main

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1 Data Mining - HW01 - 98722278

Index: 1. Let's assume you work as a data mining consultant in a company which workes on search engines. Explain how using techniques such as *Associate Rules, Clustering, Classification and Anomaly Detection* may help you. 2. Compute *Cosine distance, Correlation, Euclidean Distance and Jacard Index* for these two pair of vectors: 1. `V1 = [1, 1, 1, 1]`, `V2 = [2, 2, 2, 2]` 2. `V1 = [1, 0, 1, 0]`, `V2 = [0, 1, 0, 1]` 3. Consider finding K-nearest neighbors of a dataset. Here is the proposed algorithm: 1. What happens if there is duplicate entries in dataset? (consider the distance of duplicate entries 0) 2. How to solve this issue?

4. Compare dimentionality reduction approaches such as *PCA and SVD* versus *Aggregation based* methods.

5. What are pros and cons of sampling for reducing number of samples? Is sampling without replacement is a good approach?

6. Download Telco Churn dataset

    1. Analyze dataset
    2. Implement *Apriori* algorithm from scratch. Regarding aforementioned dataset, find proper parameteres. By increasing and decreasing different parameters such as *confidence* and *support* report the changes.
    3. As the output, report finest extract rules

7. In this section, the goal is to train *KNN* and *DecisionTree* on Fashion-MNIST

8. DecisionTree

    1. Preprocessing

Algorithm 2.1 Algorithm for finding K nearest neighbors.

for $i = 1$ to *number of data objects* **do**
  Find the distances of the i^{th} object to all other objects.
  Sort these distances in decreasing order.
  (Keep track of which object is associated with each distance.)
  return the objects associated with the first K distances of the sorted list
end for

proposed alg

2. Split into Train, test and Validation
3. Train models

4. Report accuracy, recall and F-score metrics

9. KNN

   1. Preprocessing
   2. Feature Extraction
   3. Split into Train, test and Validation
   4. Train models

   5. Report accuracy, recall and F-score metrics

In [224]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

%matplotlib inline
```

1.1 1 Classification, Clustering, Rules, Anomaly, etc in Search Engines

The most important feature of search engines is that they must provide result based on their relevance. But to achieve these ranking for millions of possible outputs, search engines collect data and apply different machine learning methods to achieve some score for each possible result or any combination of them. Let's go throughout the some of methods such as Classification, Clustering, etc to clarify the situation.

Classification enables the machine to differetiate between different classes of contents. For instace, you looking for a laptop for you needs, so the machine should be able to classify the content on the websites into different categories and show you the results that only contain the classes you looking for. As we said there are billion of websites out there so by just classifying the entire data into few categories (your keywords) the search space will be much smaller to analyze for other steps.

Now let's consider the effect of **Association Rules**. Consider previous example which you wanted to buy a laptop. It is a general case and after searching it you might not find wat you were looking for. Search engine needs more keyword to specificly find your interests. So you add a laptop for teaching purposes. So, by adding this keyword, search engines knows some rules that people who bought these type of laptops, also might need microphone and a good webcam too. So if you try to search for mic or camera, you will get mostly results related to match with the requirement of having a lecture.

But what is **Anomaly Detection**? In previous example, you are a student and looking for a mid-range devices because you need only a mediocre voice quality plus simple webcam to just communicate better. Mostly you are engaged with slides rather than your face! Anomaly means something that is not usual within results. In our case, most of the population who want laptop, mic and camera might be students or university lectureres, but gamers are here too. They need much more powerfull mic and cameras. So if you are student, you are not looking for a 2K resolution! Here the population wit less quantity is anomaly and need to be considered with different rules. Another example for this can be the typo in another languages. For instance, in middle eastern countries, most of the people forget to switch language to english and write their keywords in

Arabic script. In this case a undefined word is being used enormously only for few IP ranges. So it triggers and alert and make the search engine to learn that anomalous behavior and convert it to a feature!

Clustering is similar to classification but with this difference that the distance metric is the core of clustering which enables us to rank different results based on their distances to different center of clusters. Clusters provide topic-based results which also can be incorporated within an another cluster where enables hierarchical understanding of different topics and catergories. Clustering can be used for group of people in a particular location, for instance, people in middle east search for different clothes in summer than people in Russia. Or another case would be you looking for a specific keyword but it is rare or you don't enjoy the result, then search engine use clusters and replace the word you used by a more related word using underlying meaning of the keywords based on the clusters they are near to.

PPS: 1. Note that all of the previously mentioned approaches can be combined and even can be embedded within each other to provide more robust algorithms. 2. Also, I have mostly used "word" and "keyword" as the input. Same definitions can be used for all type of inputs such as music or images.

1.2 2 *Cosine distance, Correlation, Euclidean Distance and Jacard Index* for

1. `V1 = [1, 1, 1, 1],V2 = [2, 2, 2, 2]`
2. `V1 = [1, 0, 1, 0],V2 = [0, 1, 0, 1]`

```
In [3]: def cosine_distance(v1, v2):
            """
            Computes the cosine distance between two ND vectors
            s = V1.V2 / (|A|.|B|)

            :param v1: First vector
            :param v2: Second Vector
            :return: A float number
            """
            v1 = np.array(v1)
            v2 = np.array(v2)

            dot_product = np.sum([v1_ * v2_ for v1_, v2_ in zip(v1, v2)])
            return dot_product / (np.sqrt(np.sum(v1 ** 2)) * np.sqrt(np.sum(v2 ** 2)))
```

```
In [4]: def correlation(v1, v2):
            """
            Computes the correlation between two ND vectors
            s = ((v1- v1_mean).(v2-v2_mean)) / sqrt((v1- v1_mean)**2.(v2-v2_mean)**2)

            :param v1: First vector
            :param v2: Second Vector
            :return: A float number
            """
            v1 = np.array(v1)
            v2 = np.array(v2)
```

```
    v1_norm = v1 - np.mean(v1)
    v2_norm = v2 - np.mean(v2)

    cov = np.sum([v1_ * v2_ for v1_, v2_ in zip(v1_norm, v2_norm)])
    denom = np.sqrt(np.sum(v1_norm**2) * np.sum(v2_norm**2))
    return  cov / denom
```

In [5]:
```
def euclidean_distance(v1, v2):

    """
    Computes the correlation between two ND vectors
    s = sum((v1-v2)**2)

    :param v1: First vector
    :param v2: Second Vector
    :return: A float number
    """
    v1 = np.array(v1)
    v2 = np.array(v2)

    return np.sqrt(np.sum([(v1_ - v2_)**2 for v1_, v2_ in zip(v1, v2)]))
```

In [6]:
```
def jaccard_index(v1, v2):
    """
    Computes the Jaccard index between two ND vectors
    s = intersection(v1, v2) / union(v1, v2)

    :param v1: First vector
    :param v2: Second Vector
    :return: A float number
    """
    m11 = np.sum(v1 & v2)
    m01 = np.sum(~v1 & v2)
    m10 = np.sum(v1 & ~v2)
    return m11 / (m11 + m01 + m10)
```

In [7]:
```
v1 = np.array([1, 1, 1, 1])
v2 = np.array([2, 2, 2, 2])
print('Cosine={}, Correlation={}, Eculidean={}'.format(cosine_distance(v1, v2), correla
```

```
Cosine=1.0, Correlation=nan, Eculidean=2.0


c:\users\nikan\appdata\local\programs\python\python36\lib\site-packages\ipykernel_launcher.py:
```

In [9]:
```
v1 = np.array([1, 0, 1, 0])
v2 = np.array([0, 1, 0, 1])
```

Algorithm 2.1 Algorithm for finding K nearest neighbors.

```
for i = 1 to number of data objects do
    Find the distances of the i^th object to all other objects.
    Sort these distances in decreasing order.
    (Keep track of which object is associated with each distance.)
    return the objects associated with the first K distances of the sorted list
end for
```

proposed alg

```
        print('Cosine={}, Correlation={}, Eculidean={}, Jaccard={}'.format(cosine_distance(v1,
                                                                               euclidean_distance(
```

```
Cosine=0.0, Correlation=-1.0, Eculidean=2.0, Jaccard=0.0
```

1.3 3 K-Nearest Neighbors:

1. What happens if there is duplicate entries in dataset? (consider the distance of duplicate entries 0)
2. How to solve this issue?

1.3.1 3.A Duplicate entries

If we have duplicate entries which means zero distance in our distance transformed matrix of data, then for each entry `i` if we have for instance `j` duplicates, then `i`'s top `js` anwer would be only duplicate information so in KNN algorithm `j`th items out of `k` will be duplicate and there is zero learning.

1.3.2 3.B Solving duplicate entries

To solve the aforementioned issue, we can incorporate different approaches. Depending on distance metric, if we can ensure that two same object have zero distance then 1. After constructing NxN matrix of N entries of our dataset, we can simply remove all objects with index `j` with zero distance for every row `i`. This is slow but robust appraoch as we ensure all data is cleansed. 2. This approach works as post processesing and is faster than previous one. In this method when we want to return the top `K` results of for a specific input, we do not return `K` objects as there may be duplicate objects. We first find these objects by couting zero distance values, let's say `M` then returning `K+M` top results omitting index of items included by `M`.

1.4 4 Comparison of *PCA and SVD* vs. *Aggregation based* dimentionality reduction methods.

Methods such as PCA are statistical approaches where they use informations such as variance to extract most useful attributes of the given dataset. In case of PCA, in simple terms, it first looks for the dimension with most of variation in original data and creates a covariance matrix of these variations. Then a transformation is applied to the original dimensions to achieve almost same representation but with much less data. So, the goal of PCA or SVD is preserve the original varations of data meanwhile reducing number of attributes as much as possible.

In aggregation methods, the goal is the reduce variation to have more consistent and general (stable?) interpretation of the original data to extract more generalized rules. For instance, combining cities into regions which will tend to coarse info but more consistent inter or intra region wise.

Another point that should be mentioned is that PCA or SVD has defined form of statistical measurements meanwhile aggregation methods are some heuristics that may not be applicable task to task or need to be defined for different set of data/tasks/algorithms.

1.5 5 Pros and cons of sampling? Sampling without replacement?

For many tasks the pure obtained data are too big and time consuming to be processed. So, to reduce the costs of experiment and required time we prefer to sample a small subset of original data.

Sampling enables us to have almost all available information in original data with much fewer number of objects. This leads to huge speed up and much less expenses. But the problem is how we are going to choose a sample that could be representive of our entire data. Sampling means dopping most of data which leads to loss of information where maybe drasticly disastrous if dropped samples contain rare but desired information (think the case of anomaly detection).

Simply put, a trade of between speed and quality of data is the real challenge.

Sampling w/ replacement vs wo/ replacement:

First of all, sampling with replacement means each time we try to sample an object, we give equal probability same as the intial probability of all objects but in case of without replacement, after an object got selected, we remove it from the pool or make probability of it getting selected equal to zero.

What happens in the first case is that the sampled population has covariance of zero which means samples are in the vicinity of their expected value. But in the case of without replacement, a data with standard deviation of sigma will have a non-zero covaraince due to biased more to the last items. But if we sample infinitely from a population without replacement, we will have covariance of zero because of the law of large numbers (Bernouli LLNs).

What we are looking for is a sampling with lower variance from the original dataset. Sampling with replacement achieve same expectation of original dataset meanwhile sampling without replacement may exactly sample the original dataset in the way that leads to same mean and zero variance for the corresponding distibution. So in real world, we looking for learning new things so sampling with replacement is not good approach in machine learning tasks as it may lead to biased learning or failing completely in imbalanced learning challenges.

1.6 6 Telco Churn dataset Apriori

1. Analyze dataset
2. Implement *Apriori*
3. Find proper parameteres
4. As the output, report finest extracted rules

1.6.1 6.A Analyze dataset

```
In [195]: df = pd.read_csv("..\data\TelcoChurn.csv")
          print(df.info())
          df.head(5)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
None
```

```
Out[195]:    customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
          0  7590-VHVEG  Female              0     Yes         No       1           No
          1  5575-GNVDE    Male              0      No         No      34          Yes
          2  3668-QPYBK    Male              0      No         No       2          Yes
          3  7795-CFOCW    Male              0      No         No      45           No
          4  9237-HQITU  Female              0      No         No       2          Yes

                MultipleLines InternetService OnlineSecurity  ... DeviceProtection  \
          0  No phone service             DSL             No  ...               No
          1                No             DSL            Yes  ...              Yes
          2                No             DSL            Yes  ...               No
          3  No phone service             DSL            Yes  ...              Yes
```

```
4                 No     Fiber optic             No  ...               No

  TechSupport StreamingTV StreamingMovies        Contract PaperlessBilling  \
0          No          No              No  Month-to-month              Yes
1          No          No              No        One year               No
2          No          No              No  Month-to-month              Yes
3         Yes          No              No        One year               No
4          No          No              No  Month-to-month              Yes

              PaymentMethod MonthlyCharges  TotalCharges Churn
0          Electronic check          29.85         29.85    No
1              Mailed check          56.95        1889.5    No
2              Mailed check          53.85        108.15   Yes
3 Bank transfer (automatic)          42.30       1840.75    No
4          Electronic check          70.70        151.65   Yes

[5 rows x 21 columns]
```

In [196]:

```python
# deleting customerID as it is useless in our case.
del df['customerID']
df.head(1)
```

Out[196]:

```
   gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  Female              0     Yes         No       1           No

      MultipleLines InternetService OnlineSecurity OnlineBackup  \
0  No phone service             DSL             No          Yes

  DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0               No          No          No              No  Month-to-month

  PaperlessBilling     PaymentMethod  MonthlyCharges TotalCharges Churn
0              Yes  Electronic check           29.85        29.85    No
```

In [197]:

```python
print('gender:',df.gender.unique())
print('SeniorCitizen:',df.SeniorCitizen.unique())
print('Partner:',df.Partner.unique())
print('Dependents:',df.Dependents.unique())
print('tenure:',df.tenure.unique())
print('PhoneService:',df.PhoneService.unique())
print('MultipleLines:',df.MultipleLines.unique())
print('InternetService:',df.InternetService.unique())
print('OnlineSecurity:',df.OnlineSecurity.unique())
print('OnlineBackup:',df.OnlineBackup.unique())
print('TechSupport:',df.TechSupport.unique())
print('StreamingTV:',df.StreamingTV.unique())
print('StreamingMovies:',df.StreamingMovies.unique())
print('Contract:',df.Contract.unique())
```

```python
print('PaperlessBilling:',df.PaperlessBilling.unique())
print('MonthlyCharges:',df.MonthlyCharges.unique())
print('TotalCharges:',df.TotalCharges.unique())
print('PaymentMethod:',df.PaymentMethod.unique())
print('Churn:',df.Churn.unique())

df.SeniorCitizen.replace([0, 1], ['No', 'Yes'], inplace=True)

# in below cases we aggregate "no internet service" and "No"
df.MultipleLines.replace(["No", "Yes", "No phone service"],
                         ["No", "Yes", "No"], inplace= True)
df.OnlineSecurity.replace(["No", "Yes", "No phone service"],
                          ["No", "Yes", "No"], inplace= True)
df.OnlineBackup.replace(["No", "Yes", "No phone service"],
                        ["No", "Yes", "No"], inplace= True)
df.TechSupport.replace(["No", "Yes", "No phone service"],
                       ["No", "Yes", "No"], inplace= True)
df.StreamingTV.replace(["No", "Yes", "No phone service"],
                       ["No", "Yes", "No"], inplace= True)
df.StreamingMovies.replace(["No", "Yes", "No phone service"],
                           ["No", "Yes", "No"], inplace= True)

# aggregating "one year" and "two year"
df.Contract.replace(["Month-to-month", "One year", "Two year"],
                    ["Monthly", "Yearly", "Yearly"], inplace= True)

# aggregating "Electronic check" and "Mailed check" into one and
# "Bank transfer (automatic)" and "Credit card (automatic)" into another
df.PaymentMethod.replace(["Electronic check", "Mailed check",
                 "Bank transfer (automatic)", "Credit card (automatic)"],
                ["Check", "Check", "automatic", "automatic"], inplace= True)

df.head(5)
```

```
gender: ['Female' 'Male']
SeniorCitizen: [0 1]
Partner: ['Yes' 'No']
Dependents: ['No' 'Yes']
tenure: [ 1 34  2 45  8 22 10 28 62 13 16 58 49 25 69 52 71 21 12 30 47 72 17 27
  5 46 11 70 63 43 15 60 18 66  9  3 31 50 64 56  7 42 35 48 29 65 38 68
 32 55 37 36 41  6  4 33 67 23 57 61 14 20 53 40 59 24 44 19 54 51 26  0
 39]
PhoneService: ['No' 'Yes']
MultipleLines: ['No phone service' 'No' 'Yes']
InternetService: ['DSL' 'Fiber optic' 'No']
OnlineSecurity: ['No' 'Yes' 'No internet service']
OnlineBackup: ['Yes' 'No' 'No internet service']
TechSupport: ['No' 'Yes' 'No internet service']
```

```
StreamingTV: ['No' 'Yes' 'No internet service']
StreamingMovies: ['No' 'Yes' 'No internet service']
Contract: ['Month-to-month' 'One year' 'Two year']
PaperlessBilling: ['Yes' 'No']
MonthlyCharges: [29.85 56.95 53.85 ... 63.1  44.2  78.7 ]
TotalCharges: ['29.85' '1889.5' '108.15' ... '346.45' '306.6' '6844.5']
PaymentMethod: ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']
Churn: ['No' 'Yes']
```

Out[197]:

```
   gender SeniorCitizen Partner Dependents  tenure PhoneService MultipleLines  \
0  Female            No     Yes         No       1           No            No
1    Male            No      No         No      34          Yes            No
2    Male            No      No         No       2          Yes            No
3    Male            No      No         No      45           No            No
4  Female            No      No         No       2          Yes            No

  InternetService OnlineSecurity OnlineBackup DeviceProtection TechSupport  \
0             DSL             No          Yes               No          No
1             DSL            Yes           No              Yes          No
2             DSL            Yes          Yes               No          No
3             DSL            Yes           No              Yes         Yes
4     Fiber optic             No           No               No          No

  StreamingTV StreamingMovies Contract PaperlessBilling PaymentMethod  \
0          No              No  Monthly              Yes         Check
1          No              No   Yearly               No         Check
2          No              No  Monthly              Yes         Check
3          No              No   Yearly               No     automatic
4          No              No  Monthly              Yes         Check

   MonthlyCharges TotalCharges Churn
0           29.85        29.85    No
1           56.95       1889.5    No
2           53.85       108.15   Yes
3           42.30      1840.75    No
4           70.70       151.65   Yes
```

In [198]:

```
# convert continuous values (tenure, MonthlyCharges, TotalCharges)
print(df.tenure.describe())
df.loc[(df.tenure >= 0) & (df.tenure<9), 'tenure'] = 0
df.loc[(df.tenure >= 9) & (df.tenure<29), 'tenure'] = 1
df.loc[(df.tenure >= 29) & (df.tenure<55), 'tenure'] = 2
df.loc[(df.tenure >= 55), 'tenure'] = 3
df.loc[(df.tenure == 0), 'tenure'] = 's'
df.loc[(df.tenure == 1), 'tenure'] = 'm'
df.loc[(df.tenure == 2), 'tenure'] = 'l'
```

```python
df.loc[(df.tenure == 3), 'tenure'] = 'xl'

print('\n\n',df.MonthlyCharges.describe())
df.loc[(df.MonthlyCharges >= 0) & (df.MonthlyCharges<35), 'MonthlyCharges'] = 0
df.loc[(df.MonthlyCharges >= 35) & (df.MonthlyCharges<70), 'MonthlyCharges'] = 1
df.loc[(df.MonthlyCharges >= 70) & (df.MonthlyCharges<89), 'MonthlyCharges'] = 2
df.loc[(df.MonthlyCharges >= 89), 'MonthlyCharges'] = 3
df.MonthlyCharges = df.MonthlyCharges.astype(np.uint8)
df.loc[(df.MonthlyCharges == 0), 'MonthlyCharges'] = 's'
df.loc[(df.MonthlyCharges == 1), 'MonthlyCharges'] = 'm'
df.loc[(df.MonthlyCharges == 2), 'MonthlyCharges'] = 'l'
df.loc[(df.MonthlyCharges == 3), 'MonthlyCharges'] = 'xl'

# zerp non-values from dataframe from TotalCharges
nan_values = pd.to_numeric(df['TotalCharges'],
                           errors='coerce').isnull().values.nonzero()[0]
df.loc[nan_values,'TotalCharges'] = 0
df.TotalCharges = pd.to_numeric(df['TotalCharges'], errors='coerce')

print('\n\n',df.TotalCharges.describe())
df.loc[(df.TotalCharges >= 0) & (df.TotalCharges<398), 'TotalCharges'] = 0
df.loc[(df.TotalCharges >= 398) & (df.TotalCharges<1394), 'TotalCharges'] = 1
df.loc[(df.TotalCharges >= 1394) & (df.TotalCharges<3786), 'TotalCharges'] = 2
df.loc[(df.TotalCharges >= 3786), 'TotalCharges'] = 3
df.TotalCharges = df.TotalCharges.astype(np.int8)

df.loc[(df.TotalCharges == 0), 'TotalCharges'] = 's'
df.loc[(df.TotalCharges == 1), 'TotalCharges'] = 'm'
df.loc[(df.TotalCharges == 2), 'TotalCharges'] = 'l'
df.loc[(df.TotalCharges == 3), 'TotalCharges'] = 'xl'

df.head(5)
```

```
count    7043.000000
mean       32.371149
std        24.559481
min         0.000000
25%         9.000000
50%        29.000000
75%        55.000000
max        72.000000
Name: tenure, dtype: float64


 count    7043.000000
mean       64.761692
std        30.090047
min        18.250000
```

```
25%        35.500000
50%        70.350000
75%        89.850000
max       118.750000
Name: MonthlyCharges, dtype: float64


 count    7043.000000
mean     2279.734304
std      2266.794470
min         0.000000
25%       398.550000
50%      1394.550000
75%      3786.600000
max      8684.800000
Name: TotalCharges, dtype: float64
```

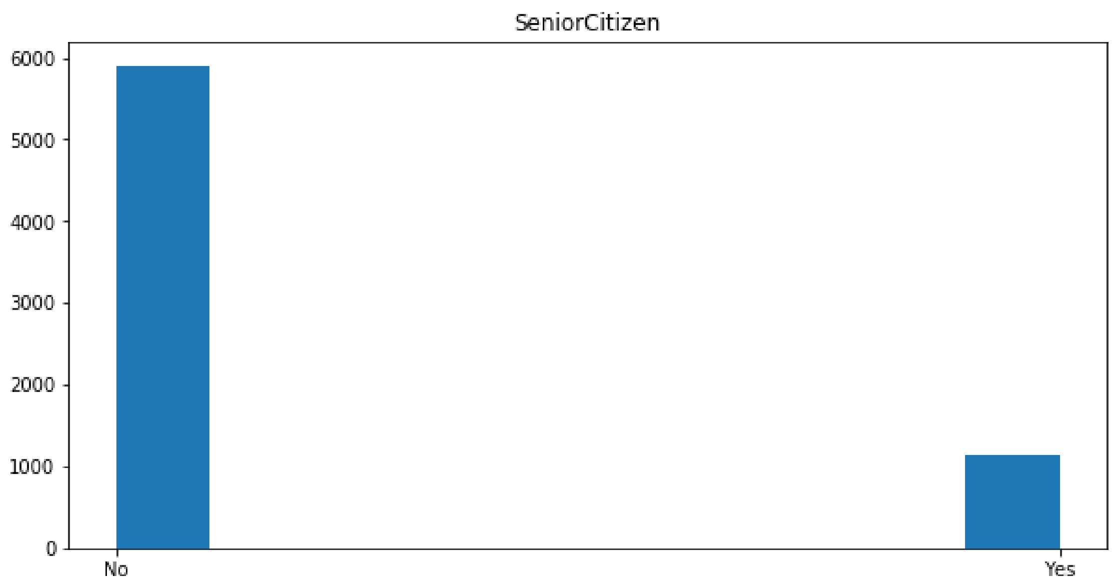
Out[198]:

```
   gender SeniorCitizen Partner Dependents tenure PhoneService MultipleLines  \
0  Female            No     Yes         No      s           No            No
1    Male            No      No         No      l          Yes            No
2    Male            No      No         No      s          Yes            No
3    Male            No      No         No      l           No            No
4  Female            No      No         No      s          Yes            No

  InternetService OnlineSecurity OnlineBackup DeviceProtection TechSupport  \
0             DSL             No          Yes               No          No
1             DSL            Yes           No              Yes          No
2             DSL            Yes          Yes               No          No
3             DSL            Yes           No              Yes         Yes
4     Fiber optic             No           No               No          No

  StreamingTV StreamingMovies Contract PaperlessBilling PaymentMethod  \
0          No              No  Monthly              Yes         Check
1          No              No   Yearly               No         Check
2          No              No  Monthly              Yes         Check
3          No              No   Yearly               No     automatic
4          No              No  Monthly              Yes         Check

  MonthlyCharges TotalCharges Churn
0              s            s    No
1              m            l    No
2              m            s   Yes
3              m            l    No
4              l            s   Yes
```

In [218]:

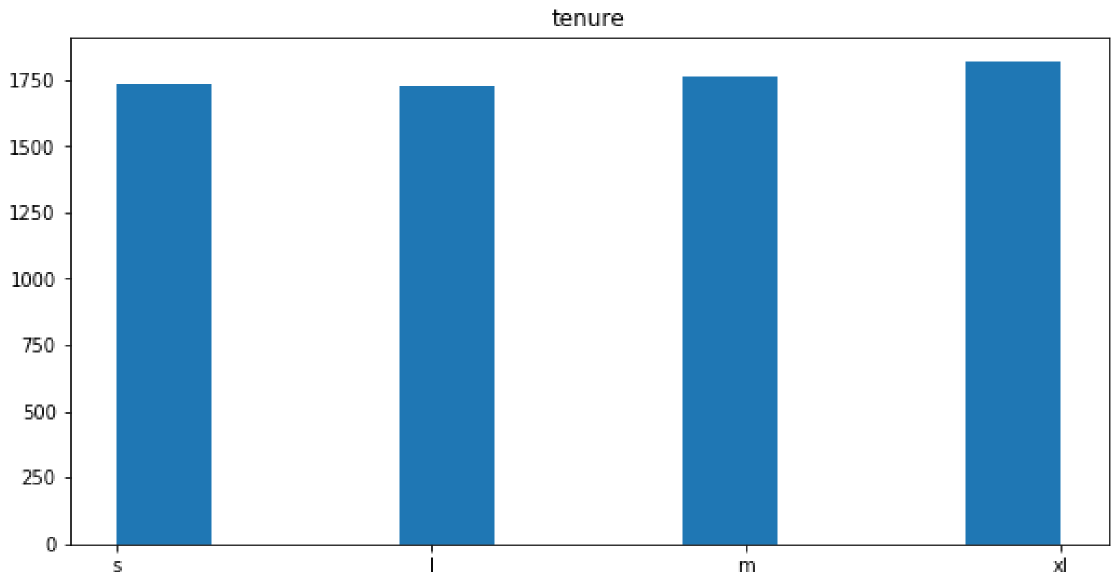
```
for i in range(len(df.columns)):
    df[df.columns[i]].hist(figsize=(10, 5), grid=False)
```

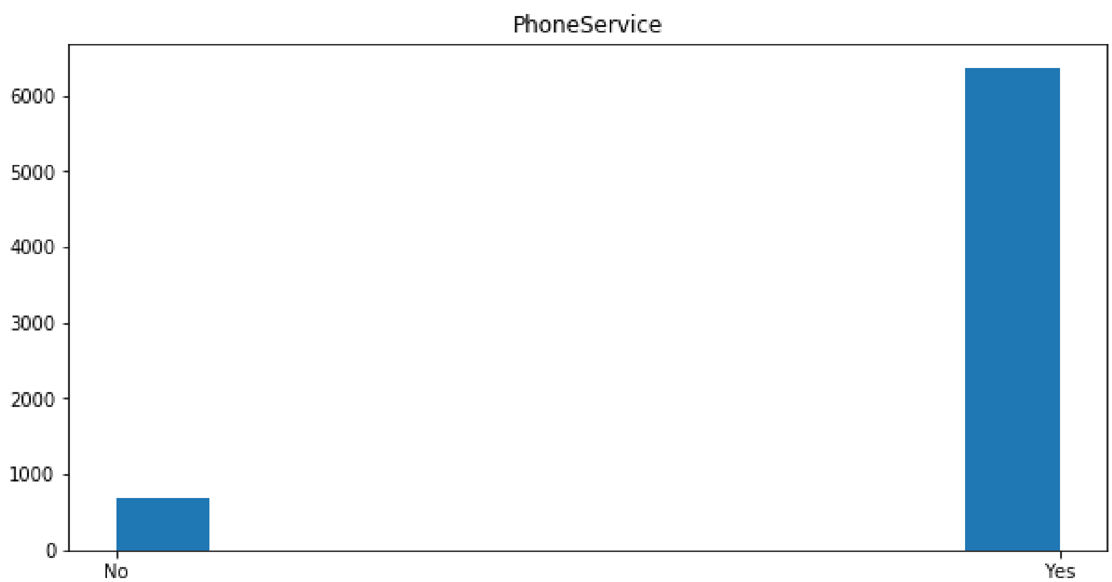
```
plt.title(df.columns[i])
plt.show()
```



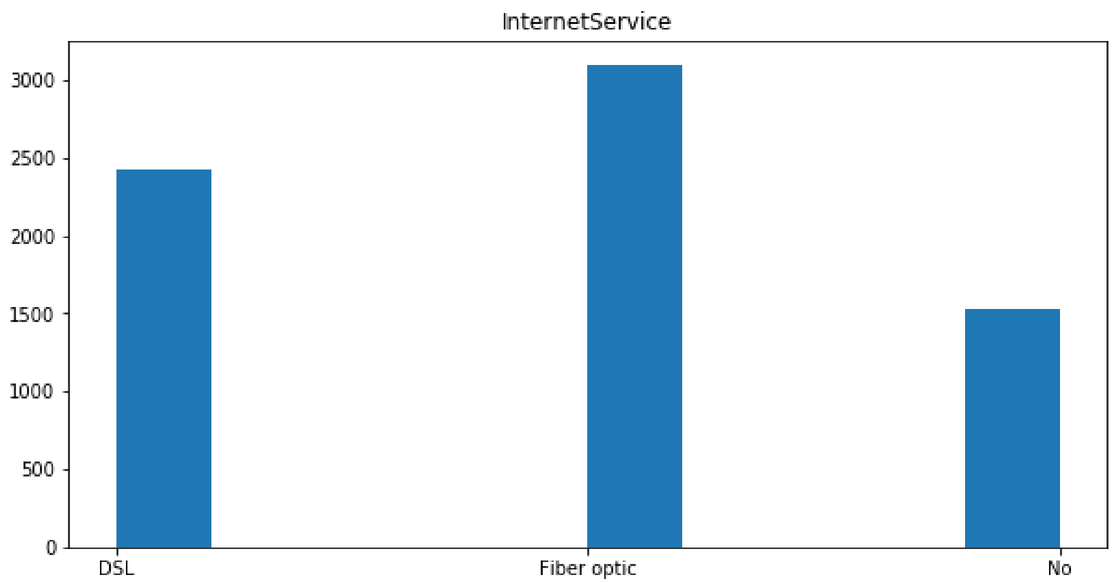

Partner
3500
3000
2500
2000
1500
1000
500
0
Yes
No

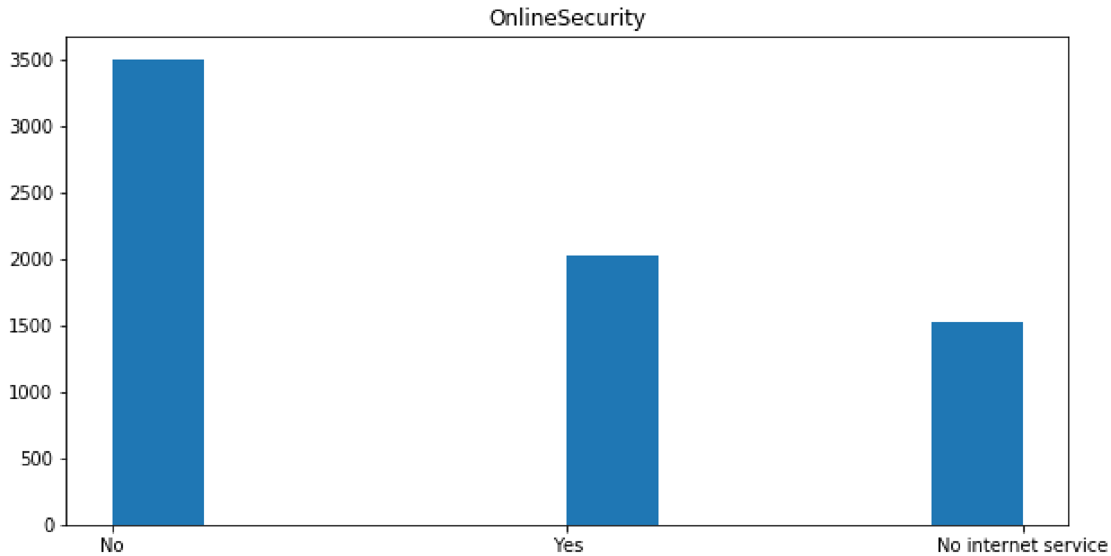

Dependents
5000
4000
3000
2000
1000
0
No
Yes

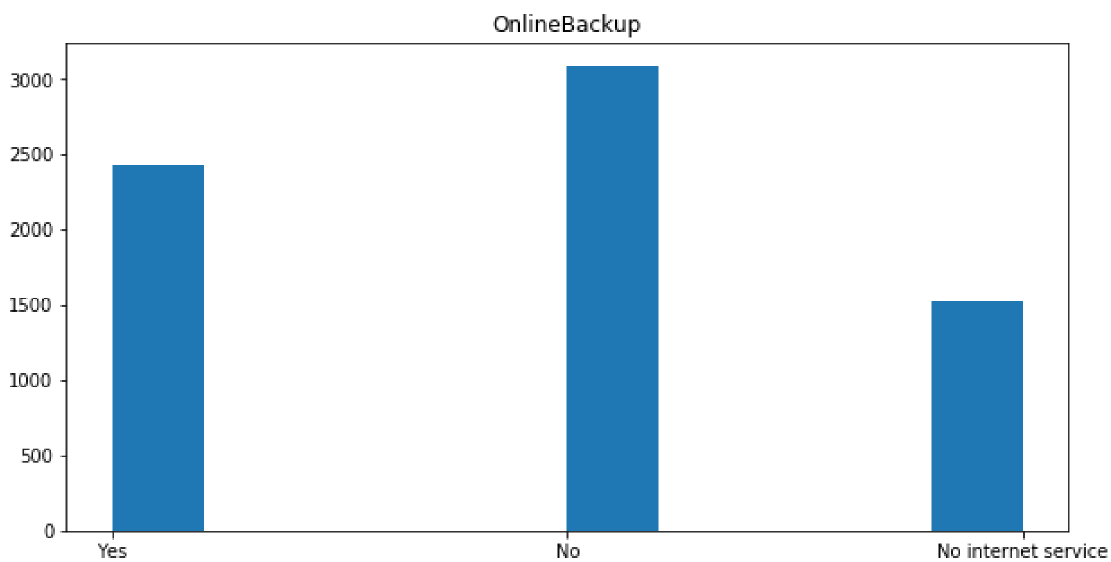

tenure
0
250
500
750
1000
1250
1500
1750
s
l
m
xl

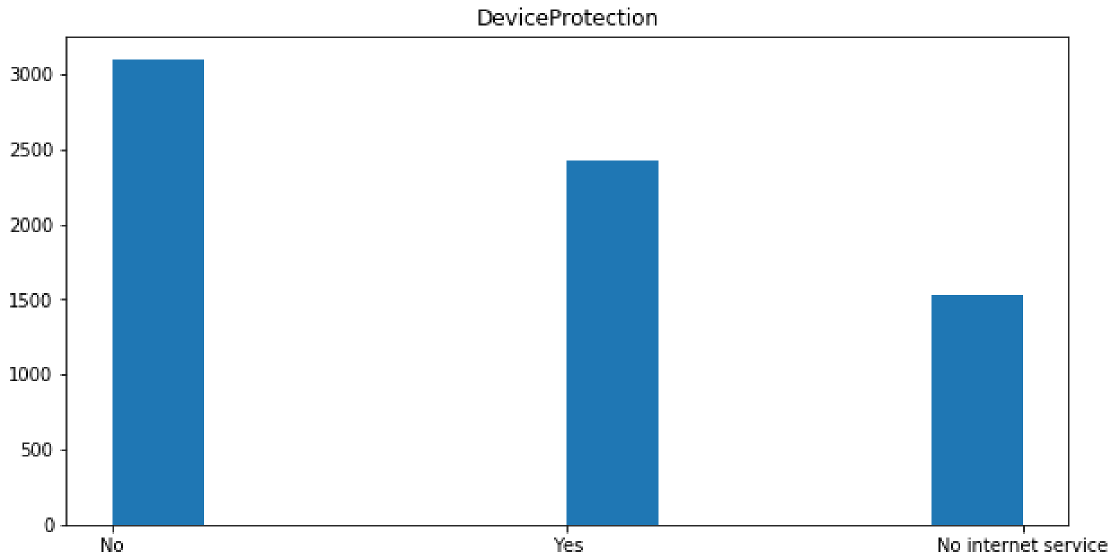

PhoneService
0
1000
2000
3000
4000
5000
6000
No
Yes

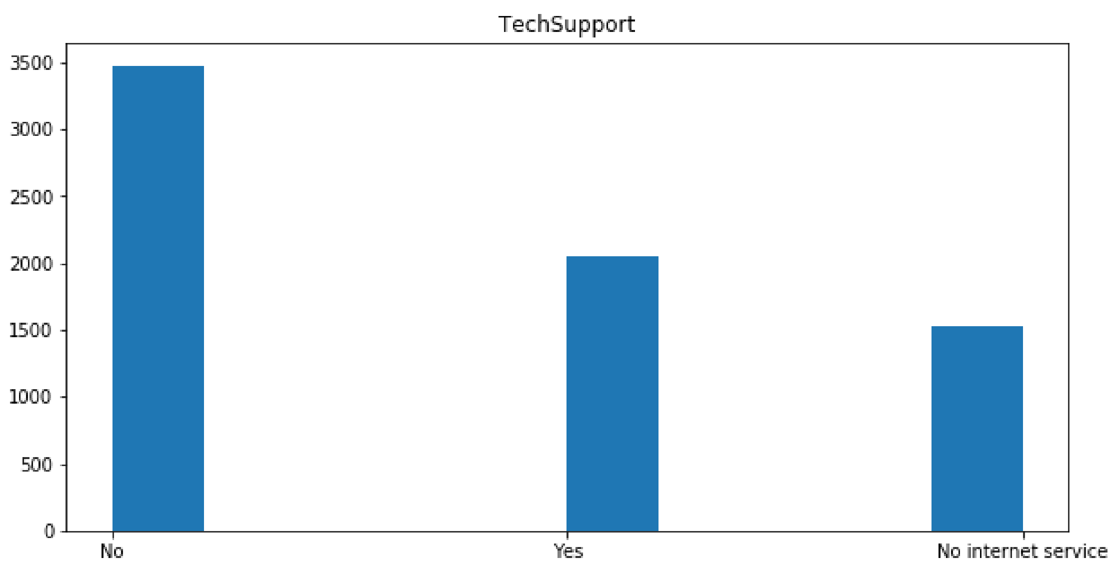

MultipleLines
4000
3500
3000
2500
2000
1500
1000
500
0
No
Yes

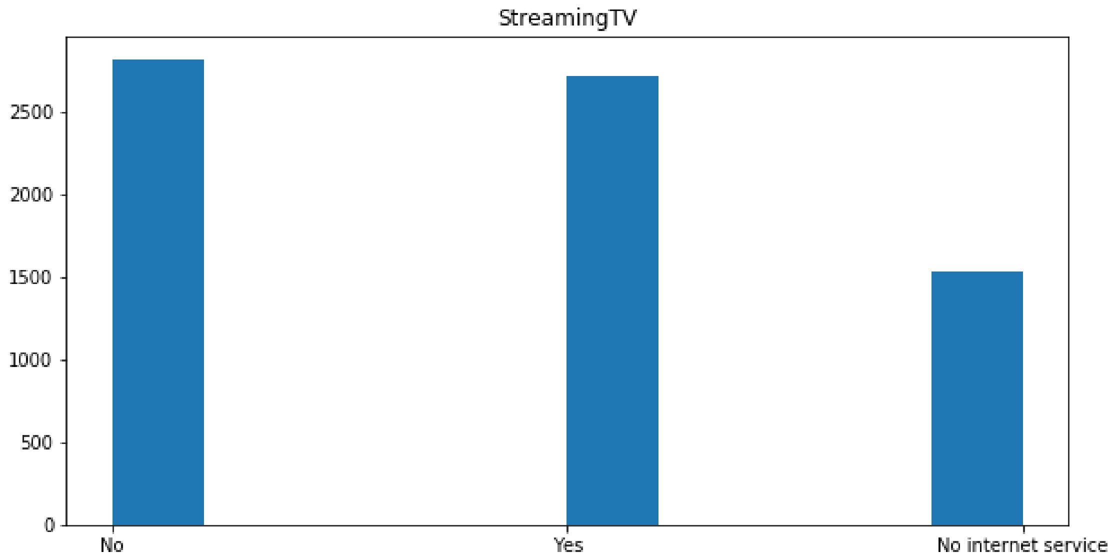

InternetService
3000
2500
2000
1500
1000
500
0
DSL
Fiber optic
No

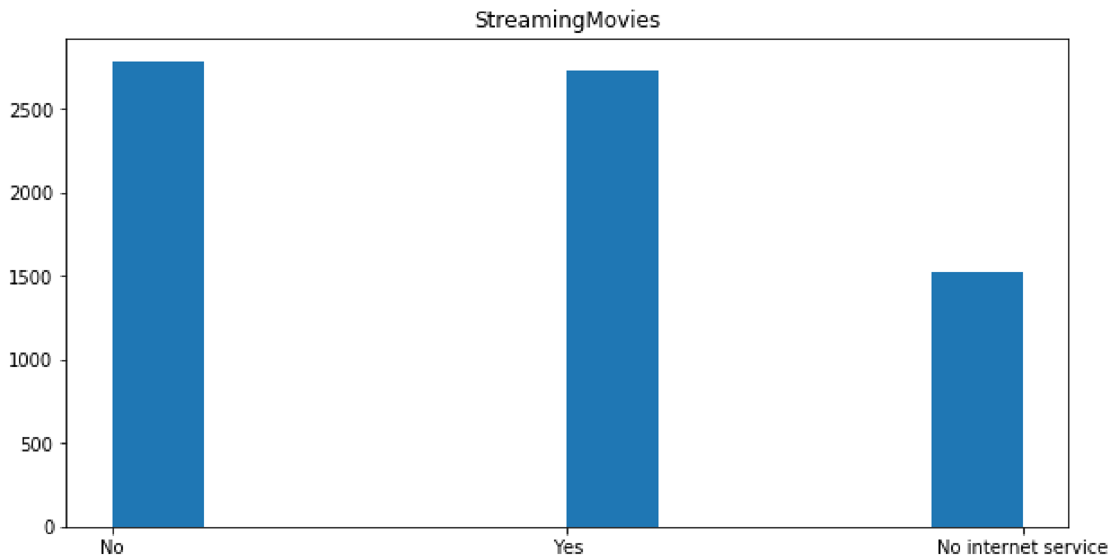

OnlineSecurity
3500
3000
2500
2000
1500
1000
500
0
No
Yes
No internet service

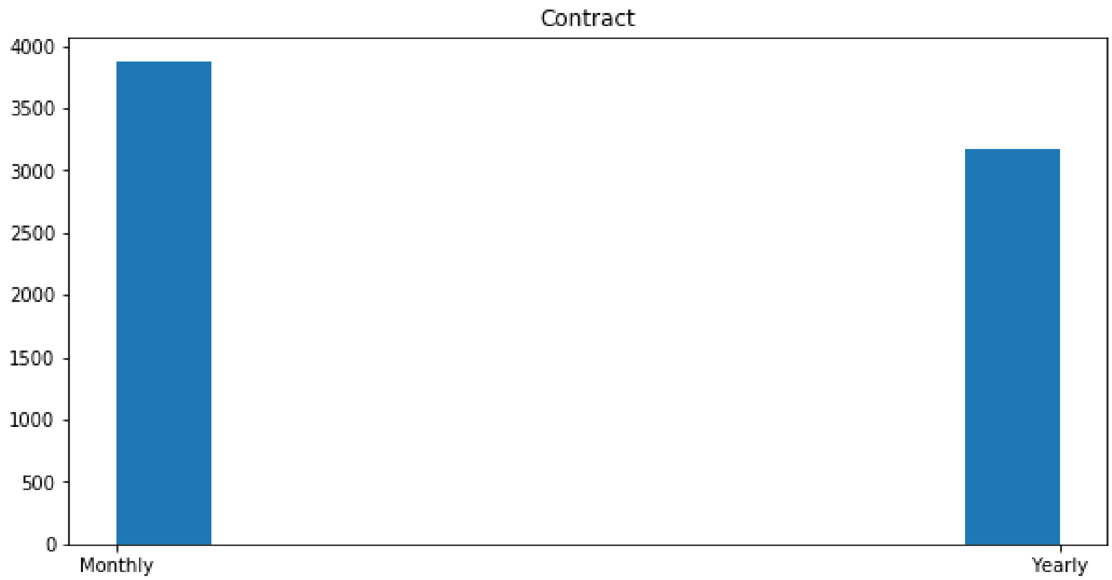

OnlineBackup
3000
2500
2000
1500
1000
500
0
Yes
No
No internet service

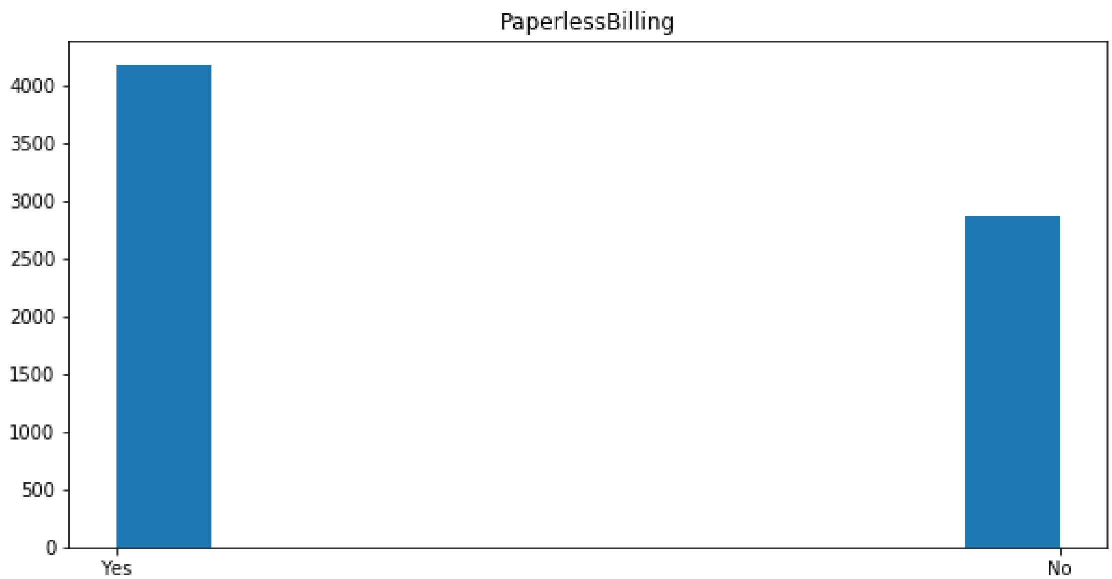

DeviceProtection
3000
2500
2000
1500
1000
500
0
No
Yes
No internet service

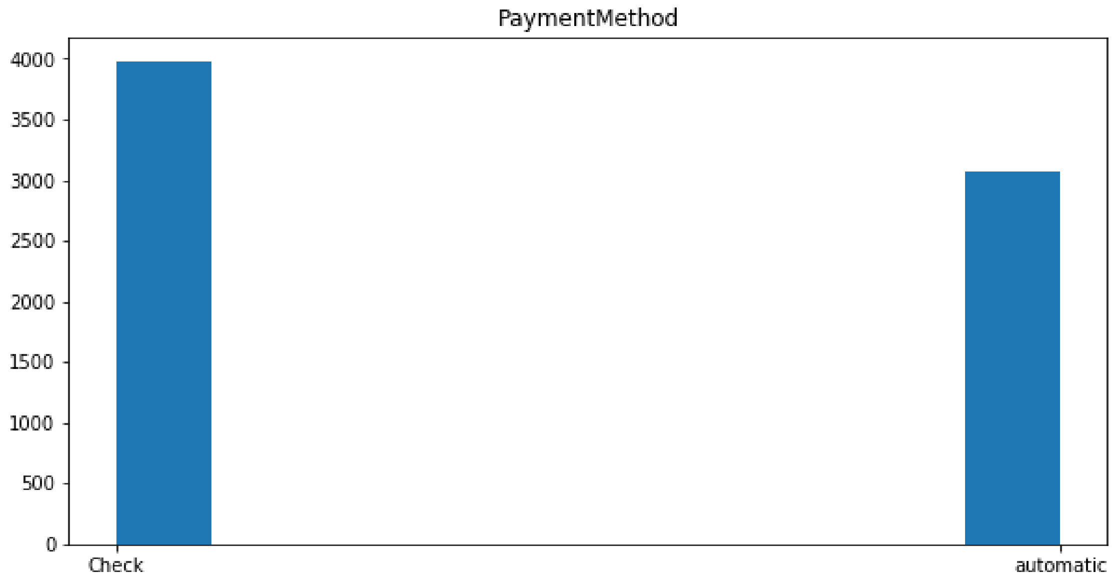

TechSupport
3500
3000
2500
2000
1500
1000
500
0
No
Yes
No internet service

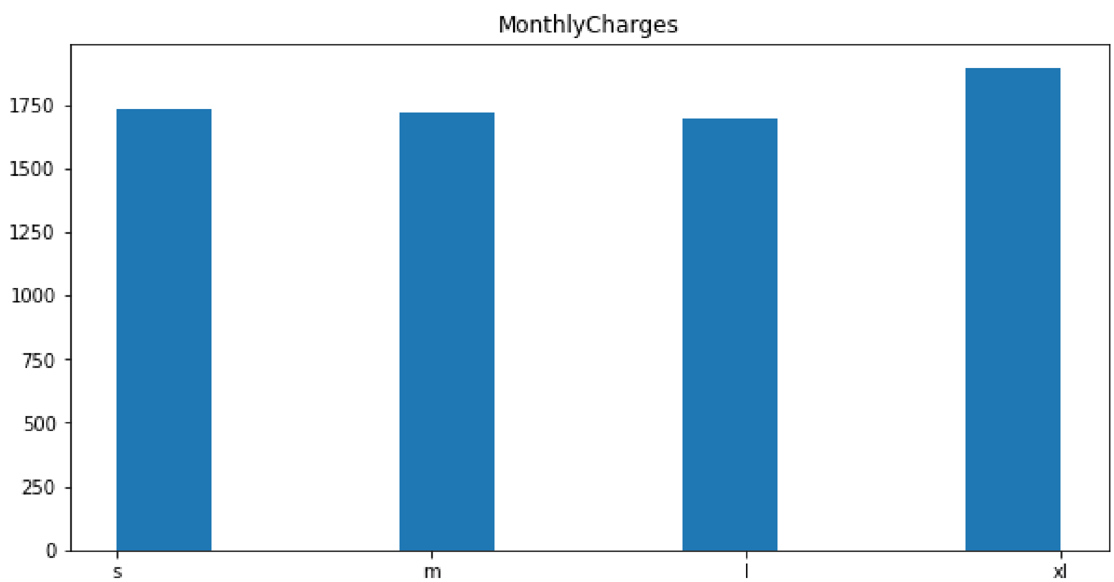

StreamingTV
0
500
1000
1500
2000
2500
No
Yes
No internet service

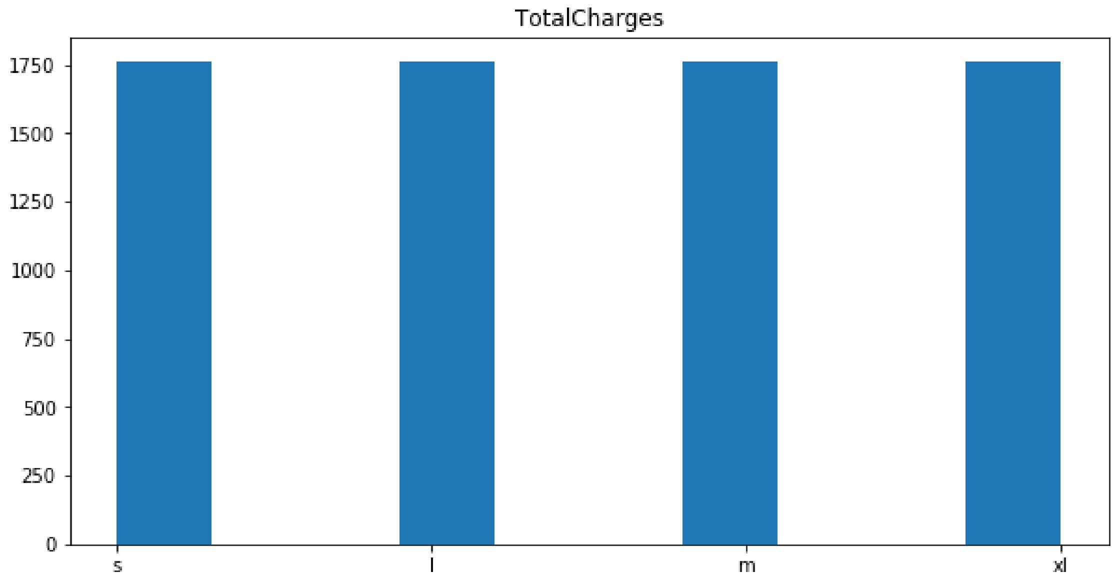

StreamingMovies
0
500
1000
1500
2000
2500
No
Yes
No internet service

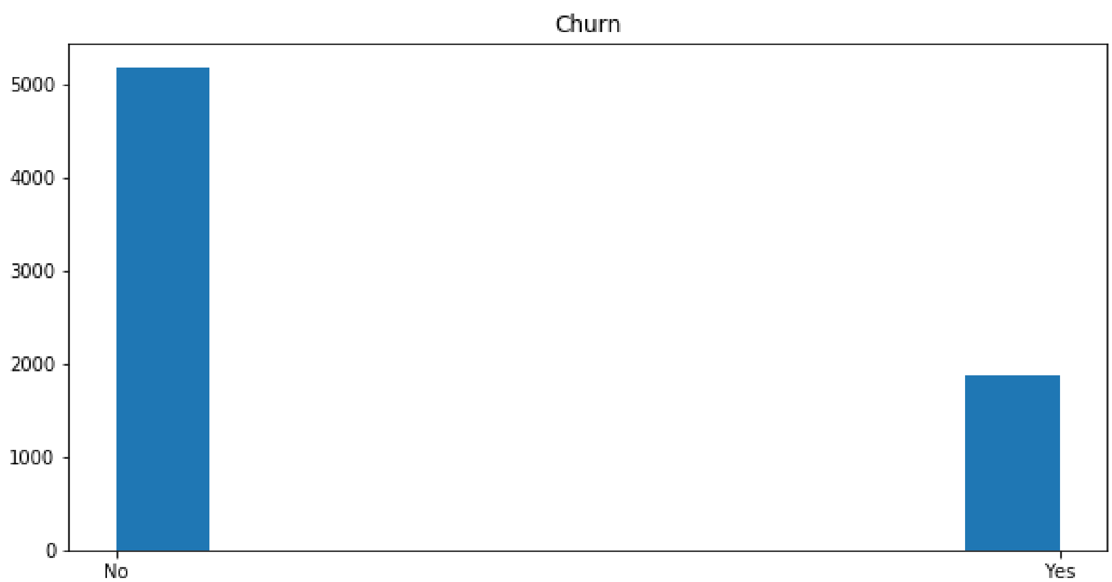

Contract
4000
3500
3000
2500
2000
1500
1000
500
0
Monthly
Yearly


PaperlessBilling
4000
3500
3000
2500
2000
1500
1000
500
0
Yes
No


PaymentMethod
4000
3500
3000
2500
2000
1500
1000
500
0
Check
automatic


MonthlyCharges
1750
1500
1250
1000
750
500
250
0
s
m
l
xl





In [219]:
```
# drop missing values
df.isna().sum()
```

Out[219]:
```
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
```

```
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

In [187]:
```
# convert entire dataframe into onehot encoded
print(df.shape)
df = pd.get_dummies(df)
print(df.shape)
df.head(5)
```

```
(7043, 20)
(7043, 53)
```

Out[187]:
```
   gender_Female  gender_Male  SeniorCitizen_No  SeniorCitizen_Yes  \
0              1            0                 1                  0
1              0            1                 1                  0
2              0            1                 1                  0
3              0            1                 1                  0
4              1            0                 1                  0

   Partner_No  Partner_Yes  Dependents_No  Dependents_Yes  tenure_l  tenure_m  \
0           0            1              1               0         0         0
1           1            0              1               0         1         0
2           1            0              1               0         0         0
3           1            0              1               0         1         0
4           1            0              1               0         0         0

   ...  MonthlyCharges_l  MonthlyCharges_m  MonthlyCharges_s  \
0  ...                 0                 0                 1
1  ...                 0                 1                 0
2  ...                 0                 1                 0
3  ...                 0                 1                 0
4  ...                 1                 0                 0
```

```
   MonthlyCharges_xl  TotalCharges_l  TotalCharges_m  TotalCharges_s  \
0                  0               0               0               1
1                  0               1               0               0
2                  0               0               0               1
3                  0               1               0               0
4                  0               0               0               1

   TotalCharges_xl  Churn_No  Churn_Yes
0                0         1          0
1                0         1          0
2                0         0          1
3                0         1          0
4                0         0          1

[5 rows x 53 columns]
```

6.B Apriori Implementation
6.C Find proper parameters
6.D Report finest extracted rules

1.7 7 Train *KNN* and *DecisionTree* on Fashion-MNIST

1. DecisionTree
    1. Preprocessing
    2. Split into Train, test and Validation
    3. Train models

    4. Report accuracy, recall and F-score metrics
2. KNN
    1. Preprocessing
    2. Feature Extraction
    3. Split into Train, test and Validation
    4. Train models

    5. Report accuracy, recall and F-score metrics

1.7.1 7.A DecisionTree

1. Preprocessing
2. Split into Train, test and Validation
3. Train models

4. Report accuracy, recall and F-score metrics

7.A.a Preprocessing In this step we apply normilization to have images with mean zero and variance of 1. This enables algorithms with distance based metrics to apply same importance to every pixel of image.

In [66]:
```
from utils import mnist_reader
x_train, y_train = mnist_reader.load_mnist('data/fashion', kind='train')
x_test, y_test = mnist_reader.load_mnist('data/fashion', kind='t10k')

print('number of train samples=', len(x_train))
print('number of test samples=', len(x_test))
print('shape of samples=', x_train[0].shape)
```

```
number of train samples= 60000
number of test samples= 10000
shape of samples= (784,)
```

In [ ]:
```
# standardization
x_train = x_train/255
x_test = x_test/255

# normalization
x_train = (x_train - x_train.mean()) / x_train.var()
x_test = (x_test - x_test.mean()) / x_test.var()
```

7.A.b Split into train, test and validation

In [ ]:
```
# split into train validation for hyper parameter tuning
import random

val_size = 10000
val_index = random.sample(range(0, len(x_train)), val_size)
split_index = np.array([0 if i in val_index else -1 for i in range(len(x_train))])
```

7.A.c Train models

In [69]:
```
# grid search model training
import numpy as np
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import PredefinedSplit
from sklearn.model_selection import GridSearchCV

parameters = {'criterion':('gini', 'entropy'), 'max_depth':[5, 10, None], 'min_samples
dt = DecisionTreeClassifier()
pds = PredefinedSplit(test_fold=split_index)

classifier = GridSearchCV(dt, parameters, cv=pds, scoring='accuracy')

classifier.fit(x_train, y_train)
```

Out[69]:
```
GridSearchCV(cv=PredefinedSplit(test_fold=array([-1, -1, ..., -1, -1])),
             error_score=nan,
             estimator=DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
```

```
                                                        criterion='gini', max_depth=None,
                                                        max_features=None,
                                                        max_leaf_nodes=None,
                                                        min_impurity_decrease=0.0,
                                                        min_impurity_split=None,
                                                        min_samples_leaf=1,
                                                        min_samples_split=2,
                                                        min_weight_fraction_leaf=0.0,
                                                        presort='deprecated',
                                                        random_state=None,
                                                        splitter='best'),
                           iid='deprecated', n_jobs=None,
                           param_grid={'criterion': ('gini', 'entropy'),
                                       'max_depth': [10, None], 'min_samples_leaf': [2, 10]},
                           pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                           scoring='accuracy', verbose=0)
```

```
In [71]: classifier.best_params_
```

```
Out[71]: {'criterion': 'entropy', 'max_depth': 10, 'min_samples_leaf': 2}
```

7.A.d Report metrics

```
In [85]: from sklearn.metrics import f1_score, recall_score, accuracy_score
         y_pred = classifier.predict(x_test)
         print('F1={}, Recall={}, Accuracy={}'.format(f1_score(y_test, y_pred, average='macro'
                                                   recall_score(y_test, y_pred, average='ma
                                                   accuracy_score(y_test, y_pred)))
```

```
F1=0.8094858144584004, Recall=0.8114000000000001, Accuracy=0.8114
```

1.7.2 7.B KNN

1. Preprocessing
2. Feature Extraction
3. Split into Train, test and Validation
4. Train models

5. Report accuracy, recall and F-score metrics

7.B.a Preprocessing

```
In [3]: from utils import mnist_reader
        x_train, y_train = mnist_reader.load_mnist('data/fashion', kind='train')
        x_test, y_test = mnist_reader.load_mnist('data/fashion', kind='t10k')

        print('number of train samples=', len(x_train))
        print('number of test samples=', len(x_test))
        print('shape of samples=', x_train[0].shape)
```

```
number of train samples= 60000
number of test samples= 10000
shape of samples= (784,)
```

7.B.b Feature extraction A feature descriptor is a representation of an image or an image patch that simplifies the image by extracting useful information and throwing away extraneous information.

In the HOG feature descriptor, the histograms of directions of gradients are used as features. Gradients (x and y derivatives) of an image are useful because the magnitude of gradients is large around edges and corners (regions of drastic intensity changes) and we know that edges and corners pack in a lot more information about object shape than flat regions.

```
In [ ]: import cv2
        import numpy as np

        def extract_hog(data, shape=(28, 28)):
            """
            Creates hitogram of gradient of images

            :param data: dataset of image using nd numpy array
            :return: A nd array of features with same length but different dim
            """

            winSize = (18,18)
            blockSize = (18,18)
            blockStride = (9,9)
            cellSize = (9,9)
            nbins = 4
            derivAperture = 1
            winSigma = 4.
            histogramNormType = 0
            L2HysThreshold = 2.0000000000000001e-01
            gammaCorrection = 0
            nlevels = 64
            hog = cv2.HOGDescriptor(winSize,blockSize,blockStride,cellSize,nbins,derivAperture
                                    histogramNormType,L2HysThreshold,gammaCorrection,nlevels)

            feature_size = hog.compute(data[0].reshape(shape)).shape[0]

            data_features = np.zeros((len(data), feature_size))
            for idx, img in enumerate(data):
                img = img.reshape(shape)
                h = hog.compute(img)
                h = h.reshape(1, -1)
                data_features[idx,:] = h
            return data_features
```

```
# extract_hog([x_train[0]]).shape
x_train_features = extract_hog(x_train)
x_test_features = extract_hog(x_test)
```

7.B.c Split into train, test and validation

```
In [ ]: # split into train validation for hyper parameter tuning
        import random

        val_size = 10000
        val_index = random.sample(range(0, len(x_train_features)), val_size)
        split_index = np.array([0 if i in val_index else -1 for i in range(len(x_train_feature
```

7.B.d Train models

```
In [15]: # grid search model training
         import numpy as np
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.model_selection import PredefinedSplit
         from sklearn.model_selection import GridSearchCV

         # parameters = {'n_neighbors':[5, 10, 20, 30, 50], 'leaf_size':[10, 20, 30, 40, 50],
         parameters = {'n_neighbors':[10, 20], 'leaf_size':[10, 20], 'p':[1, 2]}
         knn = KNeighborsClassifier()
         pds = PredefinedSplit(test_fold=split_index)

         classifier = GridSearchCV(knn, parameters, cv=pds, scoring='accuracy')

         classifier.fit(x_train_features, y_train)

Out[15]: GridSearchCV(cv=PredefinedSplit(test_fold=array([-1, -1, ..., -1, -1])),
                      error_score=nan,
                      estimator=KNeighborsClassifier(algorithm='auto', leaf_size=30,
                                                     metric='minkowski',
                                                     metric_params=None, n_jobs=None,
                                                     n_neighbors=5, p=2,
                                                     weights='uniform'),
                      iid='deprecated', n_jobs=None,
                      param_grid={'leaf_size': [10, 20], 'n_neighbors': [10, 20],
                                  'p': [1, 2]},
                      pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                      scoring='accuracy', verbose=0)
```

7.B.e Report metrics

```
In [17]: from sklearn.metrics import f1_score, recall_score, accuracy_score
         y_pred = classifier.predict(x_test_features)
         print('F1={}, Recall={}, Accuracy={}'.format(f1_score(y_test, y_pred, average='macro')
```

```
                                        recall_score(y_test, y_pred, average='ma
                                        accuracy_score(y_test, y_pred)))
```

```
F1=0.8279013513251632, Recall=0.8273999999999999, Accuracy=0.8274
```