relatorio_final

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April 7, 2017

1 Without missing data, learn the Bayesian Network parameters using SamIam

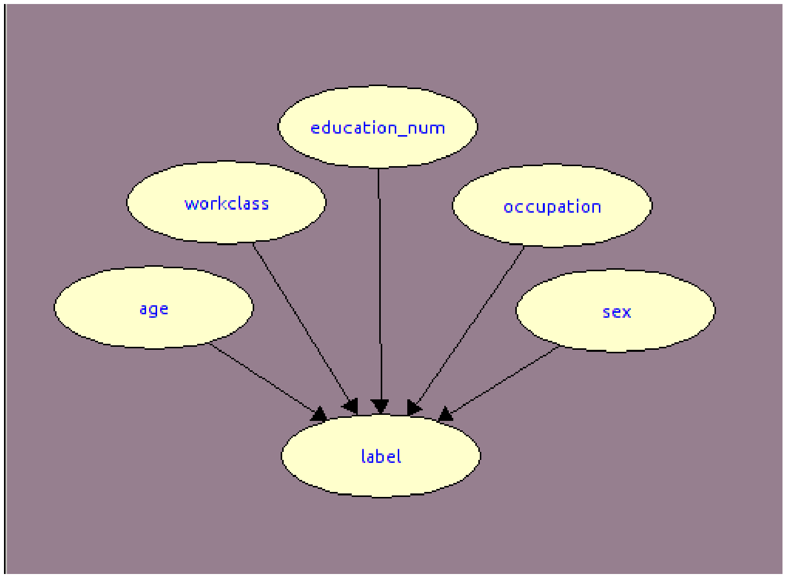
In the last homework, we selected 5 features that we thought most relevant for finding out if the person earns more than 50k dollars a year, they were:

- age
- workclass
- education-num
- occupation
- sex

We also converted all features to binary, including the label, so that we ended up with the following rule:

FEATURE	STATE 0	STATE 1
age	between 17 and 25 or greater than 65	between 26 and 65
workclass	Never-worked, Private, Self-emp-not-inc, Without pay	Federal-gov, Local-gov, Self-emp-inc, State-gov
education-num	<= 9	>= 10 (some college or greater)
occupation	All other not included in state 1	Exec-managerial, Prof-specialty, Protective-serv, Tech-support
sex	Female	Male
label	<=50K	>50K

Our initial guess of the structure of the network was the following (which corresponds to a Naive Bayes approach):



Now, we are going to stick with these features and rules, and use SamIam to learn the parameters of the network. However, we must first write new data files, considering only the selected features transformed into binary accordingly to the table above. To do this, we used the following python script:

```
# importing dependencies
import numpy as np
import pandas as pd
from IPython.display import display

# loading the data
columns_names = ["age", "workclass", "fnlwgt", "education", "education-num", \
                 "marital-status", "occupation", "relationship", "race", "sex", \
                 "capital-gain", "capital-loss", "hours-per-week", \
                 "native-country", "label"]

train_data = pd.read_csv('adult.data', header=None)
test_data = pd.read_csv('adult.test', header=None)
train_data.columns = columns_names
test_data.columns = columns_names
# display(train_data.head())
# display(test_data.head())

# removing missing data
train_data = train_data[train_data.workclass != ' ?']
train_data = train_data[train_data.occupation != ' ?']
test_data = test_data[test_data.workclass != ' ?']
test_data = test_data[test_data.occupation != ' ?']

# prepare datasets
def prepare_dataset(ds):
    dataset = ds

    # creating our custom train data DataFrame
```

```
    col_list = ['age', 'workclass', 'education-num', 'occupation', 'sex', 'label']
    dataset = dataset[col_list]


    # setting values
    workclass_state_1_values = [' Federal-gov', ' State-gov', ' Local-gov', \
                                ' Self-emp-inc']
    workclass_state_0_values = [' Never-worked', ' Private', ' Self-emp-not-inc', \
                                ' Without-pay']
    occupation_state_1_values = [' Exec-managerial', ' Prof-specialty', \
                                 ' Protective-serv', ' Tech-support']
    occupation_state_0_values = [' ?', ' Adm-clerical', ' Armed-Forces', \
                                 ' Craft-repair', ' Farming-fishing', \
                                 ' Handlers-cleaners', ' Machine-op-inspct', \
                                 ' Other-service', ' Priv-house-serv', \
                                 ' Sales', ' Transport-moving']

    # discretizing age
    dataset.loc[dataset['age'] < 26, 'age'] = 0
    dataset.loc[dataset['age'] > 65, 'age'] = 0
    dataset.loc[dataset['age'] > 0, 'age'] = 1

    # discretizing sex
    dataset.loc[dataset['sex'] == ' Male', 'sex'] = 1
    dataset.loc[dataset['sex'] == ' Female', 'sex'] = 0

    # discretizing workclass
    for val in workclass_state_1_values:
        dataset.loc[dataset['workclass'] == val, 'workclass'] = 1
    for val in workclass_state_0_values:
        dataset.loc[dataset['workclass'] == val, 'workclass'] = 0

    # discretizing education-num
    dataset.loc[dataset['education-num'] < 10, 'education-num'] = 0
    dataset.loc[dataset['education-num'] >= 10, 'education-num'] = 1

    # discretizing occupation
    for val in occupation_state_1_values:
        dataset.loc[dataset['occupation'] == val, 'occupation'] = 1
    for val in occupation_state_0_values:
        dataset.loc[dataset['occupation'] == val, 'occupation'] = 0

    # discretizing labels
    dataset.loc[dataset['label'] == ' <=50K', 'label'] = 0
    dataset.loc[dataset['label'] == ' >50K', 'label'] = 1

    return dataset


train_data = prepare_dataset(train_data)
test_data = prepare_dataset(test_data)
# display(train_data)
# display(test_data)
```

```
# writing files
train_data.to_csv('/home/arthurcgusmao/my_train_data.dat',
                  header=None, index=None, sep=',', mode='a')
test_data.to_csv('/home/arthurcgusmao/my_test_data.dat',
                 header=None, index=None, sep=',', mode='a')
```

Now we have two new files, one for the training data and another for the test data. In this part, we are only going to need the training file. We import it into SamIam, using EM. . . . . . .

2 Learn the network structure using R's bnlearn package and compare it to the structure you suggested initially.

Here we use R (with bnlearn package) to learn the structure of the network, and compare it with the structure we first suggested. We used two score-based algorithms: Hill-Climbing and Chow-Liu.

```
train_df = read.csv("my_train_data.dat")
test_df = read.csv("my_test_data.dat")

# we also transformed all data into numerical, code not included here, using
# the function as.numerical(), so that bnlearn could access the values.

# now we learn the structures
net_cl = chow.liu(train_df)
net_hc = hc(train_df)

plot(net_cl)
plot(net_hc)
```

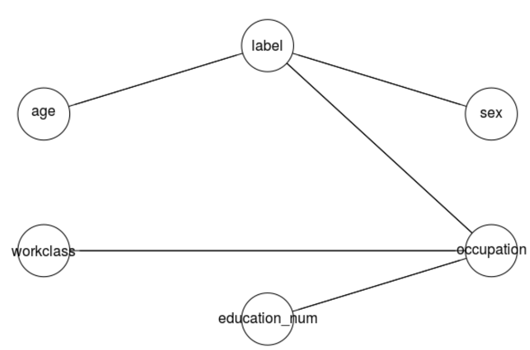


Figure 1: Network learned using Chow-Liu

From the code above, we get the two structures shown in Figure 1 and Figure 2. We can see that the structure learned by Chow-Liu is much more

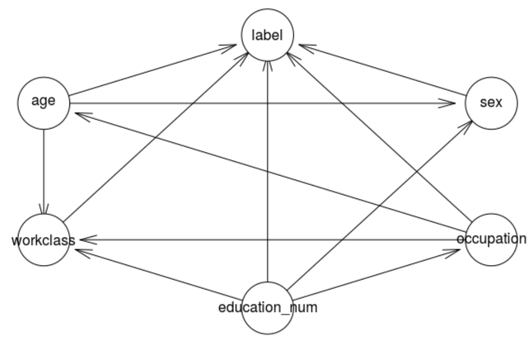


Figure 2: Network learned using Hill-Climbing

interesting and similiar to the one we expected. Hill-Climbing ended up representing too many connections (dependencies), which makes the graph too complex for the kind of problem we are trying to represent. For this reason, we select the network generated by Chow-Liu to be the one we are going to fit and try to learn the parameters.

Something we should do before that, tough, is to transform the acyclic graph into a cyclic one. Selecting the label as the root of our tree, it is now simple to decide for a direction for all arcs:

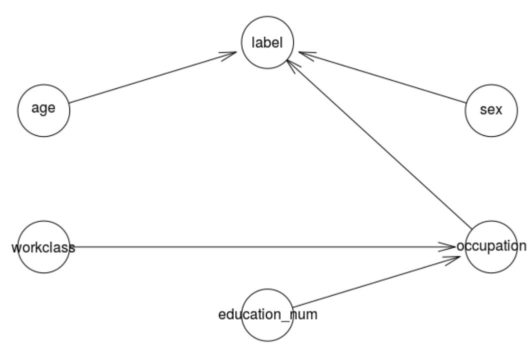


Figure 3: Our learned network with directed arcs

From Figure 3, we see that the network learned by our method is different from the one we were expecting: