TomaszBiegusCoffeePython

July 8, 2018

1 Tomasz Biegus Coffee data analysis - Python

I decided to perform two analysis, one with R and another in python, because I see the python is more used in Objectivity (maybe I'm wrong about that). I decided to use R because of great tool called DALEX, which is developed exactly for this task. In Python i perform more basic analysis.

2 1. Preliminary data processing

Imports and read the data.

```
In [1]: import matplotlib.pyplot as plt
        import pandas as pd
        from pandas.api.types import is_numeric_dtype
        from sklearn.preprocessing import MinMaxScaler
```

```
In [2]: coffee_data = pd.read_csv("coffee_data.csv")
```

Short looka at the data.

```
In [3]: coffee_data.head()
```

```
Out[3]:      region  brewing_temp  coffee_amount  preinfusion  grinding_level   TDS
        0    Panama          91.1            NaN          0.0             7.0   NaN
        1    Panama          94.0            5.9          NaN             2.0  0.14
        2  Colombia          91.6            7.0          0.0             4.0  0.13
        3    Rwanda          92.3            NaN          0.0             4.0  0.13
        4    Panama          98.9            9.5          NaN             3.0  0.11

           water_ph  plantation_height processing_method  brewing_time  mark
        0      6.67             1710.0             Honey         189.0     3
        1      3.00             1530.0             Honey          95.0     3
        2      5.51             1370.0             Honey         147.0     3
        3      7.11             1630.0             Honey         158.0     3
        4      6.06             1400.0            Washed         178.0     3
```

Define helper function to summary the data.

```
In [6]: def summary(data_frame):
            summary = pd.DataFrame(columns = ["Attribute", "%NaN", "mean", "median'
            i = 0
            for column in data_frame:
                data = data_frame[column]
                nanSum = data.isnull().sum()
                size = data.size
                nanFraction = nanSum / size
                mean = median = std = "NaN"
                if is_numeric_dtype(data):
                    mean = data.mean()
                    median = data.median()
                    std = data.std()
                summary.loc[i] = [column, nanFraction, mean, median, std]
                i+=1
            return summary
```

Check out how summary function works.

```
In [7]: print(summary(coffee_data))
```

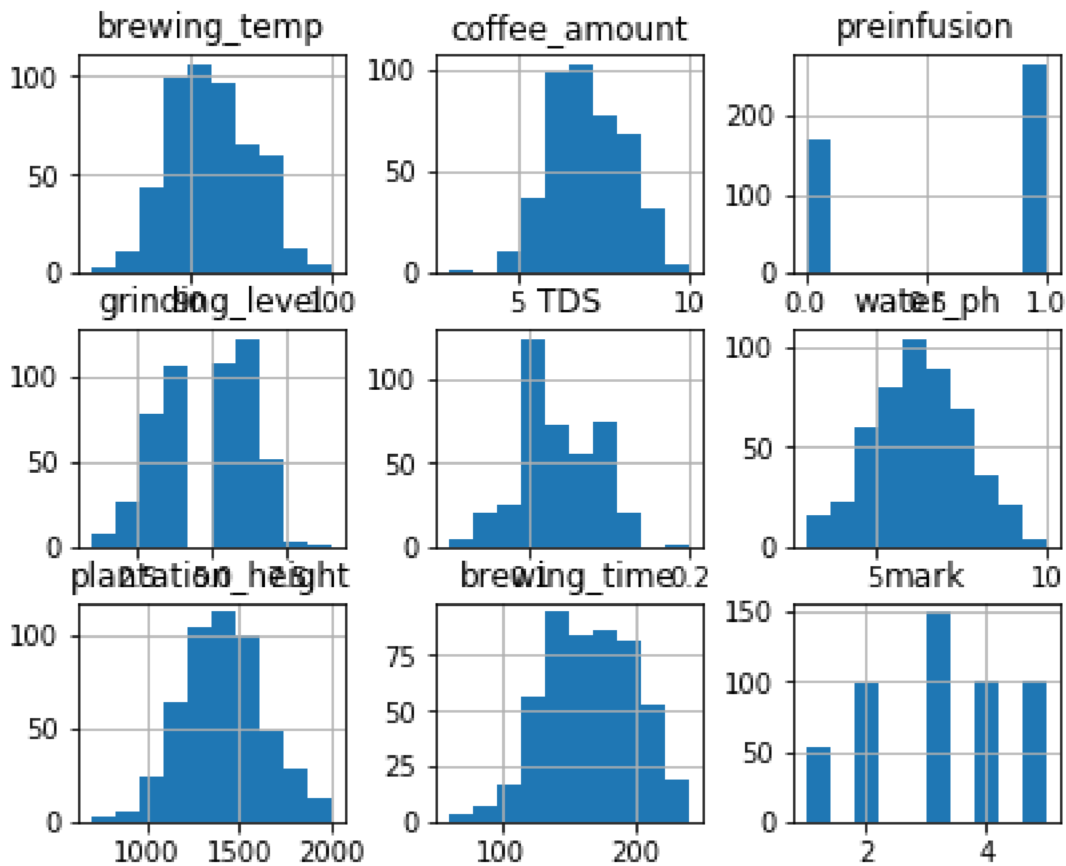
```
             Attribute   %NaN      mean median        std
0               region  0.000       NaN    NaN        NaN
1         brewing_temp  0.000    91.387   91.3    2.89638
2        coffee_amount  0.132   6.98871    6.9    1.06826
3          preinfusion  0.128  0.607798      1   0.488802
4       grinding_level  0.000     4.744      5     1.4815
5                  TDS  0.198  0.119152   0.12  0.0226998
6             water_ph  0.000   6.30366  6.285    1.34444
7    plantation_height  0.000    1405.8   1400    222.307
8    processing_method  0.000       NaN    NaN        NaN
9         brewing_time  0.000    164.84    166    33.5488
10                mark  0.000     3.194      3    1.25679
```

Define another helper function to look at distributions of numeric arguments.

```
In [50]: def plot_distributions(data_frame):
             counter = 0
             positions = [331,332,333,334,335,336,337,338,339]
             for column in data_frame:
                 data = data_frame[column]
                 if is_numeric_dtype(data):
                     plt.subplot(positions[counter])
                     data.hist()
                     plt.title(column)
                     counter+=1
             plt.subplots_adjust(top=1.0, bottom=0, left=0.10, right=0.95, hspace=(
                                 wspace=0.35)
             plt.show()
```

Look at distributions of numeric variables.

```
In [51]: plot_distributions(coffee_data)
```



Normalization of numeric data using MinMaxScaler.

```
In [52]: def normalize_numeric_data(data_frame):
             normalized_data = pd.DataFrame()
             scaler = MinMaxScaler()
             for column in data_frame:
                 data = data_frame[column]
                 if is_numeric_dtype(data):
                     data_column = data_frame[[column]]
                     null_index = data_column[column].isnull()
                     data_column.loc[~null_index, [column]] = scaler.fit_transform
                     normalized_data[column] = data_column
             return normalized_data
```

Take a look at normalized numeric data.

```
In [53]: import warnings
         warnings.filterwarnings('ignore')
```

```
normalized_data = normalize_numeric_data(coffee_data)
print(normalized_data.head())
```

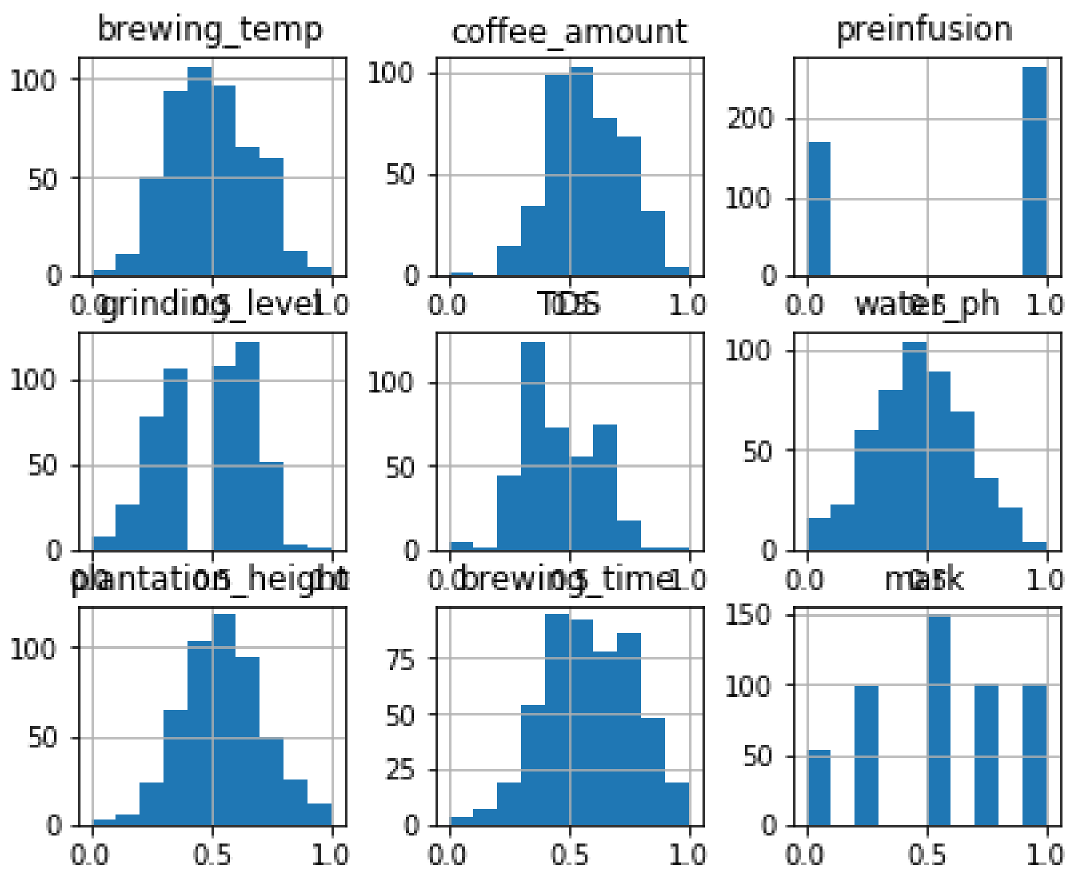
```
   brewing_temp  coffee_amount  preinfusion  grinding_level       TDS  \
0      0.476471            NaN          0.0           0.750       NaN
1      0.647059       0.414286          NaN           0.125  0.600000
2      0.505882       0.571429          0.0           0.375  0.533333
3      0.547059            NaN          0.0           0.375  0.533333
4      0.935294       0.928571          NaN           0.250  0.400000

   water_ph  plantation_height  brewing_time  mark
0  0.524286           0.776923      0.716667   0.5
1  0.000000           0.638462      0.194444   0.5
2  0.358571           0.515385      0.483333   0.5
3  0.587143           0.715385      0.544444   0.5
4  0.437143           0.538462      0.655556   0.5
```

```
In [54]: print(summary(normalized_data))
```

```
           Attribute   %NaN      mean    median       std
0       brewing_temp  0.000  0.493353  0.488235  0.170375
1      coffee_amount  0.132  0.569816  0.557143  0.152609
2        preinfusion  0.128  0.607798  1.000000  0.488802
3     grinding_level  0.000  0.468000  0.500000  0.185188
4                TDS  0.198  0.461014  0.466667  0.151332
5           water_ph  0.000  0.471951  0.469286  0.192063
6  plantation_height  0.000  0.542923  0.538462  0.171005
7       brewing_time  0.000  0.582444  0.588889  0.186382
8               mark  0.000  0.548500  0.500000  0.314198
```

```
In [55]: plot_distributions(normalized_data)
```



Look at whole data to recall the categorical variables.

```
In [56]: coffee_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 11 columns):
region               500 non-null object
brewing_temp         500 non-null float64
coffee_amount        434 non-null float64
preinfusion          436 non-null float64
grinding_level       500 non-null float64
TDS                  401 non-null float64
water_ph             500 non-null float64
plantation_height    500 non-null float64
processing_method    500 non-null object
brewing_time         500 non-null float64
mark                 500 non-null int64
dtypes: float64(8), int64(1), object(2)
memory usage: 43.0+ KB
```

```
In [ ]:
```

Deal with na values. We have big loss of rows caused by lots of na's in variables: preinfucion, coffee_amount and TDS. There are some techniques to deal with it for example by create regression models with those variables as an output (e.g model for input most probable values of coffee_amount where it's na, based on known values and another variables). Now I assume that lost of 20% of rows is acceptable.

```
In [57]: normalized_data.info()
```

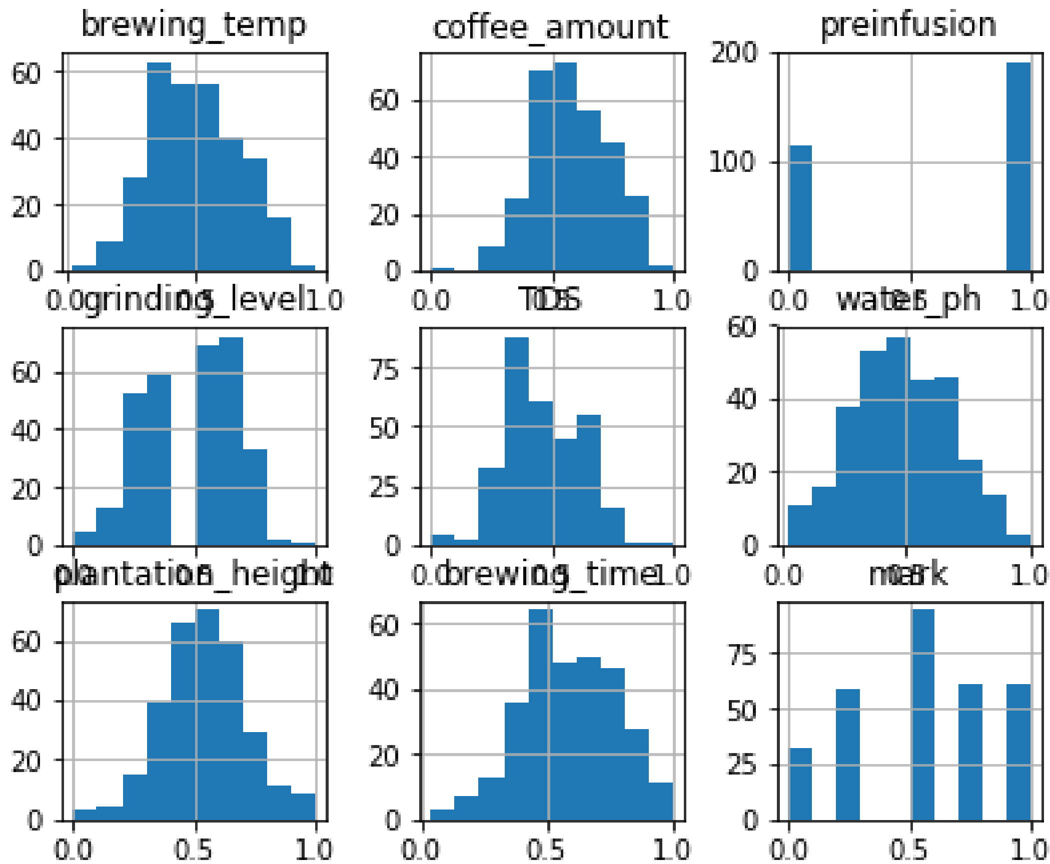
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 columns):
brewing_temp         500 non-null float64
coffee_amount        434 non-null float64
preinfusion          436 non-null float64
grinding_level       500 non-null float64
TDS                  401 non-null float64
water_ph             500 non-null float64
plantation_height    500 non-null float64
brewing_time         500 non-null float64
mark                 500 non-null float64
dtypes: float64(9)
memory usage: 35.2 KB
```

```
In [58]: numeric_clear_data = normalized_data.dropna()
```

```
In [59]: numeric_clear_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 306 entries, 2 to 499
Data columns (total 9 columns):
brewing_temp         306 non-null float64
coffee_amount        306 non-null float64
preinfusion          306 non-null float64
grinding_level       306 non-null float64
TDS                  306 non-null float64
water_ph             306 non-null float64
plantation_height    306 non-null float64
brewing_time         306 non-null float64
mark                 306 non-null float64
dtypes: float64(9)
memory usage: 23.9 KB
```

```
In [60]: plot_distributions(numeric_clear_data)
```

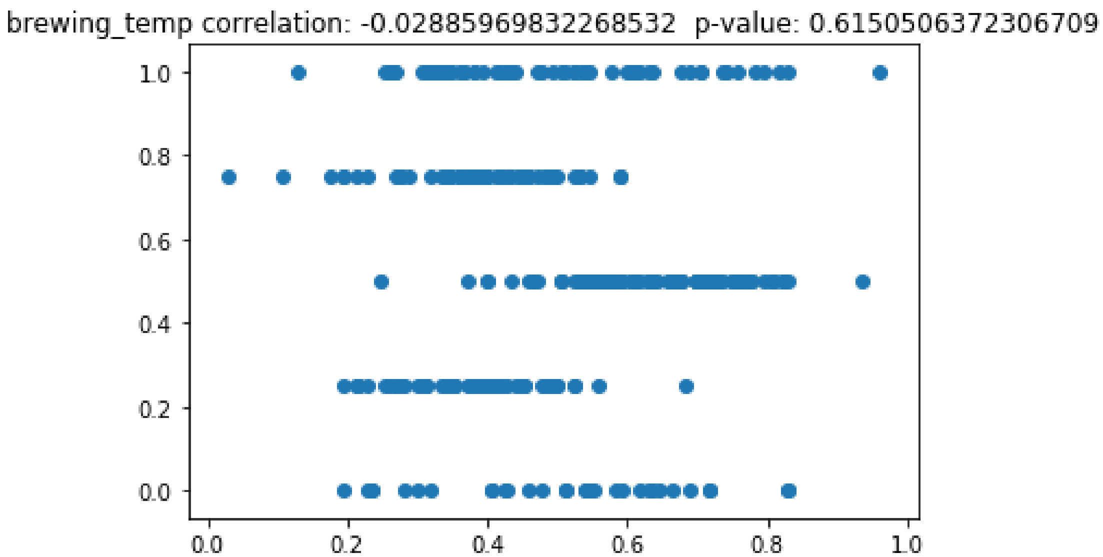


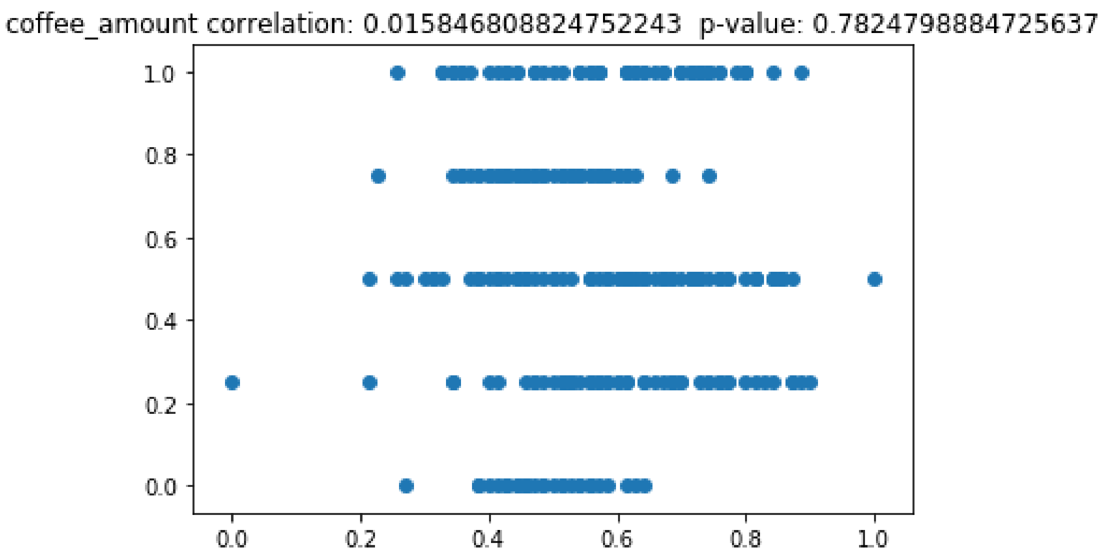
3 2. Analysis of correlation between numeric variables and mark.

Calculate and plot pearson correlation coefficients between variables and response (mark).

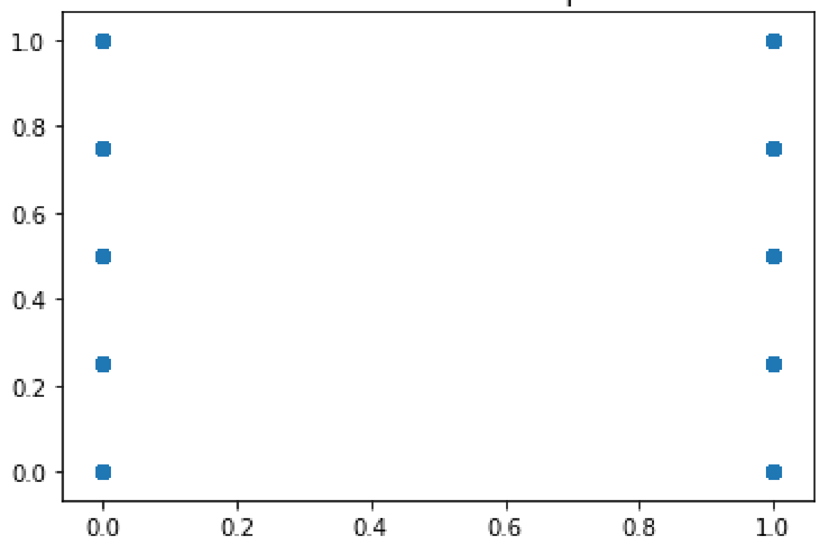
```
In [62]: from scipy.stats import pearsonr

         np_marks = numeric_clear_data[['mark']].values
         columns = list(numeric_clear_data)
         columns.remove('mark')
         for column in columns:
             np_column_data = numeric_clear_data[[column]].values
             correlation = pearsonr(np_marks, np_column_data)
             plt.scatter(np_column_data, np_marks)
             title = '{} correlation: {}  p-value: {}'.format(column, correlation[
             plt.title(title)
             plt.show()
```

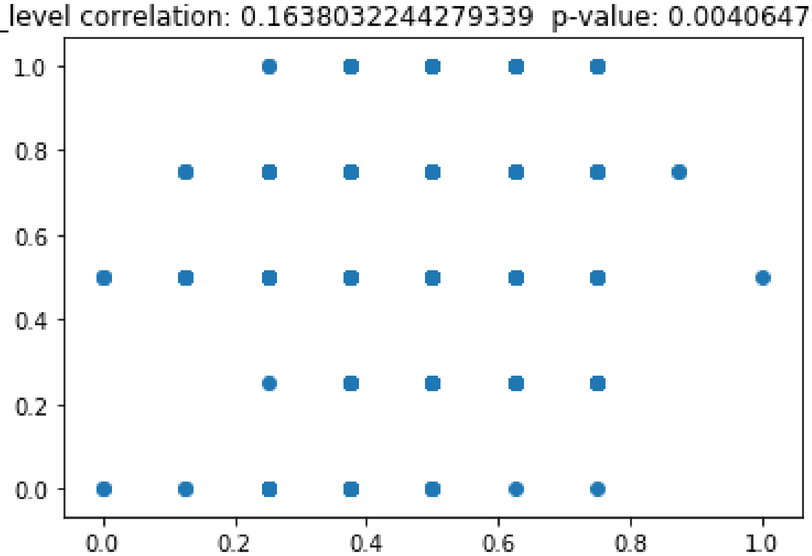

brewing_temp correlation: -0.02885969832268532 p-value: 0.6150506372306709
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

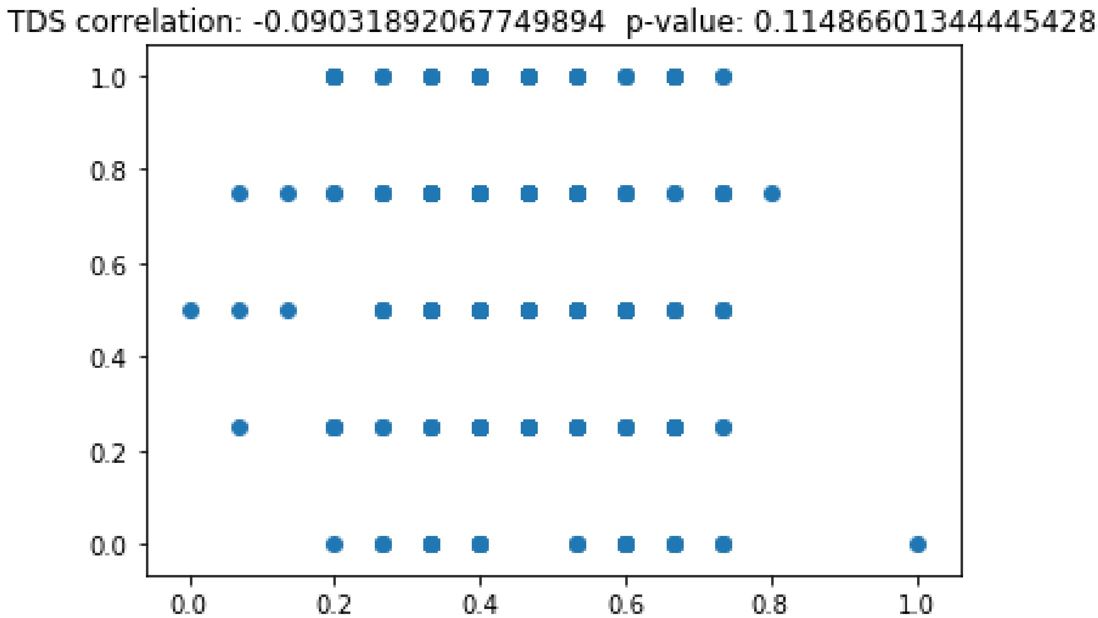

coffee_amount correlation: 0.015846808824752243 p-value: 0.7824798884725637
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

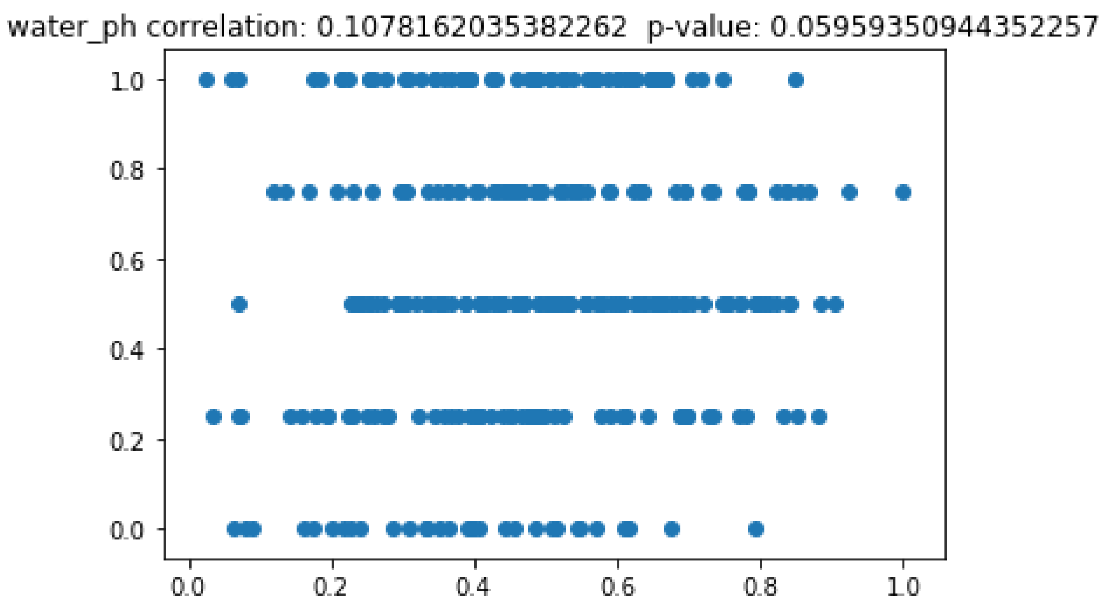
preinfusion correlation: 0.010382306027990822 p-value: 0.8564635244025991

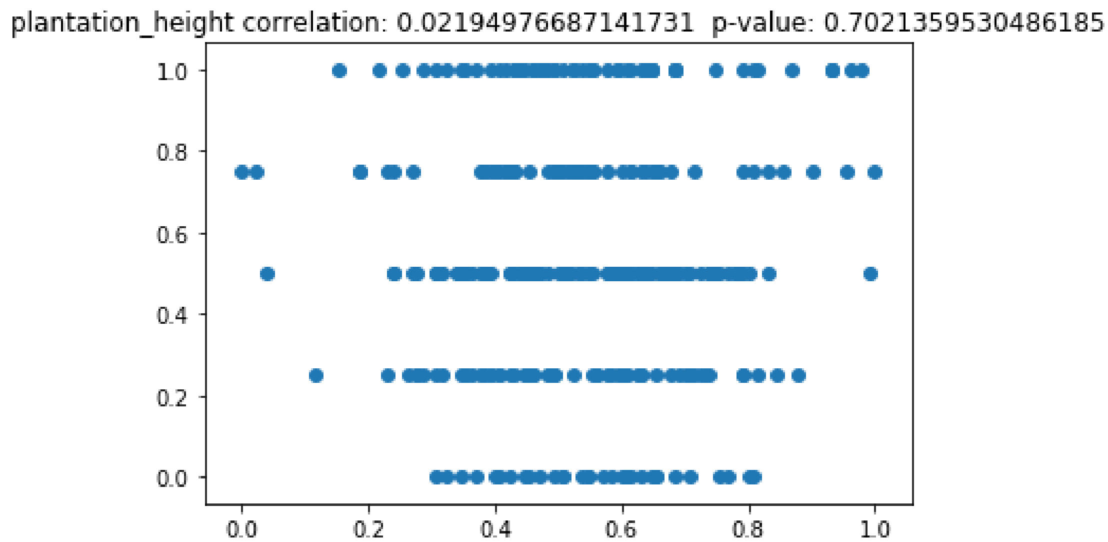


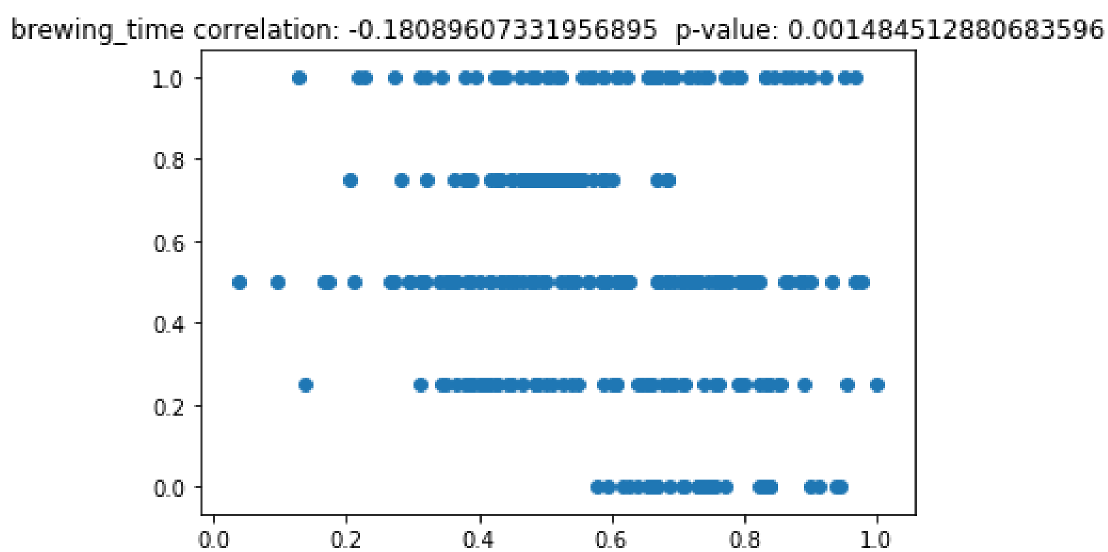
grinding_level correlation: 0.1638032244279339 p-value: 0.00406478598838625




TDS correlation: -0.09031892067749894 p-value: 0.11486601344445428
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


water_ph correlation: 0.1078162035382262 p-value: 0.05959350944352257
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0





Summary of correlation coefficients for numeric features.

```
In [63]: for column in columns:
             np_column_data = numeric_clear_data[[column]].values
             correlation = pearsonr(np_marks, np_column_data)
             print('{} correlation: {}  p-value: {}'.format(column, correlation[0]

brewing_temp correlation: -0.02885969832268532  p-value: 0.6150506372306709
coffee_amount correlation: 0.015846808824752243  p-value: 0.7824798884725637
preinfusion correlation: 0.010382306027990822  p-value: 0.8564635244025991
```

```
grinding_level correlation: 0.1638032244279339  p-value: 0.004064785988838625
TDS correlation: -0.09031892067749894  p-value: 0.11486601344445428
water_ph correlation: 0.1078162035382262  p-value: 0.05959350944352257
plantation_height correlation: 0.02194976687141731  p-value: 0.7021359530486185
brewing_time correlation: -0.18089607331956895  p-value: 0.001484512880683596
```

3.1 Summary of correlations

As we can see the strongest correlation between variable and response we have in case of brewing_time, there is negative correlation. We can also notice that second biggest correlation is for grinding_level variable. But still both correlations aren't strong.

4 3. Principal Component Analysis

Using PCA we can estimate which variables corresponds to a greatest variation in our dataset.

```
In [70]: from sklearn.decomposition import PCA

         data_without_marks = numeric_clear_data.drop('mark', 1)
         # we exclude preinfucion because in fact it's non numeric, its boolean
         data_without_marks = data_without_marks.drop('preinfusion', 1)
         pca = PCA(n_components = 3)
         pca.fit(data_without_marks)
         print(pca.explained_variance_ratio_)
         print(pca.components_[0])
```

```
[ 0.25619992  0.18701288  0.1501211 ]
[ 0.24966891 -0.34715875 -0.61016609  0.01541462  0.28473104 -0.07781754
 -0.59789517]
```

```
In [71]: data_without_marks.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 306 entries, 2 to 499
Data columns (total 7 columns):
brewing_temp         306 non-null float64
coffee_amount        306 non-null float64
grinding_level       306 non-null float64
TDS                  306 non-null float64
water_ph             306 non-null float64
plantation_height    306 non-null float64
brewing_time         306 non-null float64
dtypes: float64(7)
memory usage: 19.1 KB
```

4.1 Summary of PCA

Principal component 1 (which explains 0.526 of variance) is linear combination of original variables, where the biggest part have third original variable which is grinding_level with coefficient = -0.61016609, second bigges part of 1st PC is brewing_time with coefficient = -0.59789517. There are some valuable informations, but doe's not include relation with output, PCA explains only contribution of variables in overall data variation.

5 4. Decision trees

Decision trees use concepts of entropy and information gain to choose order of variables in forks of generated tree. Lets take a look which variable is best for first split (at thee root of a tree) in those algorithm. It can be a clue which variable is best to describe output - mark of coffee.

First build a tree classifier.

```
In [75]: from sklearn import tree

         X = numeric_clear_data.drop(["mark"], 1).values
         Y = numeric_clear_data[["mark"]].values


         tree_clf = tree.DecisionTreeRegressor()
         tree_clf = tree_clf.fit(X, Y)

         type(tree_clf.tree_)

Out[75]: sklearn.tree._tree.Tree
```

Now we have to look into tree structure. Here's function to print tree classifier as a code in Python.

```
In [76]: from sklearn.tree import _tree

         def tree_to_code(tree, feature_names):
             tree_ = tree.tree_
             feature_name = [
                 feature_names[i] if i != _tree.TREE_UNDEFINED else "undefined!"
                 for i in tree_.feature
             ]
             print ("def tree({}):".format(", ".join(feature_names)))

             def recurse(node, depth):
                 indent = "    " * depth
                 if tree_.feature[node] != _tree.TREE_UNDEFINED:
                     name = feature_name[node]
                     threshold = tree_.threshold[node]
                     print ("{}if {} <= {}:".format(indent, name, threshold))
                     recurse(tree_.children_left[node], depth + 1)
```

```
                print ("{}else:  # if {} > {}".format(indent, name, threshold)
                recurse(tree_.children_right[node], depth + 1)
            else:
                print ("{}return {}".format(indent, tree_.value[node]))

    recurse(0, 1)
```

Let's use it to see how tree in build.

```
In [78]: feature_names = list(numeric_clear_data.columns.values)
         tree_to_code(tree_clf, feature_names)
```

```
def tree(brewing_temp, coffee_amount, preinfusion, grinding_level, TDS, water_ph, p
  if brewing_time <= 0.5916666984558105:
    if coffee_amount <= 0.6499999761581421:
      if grinding_level <= 0.4375:
        if water_ph <= 0.10357142984867096:
          if plantation_height <= 0.5076923370361328:
            return [[ 0.]]
          else:  # if plantation_height > 0.5076923370361328
            return [[ 0.25]]
        else:  # if water_ph > 0.10357142984867096
          if brewing_temp <= 0.5:
            if coffee_amount <= 0.2857142984867096:
              return [[ 0.25]]
            else:  # if coffee_amount > 0.2857142984867096
              if brewing_temp <= 0.4529411792755127:
                return [[ 0.75]]
              else:  # if brewing_temp > 0.4529411792755127
                if brewing_temp <= 0.4676470756530761 7:
                  return [[ 0.5]]
                else:  # if brewing_temp > 0.46764707565307617
                  return [[ 0.75]]
          else:  # if brewing_temp > 0.5
            if grinding_level <= 0.3125:
              if brewing_time <= 0.4833333492279053:
                return [[ 0.5]]
              else:  # if brewing_time > 0.4833333492279053
                if brewing_time <= 0.49166667461395264:
                  return [[ 0.75]]
                else:  # if brewing_time > 0.49166667461395264
                  return [[ 0.5]]
            else:  # if grinding_level > 0.3125
              if brewing_temp <= 0.6352940797805786:
                if coffee_amount <= 0.4642857313156128:
                  return [[ 0.75]]
                else:  # if coffee_amount > 0.4642857313156128
                  return [[ 0.5]]
```

```
          else:  # if brewing_temp > 0.6352940797805786
            return [[ 1.]]
    else:  # if grinding_level > 0.4375
      if brewing_temp <= 0.5058823823928833:
        if coffee_amount <= 0.3857142925262451:
          return [[ 1.]]
        else:  # if coffee_amount > 0.3857142925262451
          if brewing_time <= 0.36666667461395264:
            return [[ 0.25]]
          else:  # if brewing_time > 0.36666667461395264
            if brewing_temp <= 0.46764707565307617:
              if TDS <= 0.6333333253860474:
                return [[ 0.75]]
              else:  # if TDS > 0.6333333253860474
                if plantation_height <= 0.4923076927661896:
                  return [[ 0.75]]
                else:  # if plantation_height > 0.4923076927661896
                  return [[ 0.25]]
            else:  # if brewing_temp > 0.46764707565307617
              if grinding_level <= 0.6875:
                if TDS <= 0.5:
                  return [[ 0.25]]
                else:  # if TDS > 0.5
                  return [[ 0.75]]
              else:  # if grinding_level > 0.6875
                return [[ 0.75]]
      else:  # if brewing_temp > 0.5058823823928833
        if brewing_time <= 0.5777777433395386:
          if coffee_amount <= 0.37857145071029663:
            return [[ 0.75]]
          else:  # if coffee_amount > 0.37857145071029663
            return [[ 1.]]
        else:  # if brewing_time > 0.5777777433395386
          return [[ 0.5]]
  else:  # if coffee_amount > 0.6499999761581421
    if brewing_time <= 0.5694444179534912:
      if brewing_temp <= 0.7852941155433655:
        if brewing_temp <= 0.16470588743686676:
          return [[ 0.75]]
        else:  # if brewing_temp > 0.16470588743686676
          if brewing_time <= 0.49444442987442017:
            if plantation_height <= 0.634615421295166:
              return [[ 0.25]]
            else:  # if plantation_height > 0.634615421295166
              if brewing_time <= 0.46388888359069824:
                if plantation_height <= 0.6576923131942749:
                  return [[ 0.75]]
                else:  # if plantation_height > 0.6576923131942749
```

```
                    return [[ 0.5]]
                  else:  # if brewing_time > 0.46388888359069824
                    return [[ 0.25]]
              else:  # if brewing_time > 0.49444442987442017
                return [[ 0.5]]
          else:  # if brewing_temp > 0.7852941155433655
            return [[ 1.]]
        else:  # if brewing_time > 0.5694444179534912
          if grinding_level <= 0.8125:
            return [[ 1.]]
          else:  # if grinding_level > 0.8125
            return [[ 0.5]]
    else:  # if brewing_time > 0.5916666984558105
      if coffee_amount <= 0.6071428656578064:
        if grinding_level <= 0.3125:
          if brewing_time <= 0.6083333492279053:
            return [[ 0.75]]
          else:  # if brewing_time > 0.6083333492279053
            return [[ 0.]]
        else:  # if grinding_level > 0.3125
          if brewing_time <= 0.7250000238418579:
            if brewing_temp <= 0.3588235378265381:
              if grinding_level <= 0.4375:
                return [[ 0.]]
              else:  # if grinding_level > 0.4375
                return [[ 0.25]]
            else:  # if brewing_temp > 0.3588235378265381
              if coffee_amount <= 0.5:
                if grinding_level <= 0.5625:
                  return [[ 0.75]]
                else:  # if grinding_level > 0.5625
                  return [[ 1.]]
              else:  # if coffee_amount > 0.5
                if TDS <= 0.36666667461395264:
                  return [[ 1.]]
                else:  # if TDS > 0.36666667461395264
                  if brewing_temp <= 0.5323529243469238:
                    return [[ 0.25]]
                  else:  # if brewing_temp > 0.5323529243469238
                    return [[ 0.5]]
          else:  # if brewing_time > 0.7250000238418579
            if TDS <= 0.23333334922790527:
              return [[ 1.]]
            else:  # if TDS > 0.23333334922790527
              if TDS <= 0.5666667222976685:
                if coffee_amount <= 0.4642857313156128:
                  return [[ 0.]]
                else:  # if coffee_amount > 0.4642857313156128
```

```
            if grinding_level <= 0.4375:
              return [[ 1.]]
            else:  # if grinding_level > 0.4375
              if brewing_temp <= 0.5764706134796143:
                if brewing_time <= 0.7527778148651123:
                  if water_ph <= 0.19714286923408508:
                    return [[ 0.]]
                  else:  # if water_ph > 0.19714286923408508
                    return [[ 0.25]]
                else:  # if brewing_time > 0.7527778148651123
                  return [[ 0.25]]
              else:  # if brewing_temp > 0.5764706134796143
                return [[ 0.]]
        else:  # if TDS > 0.5666667222976685
          if water_ph <= 0.35357141494750977:
            return [[ 0.25]]
          else:  # if water_ph > 0.35357141494750977
            return [[ 0.]]
else:  # if coffee_amount > 0.6071428656578064
  if brewing_temp <= 0.479411780834198:
    if coffee_amount <= 0.6928571462631226:
      if brewing_time <= 0.7861111164093018:
        if water_ph <= 0.6542856693267822:
          return [[ 0.25]]
        else:  # if water_ph > 0.6542856693267822
          return [[ 0.5]]
      else:  # if brewing_time > 0.7861111164093018
        return [[ 1.]]
    else:  # if coffee_amount > 0.6928571462631226
      if coffee_amount <= 0.8285714387893677:
        if plantation_height <= 0.29230770468711853:
          return [[ 0.25]]
        else:  # if plantation_height > 0.29230770468711853
          return [[ 1.]]
      else:  # if coffee_amount > 0.8285714387893677
        if grinding_level <= 0.5625:
          return [[ 0.25]]
        else:  # if grinding_level > 0.5625
          return [[ 0.5]]
  else:  # if brewing_temp > 0.479411780834198
    if brewing_time <= 0.6527777910232544:
      if brewing_temp <= 0.6323529481887817:
        return [[ 0.5]]
      else:  # if brewing_temp > 0.6323529481887817
        return [[ 0.]]
    else:  # if brewing_time > 0.6527777910232544
      if TDS <= 0.7000000476837158:
        if grinding_level <= 0.4375:
```

```
          if plantation_height <= 0.5692307949066162:
            if water_ph <= 0.6535714268684387:
              return [[ 1.]]
            else:  # if water_ph > 0.6535714268684387
              return [[ 0.5]]
          else:  # if plantation_height > 0.5692307949066162
            return [[ 0.5]]
        else:  # if grinding_level > 0.4375
          if brewing_temp <= 0.49705883860588074:
            return [[ 0.25]]
          else:  # if brewing_temp > 0.49705883860588074
            return [[ 0.5]]
      else:  # if TDS > 0.7000000476837158
        if water_ph <= 0.46642857789993286:
          return [[ 0.]]
        else:  # if water_ph > 0.46642857789993286
          return [[ 0.5]]
```

5.1 Summary of decision tree approach

The most important part of generated code is:

if brewing_time <= 0.5916666984558105: if coffee_amount <= 0.6499999761581421:

So, decision tree classifier found that the best variables in terms of information gain are brewing_time followed by coffee_amount:

6 5. Nonnumeric (nominal and ordinal) variables

In [79]:
```
['region', 'preinfusion', 'processing_method']
```

Out[79]:
```
['region', 'preinfusion', 'processing_method']
```

In [80]:
```
region_data = coffee_data[['region', 'mark']]
aggregated = region_data.groupby('region').agg(['mean', 'median', 'std', '
aggregated
```

Out[80]:

	mark			
	mean	median	std	count
region				
Guatemala	5.000000	5	NaN	1
Brazil	3.400000	3	1.140175	5
Panama	3.274809	3	1.312973	131
Rwanda	3.223301	3	1.244061	103
Ethiopia	3.214286	3	1.397276	28
Colombia	3.203704	3	1.187667	54
Kenya	3.109756	3	1.233540	164
Honduras	2.928571	3	1.206666	14

```
In [81]: region_data = coffee_data[['preinfusion', 'mark']]
         aggregated = region_data.groupby('preinfusion').agg(['mean', 'median', 'st
         aggregated
```

```
Out[81]:                  mark
                          mean median       std count
         preinfusion
         1.0          3.184906      3  1.282073   265
         0.0          3.134503      3  1.273962   171
```

```
In [109]: region_data = coffee_data[['processing_method', 'mark']]
          aggregated = region_data.groupby('processing_method').agg(['mean', 'media
          aggregated
```

```
Out[109]:                       mark
                                mean median       std count
          processing_method
          Pulped Natural    3.352941      3  1.411612    17
          Washed            3.232673      3  1.250004   202
          Honey             3.180812      3  1.235494   271
          Natural           2.500000      2  1.649916    10
```

7 6. Overall summary

7.0.1 Numeric variables

Correlations: Strongest correlation between variable and response we have in case of brewing_time, second biggest correlation is in case of grinding_level

PCA: Based on PCA the most important variable in terms of explanation of overall variance is grinding_level followed by brewing_time

DecisionTree approach:

Decision tree classifier found that the best variables in terms of information gain are brewing_time followed by coffee_amount.

So in case of numerc attributes we can point brewing_time as most predictive feature.

7.0.2 All variables

The most difficult part of analysis was comparsion between numeric and non numeric variables. First though is discretization of numeric attributes and compare all of them as nonnumeric, or compare efficiency of classifiers/regressors based sets ov variables with excluded ones one by one. I've decided to use very nice tool in R-language to perform the rest of analysis. Because R have great library to "unblackboxing" machine learning models in particular, can rank the importance of variables. So at this point i decided to end analysis, but i can continue it in python if necessary.