if type_=='categorical':
                  for var in var_list:
                      ct = pd.crosstab(bank[var], bank.y)
                      print(ct)
                      ax = ct.plot.bar(stacked=True)
                      ax.set_title(var)
                      plt.show()
              elif type_=='numerical':
                  for var in var_list:
                      x_multi = [bank[var][bank.y==i].values for i in set(bank.y)]
                      plt.hist(x_multi, bins=10, histtype='bar')
                      plt.title(var)
                      plt.legend(x_multi, labels = np.unique(bank.y))
                      plt.show()
```

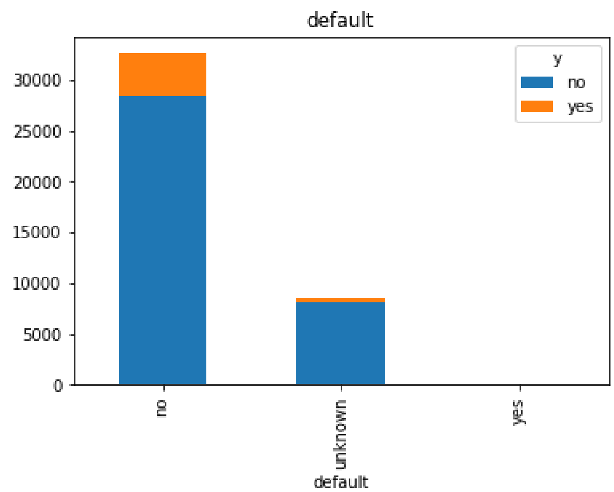
i) Highest 3 categorical:

```
In [156]: plots(list(map(lambda x: x[0], categorical_list[:3])))
```

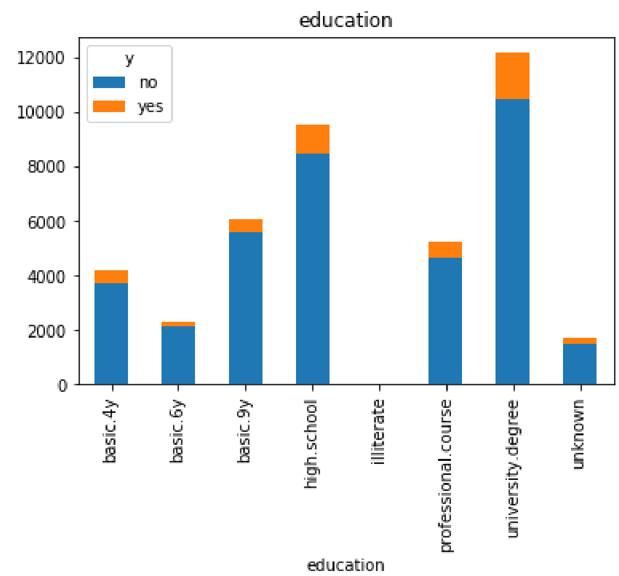
```
y             no   yes
contact
cellular   22291  3853
telephone  14257   787
```



y	no	yes
default		
no	28391	4197
unknown	8154	443
yes	3	0



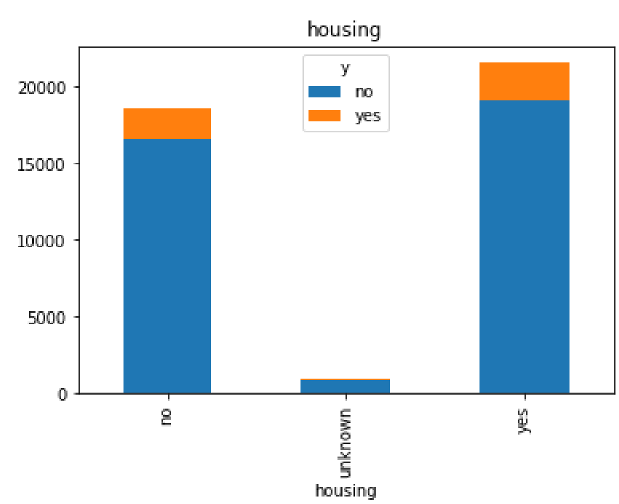
y	no	yes
education		
basic.4y	3748	428
basic.6y	2104	188
basic.9y	5572	473
high.school	8484	1031
illiterate	14	4
professional.course	4648	595
university.degree	10498	1670
unknown	1480	251



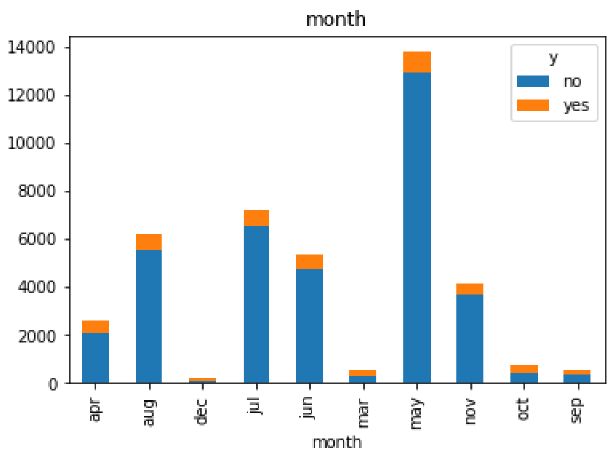
ii) Lowest 3 categorical:

```
In [157]: plots(list(map(lambda x: x[0], categorical_list[-3:])))
```

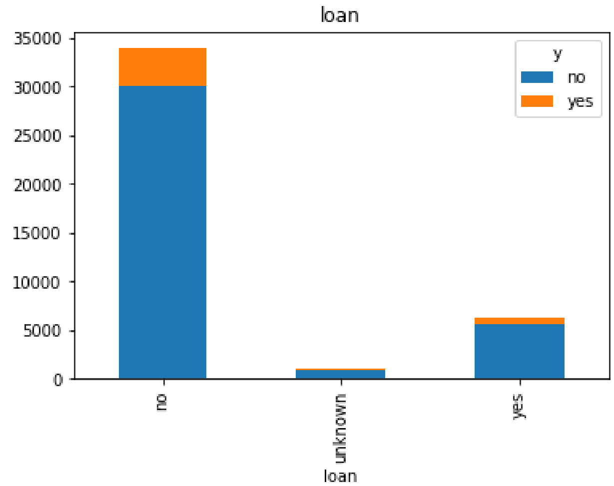
```
y            no   yes
housing
no        16596  2026
unknown     883   107
yes       19069  2507
```



```
y          no  yes
month
apr      2093  539
aug      5523  655
dec        93   89
jul      6525  649
jun      4759  559
mar       270  276
may     12883  886
nov      3685  416
oct       403  315
sep       314  256
```



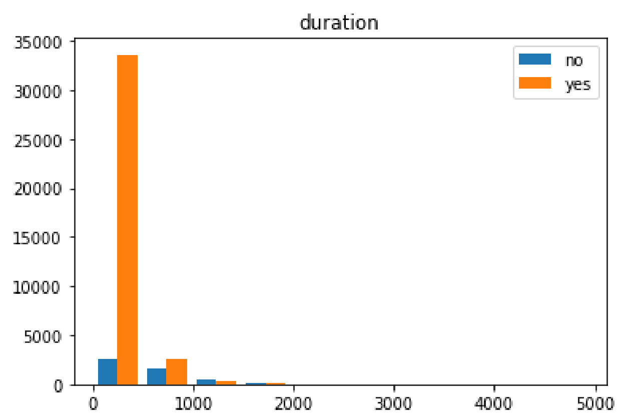

```
y           no   yes
loan
no       30100  3850
unknown    883   107
yes       5565   683
```

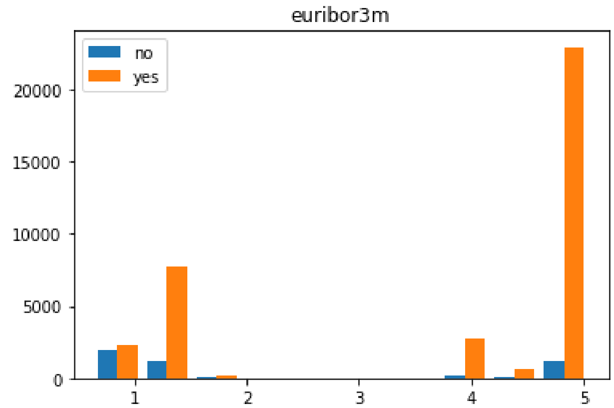


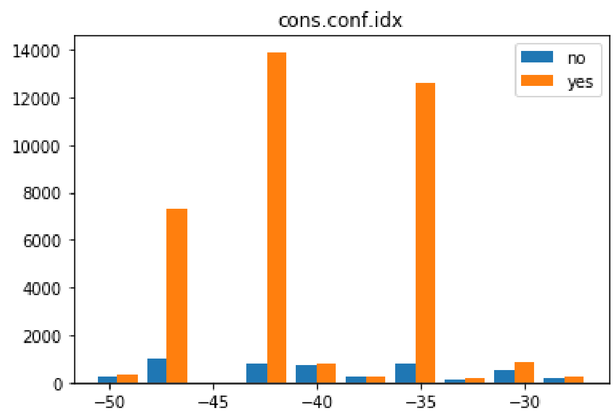
iii) Highest 3 numerical:

```
In [158]: plots(list(map(lambda x: x[0], numerical_list[:3])), type_='numerical')
```

```
/usr/local/lib/python3.6/dist-packages/matplotlib/legend.py:1363: UserWarning: You have mixed po
  warnings.warn("You have mixed positional and keyword "
```



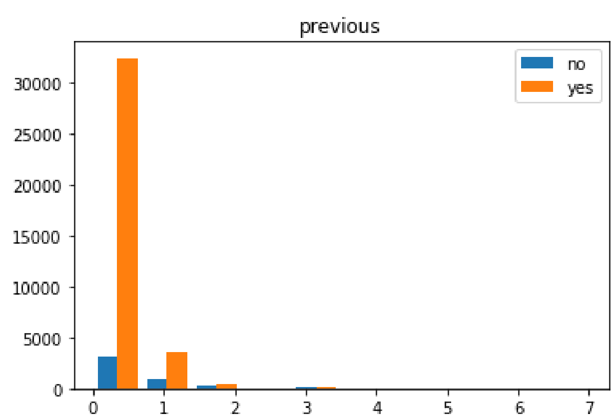


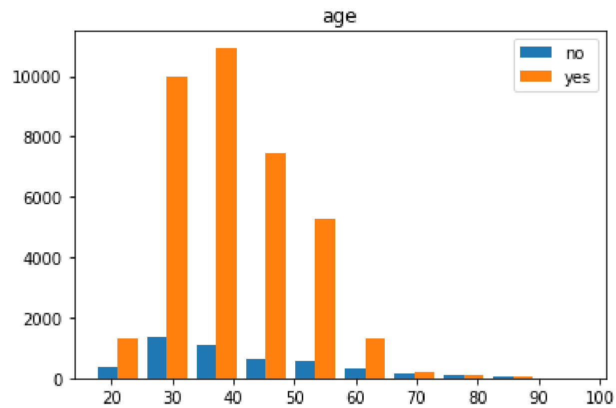


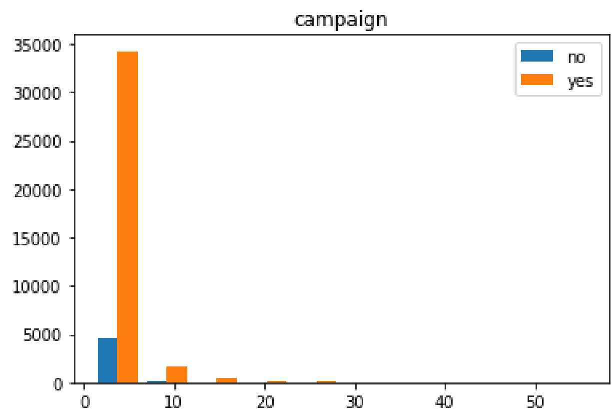
iv) Lowest 3 numerical:

```
In [159]: plots(list(map(lambda x: x[0], numerical_list[-3:])), type_='numerical')
```

```
/usr/local/lib/python3.6/dist-packages/matplotlib/legend.py:1363: UserWarning: You have mixed po
  warnings.warn("You have mixed positional and keyword "
```







Data preprocessing

Task 1: Normalize the range of values of numerical features. If values are all positive or all negative, normalize them into [0, 1] or [-1, 0], respectively. Otherwise, normalize them into [-1, 1]. For each normalized numerical feature, submit the ranges of its original and normalized values.

```
In [160]: bank_numericals = bank[numerical_cols]
          p_mask = list(map(lambda x: all(bank_numericals[x]>=0), numerical_cols))
          n_mask = list(map(lambda x: all(bank_numericals[x]<0), numerical_cols))
          p_n_mask = list(map(lambda x: not(all(bank_numericals[x]>=0) or
                                            all(bank_numericals[x]<0)), numerical_cols))
          p_cols = numerical_cols[p_mask]
          n_cols = numerical_cols[n_mask]
          p_n_cols = numerical_cols[p_n_mask]
          p_cols, n_cols, p_n_cols
```

Out[160]:
```
(Index(['age', 'duration', 'campaign', 'pdays', 'previous', 'cons.price.idx',
        'euribor3m', 'nr.employed'],
       dtype='object'),
 Index(['cons.conf.idx'], dtype='object'),
 Index(['emp.var.rate'], dtype='object'))
```

In [161]:
```
def scale(data, cols, range_=(0,1)):
    min_max_scaler_p = MinMaxScaler(feature_range=range_)
    return min_max_scaler_p.fit_transform(data[cols])
```

In [162]:
```
scaled_p = pd.DataFrame(scale(bank, p_cols), columns=p_cols)
scaled_n = pd.DataFrame(scale(bank, n_cols, range_=(-1,0)), columns=n_cols)
scaled_p_n = pd.DataFrame(scale(bank, p_n_cols, range_=(-1,1)), columns=p_n_cols)
scaled_bank_numericals = pd.concat([scaled_p, scaled_n, scaled_p_n], axis=1)
```

In [163]:
```
scaled_bank_numericals.head()
```

Out[163]:

	age	duration	campaign	pdays	previous	cons.price.idx	euribor3m
0	0.481481	0.053070	0.0	1.0	0.0	0.698753	0.957379
1	0.493827	0.030297	0.0	1.0	0.0	0.698753	0.957379
2	0.246914	0.045954	0.0	1.0	0.0	0.698753	0.957379
3	0.283951	0.030704	0.0	1.0	0.0	0.698753	0.957379
4	0.481481	0.062424	0.0	1.0	0.0	0.698753	0.957379

	nr.employed	cons.conf.idx	emp.var.rate
0	0.859735	-0.39749	0.875
1	0.859735	-0.39749	0.875
2	0.859735	-0.39749	0.875
3	0.859735	-0.39749	0.875
4	0.859735	-0.39749	0.875

In [164]:
```
np.set_printoptions(precision=3)
range_list = list(map(lambda x: {x: {'original range':[bank_numericals[x].min(),
                                                        bank_numericals[x].max()],
                        'scaled range': [scaled_bank_numericals[x].min(),
                                         scaled_bank_numericals[x].max()]}}
                                , numerical_cols))


for i in range_list:
    for key, value in i.items():
        for r_type, r in value.items():
            print('for numerical variable {}:\n\t the {} is {}\n'
                  .format(key,r_type, r))
```

```
for numerical variable age:
	 the original range is [17, 98]

for numerical variable age:
	 the scaled range is [0.0, 1.0]
```

```
for numerical variable duration:
        the original range is [0, 4918]

for numerical variable duration:
        the scaled range is [0.0, 1.0]

for numerical variable campaign:
        the original range is [1, 56]

for numerical variable campaign:
        the scaled range is [0.0, 0.9999999999999999]

for numerical variable pdays:
        the original range is [0, 999]

for numerical variable pdays:
        the scaled range is [0.0, 1.0]

for numerical variable previous:
        the original range is [0, 7]

for numerical variable previous:
        the scaled range is [0.0, 1.0]

for numerical variable emp.var.rate:
        the original range is [-3.4, 1.4]

for numerical variable emp.var.rate:
        the scaled range is [-1.0, 1.0]

for numerical variable cons.price.idx:
        the original range is [92.20100000000001, 94.76700000000001]

for numerical variable cons.price.idx:
        the scaled range is [0.0, 1.0]

for numerical variable cons.conf.idx:
        the original range is [-50.8, -26.9]

for numerical variable cons.conf.idx:
        the scaled range is [-1.0, 0.0]

for numerical variable euribor3m:
        the original range is [0.634, 5.045]

for numerical variable euribor3m:
        the scaled range is [0.0, 1.0]
```

```
for numerical variable nr.employed:
	 the original range is [4963.6, 5228.1]

for numerical variable nr.employed:
	 the scaled range is [0.0, 1.0]
```

Task 2: Encode categorical features using one-hot representation scheme. For example, assuming that there is a 'state' feature with three categorical values, 'PA', 'NY' and 'NJ'. Create three new binary features, namely 'state_is_PA', 'state_is_NY' and 'state_is_NJ' to replace 'state', where the feature values are either 0 or 1. For each new binary feature, count and report the number of value 1, e.g., "state_is_PA": 15000, "state_is_NY": 20000 and "state_is_NJ": 10000.

In [165]:
```
categorical_cols = categorical_cols.drop(['contact', 'y'])
```

In [166]:
```
def OneHot(data, var_list):
    try:
        one_hot_bank = pd.DataFrame()
        for var in var_list:
            one_hot = LabelBinarizer()
            one_hot_res = one_hot.fit_transform(bank[var])
            col = list(map(lambda x: '{}_is_'.format(var)+x,
                           one_hot.classes_))
            one_hot_bank = pd.concat([one_hot_bank,
                                      pd.DataFrame(one_hot_res, columns=col)],
                                      axis=1)
        # labelbinarizer not working for 2 classes
        telephone = np.array([0]*len(bank))
        cellular = np.array([0]*len(bank))
        telephone[bank.index[bank.contact == 'telephone']]=1
        cellular[bank.index[bank.contact == 'cellular']]=1
        contact = pd.DataFrame({'telephone': telephone,
                     'cellular':cellular})
        contact.columns = ['contact_is_telephone', 'contact_is_cellular']
        one_hot_bank = pd.concat([one_hot_bank, contact], axis=1)
        return one_hot_bank
    except Exception as e:
        print(e)
```

In [171]:
```
one_hot_bank = OneHot(bank, categorical_cols)
preprocessed_bank = pd.concat([one_hot_bank, scaled_bank_numericals], axis=1)
preprocessed_bank.to_csv('preprocessed_bank_marketing_data.csv')
preprocessed_bank.head()
```

Out[171]:
```
   job_is_admin.  job_is_blue-collar  job_is_entrepreneur  job_is_housemaid  \
0              0                   0                    0                 1
```

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

   job_is_management  job_is_retired  job_is_self-employed  job_is_services  \
0                  0               0                     0                0
1                  0               0                     0                1
2                  0               0                     0                1
3                  0               0                     0                0
4                  0               0                     0                1

   job_is_student  job_is_technician      ...            age  duration  \
0               0                  0      ...       0.481481  0.053070
1               0                  0      ...       0.493827  0.030297
2               0                  0      ...       0.246914  0.045954
3               0                  0      ...       0.283951  0.030704
4               0                  0      ...       0.481481  0.062424

   campaign  pdays  previous  cons.price.idx  euribor3m  nr.employed  \
0       0.0    1.0       0.0        0.698753   0.957379     0.859735
1       0.0    1.0       0.0        0.698753   0.957379     0.859735
2       0.0    1.0       0.0        0.698753   0.957379     0.859735
3       0.0    1.0       0.0        0.698753   0.957379     0.859735
4       0.0    1.0       0.0        0.698753   0.957379     0.859735

   cons.conf.idx  emp.var.rate
0       -0.39749         0.875
1       -0.39749         0.875
2       -0.39749         0.875
3       -0.39749         0.875
4       -0.39749         0.875

[5 rows x 63 columns]
```

In [191]:
```
for col in one_hot_bank.columns:
    print('the number of value 1 in {} = {}'
          .format(col, len(one_hot_bank[one_hot_bank[col]==1])))
```

```
the number of value 1 in job_is_admin. = 10422
the number of value 1 in job_is_blue-collar = 9254
the number of value 1 in job_is_entrepreneur = 1456
the number of value 1 in job_is_housemaid = 1060
the number of value 1 in job_is_management = 2924
the number of value 1 in job_is_retired = 1720
the number of value 1 in job_is_self-employed = 1421
the number of value 1 in job_is_services = 3969
the number of value 1 in job_is_student = 875
```

```
the number of value 1 in job_is_technician = 6743
the number of value 1 in job_is_unemployed = 1014
the number of value 1 in job_is_unknown = 330
the number of value 1 in marital_is_divorced = 4612
the number of value 1 in marital_is_married = 24928
the number of value 1 in marital_is_single = 11568
the number of value 1 in marital_is_unknown = 80
the number of value 1 in education_is_basic.4y = 4176
the number of value 1 in education_is_basic.6y = 2292
the number of value 1 in education_is_basic.9y = 6045
the number of value 1 in education_is_high.school = 9515
the number of value 1 in education_is_illiterate = 18
the number of value 1 in education_is_professional.course = 5243
the number of value 1 in education_is_university.degree = 12168
the number of value 1 in education_is_unknown = 1731
the number of value 1 in default_is_no = 32588
the number of value 1 in default_is_unknown = 8597
the number of value 1 in default_is_yes = 3
the number of value 1 in housing_is_no = 18622
the number of value 1 in housing_is_unknown = 990
the number of value 1 in housing_is_yes = 21576
the number of value 1 in loan_is_no = 33950
the number of value 1 in loan_is_unknown = 990
the number of value 1 in loan_is_yes = 6248
the number of value 1 in month_is_apr = 2632
the number of value 1 in month_is_aug = 6178
the number of value 1 in month_is_dec = 182
the number of value 1 in month_is_jul = 7174
the number of value 1 in month_is_jun = 5318
the number of value 1 in month_is_mar = 546
the number of value 1 in month_is_may = 13769
the number of value 1 in month_is_nov = 4101
the number of value 1 in month_is_oct = 718
the number of value 1 in month_is_sep = 570
the number of value 1 in day_of_week_is_fri = 7827
the number of value 1 in day_of_week_is_mon = 8514
the number of value 1 in day_of_week_is_thu = 8623
the number of value 1 in day_of_week_is_tue = 8090
the number of value 1 in day_of_week_is_wed = 8134
the number of value 1 in poutcome_is_failure = 4252
the number of value 1 in poutcome_is_nonexistent = 35563
the number of value 1 in poutcome_is_success = 1373
the number of value 1 in contact_is_telephone = 15044
the number of value 1 in contact_is_cellular = 26144
```