FAIKR Project Module 3

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1 FAIKR Module 3 Project

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1.1 Aims of the Project:

1. Create a **Pipeline** which is able to handle Bayesian Network creation starting from **any Dataset**.
2. Build a **Bayesian Network Model** starting from a Dataset downloaded from Kaggle
3. Test the Network through queries inspired by the module's content.

Library imports:

[ ]:
```
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
from scipy.stats import chi2_contingency
import numpy as np
from IPython.display import display
```

1.2 The Dataset

Dataset Link : https://www.kaggle.com/datasets/stackoverflow/stack-overflow-2018-developer-survey

The chosen dataset contains results from a survey Taken by the Stack Overflow Community in the year 2018.

The Survey originally covered numerous different topics concerning the ICT world, but we were mostly interested in **Data regarding the user profiles**.

So we decided to apply some pre-processing to reduce the number of variables, but also to simplify the dataset so that the Bayesian Model built from it would become more manageable and readable.

[ ]:
```
%%capture
#Supresses stderr about Mixed-Type Data
df = pd.read_csv('dataset/survey_results_public.csv', sep=',')
```

[ ]:
```
display(df.describe())
```

	Respondent	AssessJob1	AssessJob2	AssessJob3	AssessJob4	\
count	98855.000000	66985.000000	66985.000000	66985.000000	66985.000000	
mean	50822.971635	6.397089	6.673524	5.906875	4.065791	
std	29321.650410	2.788428	2.531202	2.642734	2.541196	
min	1.000000	1.000000	1.000000	1.000000	1.000000	
25%	25443.500000	4.000000	5.000000	4.000000	2.000000	
50%	50823.000000	7.000000	7.000000	6.000000	4.000000	
75%	76219.500000	9.000000	9.000000	8.000000	6.000000	
max	101592.000000	10.000000	10.000000	10.000000	10.000000	

	AssessJob5	AssessJob6	AssessJob7	AssessJob8	AssessJob9	\
count	66985.000000	66985.000000	66985.000000	66985.000000	66985.000000	
mean	3.953243	4.407196	5.673181	4.225200	7.640009	
std	2.520499	2.502069	2.923998	2.507411	2.407457	
min	1.000000	1.000000	1.000000	1.000000	1.000000	
25%	2.000000	2.000000	3.000000	2.000000	6.000000	
50%	3.000000	4.000000	6.000000	4.000000	8.000000	
75%	6.000000	6.000000	8.000000	6.000000	10.000000	
max	10.000000	10.000000	10.000000	10.000000	10.000000	

	…	JobEmailPriorities6	JobEmailPriorities7	ConvertedSalary	\
count	…	46213.00000	46213.000000	4.770200e+04	
mean	…	4.97425	4.836388	9.578086e+04	
std	…	1.86063	1.659844	2.023482e+05	
min	…	1.00000	1.000000	0.000000e+00	
25%	…	4.00000	4.000000	2.384400e+04	
50%	…	5.00000	5.000000	5.507500e+04	
75%	…	7.00000	6.000000	9.300000e+04	
max	…	7.00000	7.000000	2.000000e+06	

	AdsPriorities1	AdsPriorities2	AdsPriorities3	AdsPriorities4	\
count	60479.000000	60479.000000	60479.000000	60479.000000	
mean	2.726880	3.805784	3.340945	3.782470	
std	1.881078	1.821323	1.673485	1.844864	
min	1.000000	1.000000	1.000000	1.000000	
25%	1.000000	2.000000	2.000000	2.000000	
50%	2.000000	4.000000	3.000000	4.000000	
75%	4.000000	5.000000	5.000000	5.000000	
max	7.000000	7.000000	7.000000	7.000000	

	AdsPriorities5	AdsPriorities6	AdsPriorities7
count	60479.000000	60479.000000	60479.000000
mean	4.383604	5.138809	4.821459
std	1.931746	1.853249	1.874895
min	1.000000	1.000000	1.000000
25%	3.000000	4.000000	3.000000
50%	5.000000	6.000000	5.000000
75%	6.000000	7.000000	7.000000

```
max          7.000000       7.000000       7.000000

[8 rows x 42 columns]
```

1.3 Chosen Attributes

Most of the Dataset attributes consisted in **answers to open question** which would have been hard to manage and also contained mixed-type data.

Among the user's information the following attributes have been chosen:

- ***Hobby***: *True if the user considers Coding a Hobby.*
- ***OpenSource***: *True if the user considers itself an OpenSource supporter*
- ***Country***: *The user's Country of origin*
- ***Employment***: *The user's employement type (Full-Time Part-Time…)*
- ***Education***: *The user's Formal Education (e.g., Bachelor, Master's Degree, etc.)*
- ***Undergrad Major***: *The user's major during it's Undergraduate studies*
- ***Job Satisfaction***: *A score between 1 and 7 representing the user's Jobs Satisfaction*
- ***Salary***: *The user's Salary Converted in USD*

[ ]:
```
columns=['Hobby','OpenSource','Country','Employment',\
    'FormalEducation','UndergradMajor','JobSatisfaction','ConvertedSalary']

data=df.get(columns).dropna()


data = data.rename(columns={'FormalEducation':'Education', 'ConvertedSalary':
 ↪'Salary'})
data.head()
```

[ ]:
```
  Hobby OpenSource         Country          Employment  \
1   Yes        Yes  United Kingdom  Employed full-time
4   Yes         No    South Africa  Employed full-time
5   Yes         No  United Kingdom  Employed full-time
6   Yes        Yes   United States  Employed full-time
8   Yes        Yes   United States  Employed full-time

                                          Education  \
1          Bachelor's degree (BA, BS, B.Eng., etc.)
4  Some college/university study without earning …
5          Bachelor's degree (BA, BS, B.Eng., etc.)
6  Some college/university study without earning …
8  Some college/university study without earning …

                                      UndergradMajor          JobSatisfaction  \
1  A natural science (ex. biology, chemistry, phy…  Moderately dissatisfied
4  Computer science, computer engineering, or sof…       Slightly satisfied
5  Computer science, computer engineering, or sof…     Moderately satisfied
6  Computer science, computer engineering, or sof…       Slightly satisfied
```

```
8  Fine arts or performing arts (ex. graphic desi…     Moderately satisfied

      Salary
1    70841.0
4    21426.0
5    41671.0
6   120000.0
8   250000.0
```

The ***JobSatisfaction*** values have been remapped into an integer scale.

[ ]:
```
js_dict = {
    'Extremely dissatisfied':0,
    'Moderately dissatisfied':1,
    'Slightly dissatisfied':2,
    'Neither satisfied nor dissatisfied':3,
    'Slightly satisfied':4,
    'Moderately satisfied':5,
    'Extremely satisfied':6,
}

data['JobSatisfaction']=data['JobSatisfaction'].map(js_dict)
```

The Dataset has been pruned from entries which had a ***Formal Education*** different from a *Bachelor's Degree, a Master's Degree or a Ph.D* to **reduce the complexity** of the Model.

[ ]:
```
data = data.replace('Bachelor’s degree (BA, BS, B.Eng., etc.)',"Bachelor")
data = data.replace('Master’s degree (MA, MS, M.Eng., MBA, etc.)',"Master")
data = data.replace('Other doctoral degree (Ph.D, Ed.D., etc.)',"Ph.D")
data = data[data['Education'].isin(['Bachelor','Master','Ph.D'])]
```

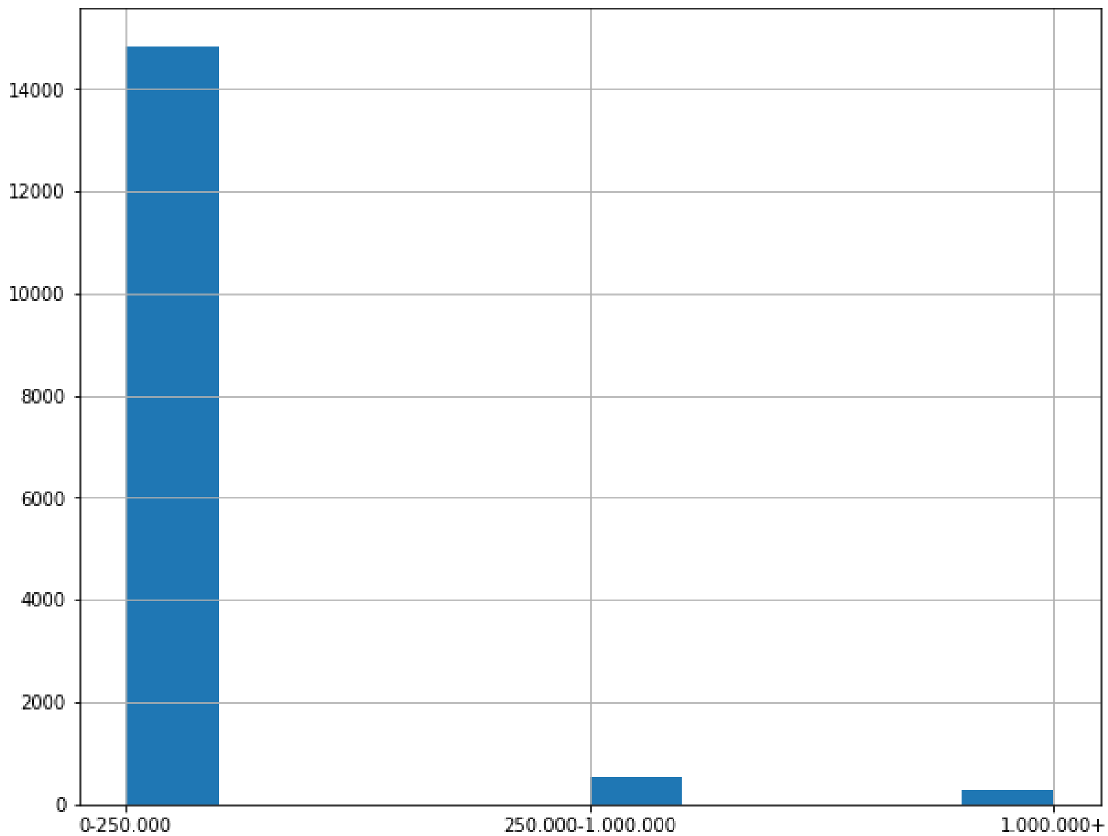
We considered data concerning only the **three most represented countries** in the Dataset.

[ ]:
```
countries=data.groupby('Country').size().sort_values()[-3:].index.tolist()
data = data[data['Country'].isin(countries)]
```

The ***Converted Salary*** attribute has been discretized into three ranges to reduce the Dataset Complexity and to Work on **Categorical Values**.

[ ]:
```
plt.figure(figsize=(10,8))
data.Salary=data.Salary.map(lambda x: '0-250.000' if x<=250000 else '250.000-1.
 ↪000.000' if x<=1000000 else '1.000.000+')
data.Salary.hist()
```

[ ]:
```
<AxesSubplot:>
```



The ***Undergrad Major*** Attribute has been Binarized into "STEM" and "NON STEM" majors.

[ ]:
```
stem=['A natural science (ex. biology, chemistry, physics)',
 'Computer science, computer engineering, or software engineering',
 'Web development or web design',
 'Another engineering discipline (ex. civil, electrical, mechanical)',
 'Mathematics or statistics',
 'Information systems, information technology, or system administration',
]

not_stem=[ 'A social science (ex. anthropology, psychology, political science)',
 'A humanities discipline (ex. literature, history, philosophy)',
 'A business discipline (ex. accounting, finance, marketing)',
 'Fine arts or performing arts (ex. graphic design, music, studio art)',
 'A health science (ex. nursing, pharmacy, radiology)',
]

data=data[data['UndergradMajor'].isin(stem+not_stem)]
data.UndergradMajor=data.UndergradMajor.map(lambda x: 'STEM' if x in stem else␣
 ↪'NOT_STEM')
```

1.3.1 Content of the Dataset after applying pre-processing:

```
[ ]: display(data.head())
```

```
   Hobby OpenSource          Country          Employment Education  \
1    Yes        Yes   United Kingdom  Employed full-time  Bachelor
5    Yes         No   United Kingdom  Employed full-time  Bachelor
22    No         No   United Kingdom  Employed full-time  Bachelor
24   Yes         No            India  Employed full-time    Master
27    No         No    United States  Employed full-time  Bachelor

   UndergradMajor  JobSatisfaction              Salary
1            STEM                1           0-250.000
5            STEM                5           0-250.000
22           STEM                4           0-250.000
24           STEM                5           0-250.000
27       NOT_STEM                5   250.000-1.000.000
```

```
[ ]: for col in data.columns:

        print(col, ":", data[col].unique())
```

```
Hobby : ['Yes' 'No']
OpenSource : ['Yes' 'No']
Country : ['United Kingdom' 'India' 'United States']
Employment : ['Employed full-time' 'Employed part-time'
 'Independent contractor, freelancer, or self-employed']
Education : ['Bachelor' 'Master' 'Ph.D']
UndergradMajor : ['STEM' 'NOT_STEM']
JobSatisfaction : [1 5 4 0 6 2 3]
Salary : ['0-250.000' '250.000-1.000.000' '1.000.000+']
```

1.4 Bayesian Network Creation

We decided to test the Dataset Attribute independence through a $Chi^2 Test$ since we are working with Categorical Values.

Each attribute's indipendence has been tested with all the others and a Contingency matrix has been Created.

Function that computes Tests on all the Dataset Attributes independences and creates a Contingency matrix:

- For Readability We decided to set all the the test outpus to 1 if their p values are greater or equal to α.

1.4.1 Chi-Square Test:

The Chi-square test of independence is a statistical hypothesis test used to determine whether two categorical or nominal variables are likely to be related or not.

A test of independence assesses whether observations consisting of measures on two variables, expressed in a contingency table, are independent of each other.

The test Consists in the following steps:

1. Defining an Hypothesis:
    - `Null Hypothesis (H0)`: Two variables are independent.
    - `Alternate Hypothesis (H1)`: Two variables are not independent.
2. Calculating a **Contingency Table** for both Attributes tested:
    - Table showing the distribution of one variable in rows and another in columns.
3. Find the Expected Value
    - A and B are independent iff $P(A \cap B) = P(A) * P(B)$
4. Calculate the $p - value$:
    - $\chi^2 = \Sigma \frac{(O_i - E_i)^2}{E_i}$
    - Where:
        - E_i is the expected value computed in the previous step.
        - O_i is the number of observations of type i
5. Accept or Reject The Hypothesis:
    - Decide $\alpha =$ Significance level of the Test
    - if: $p - value > \alpha$ `H0` is accepted.
    - Otherwise: `H1` is accepted

[ ]:
```
def chi2_contingency_mat(data,alpha=None):
    s=data.columns.size
    a = 0
    b = 0
    mat=np.zeros((s,s))
    for i in data.columns:
        for j in data.columns:
            contigency_pct = pd.crosstab(data[i], data[j])
            c, p, dof, expected = chi2_contingency(contigency_pct)
            mat[a][b]=p
            b=b+1
        a = a+1
        b=0
    if alpha:
        mat[mat>=alpha]=1
        mat[mat<alpha]=0
    return mat
```

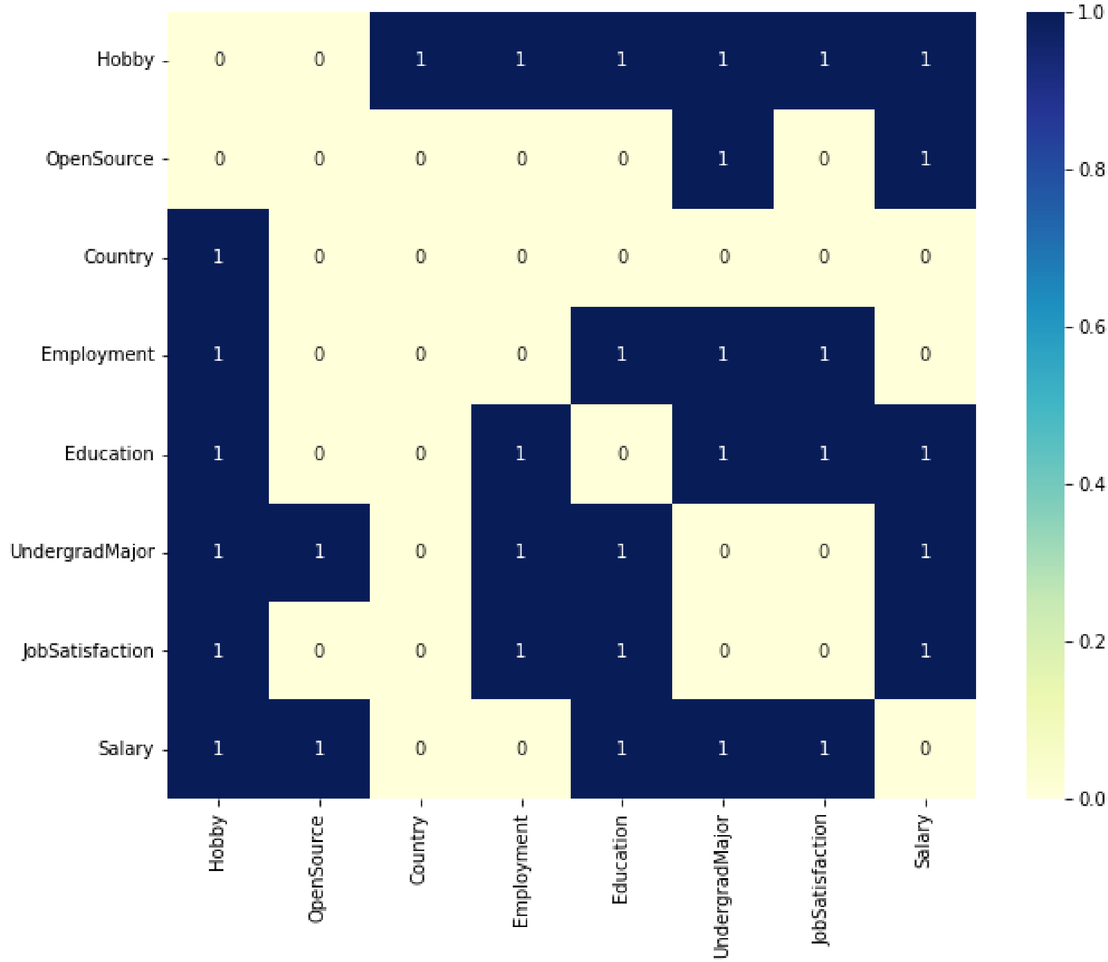
Chi^2 Contingency matrix plot:

- α has been set to 5×10^{-7} to take in consideration only **Highly Dependent** attributes and take less risk in misjudging the results.

[ ]:
```
chi2Mat=chi2_contingency_mat(data,5e-7)
labels = list(data.columns)
plt.figure(figsize=(10,8))
```

```
sns.heatmap(chi2Mat,annot=True, xticklabels=labels,␣
↪yticklabels=labels,cmap="YlGnBu")
```

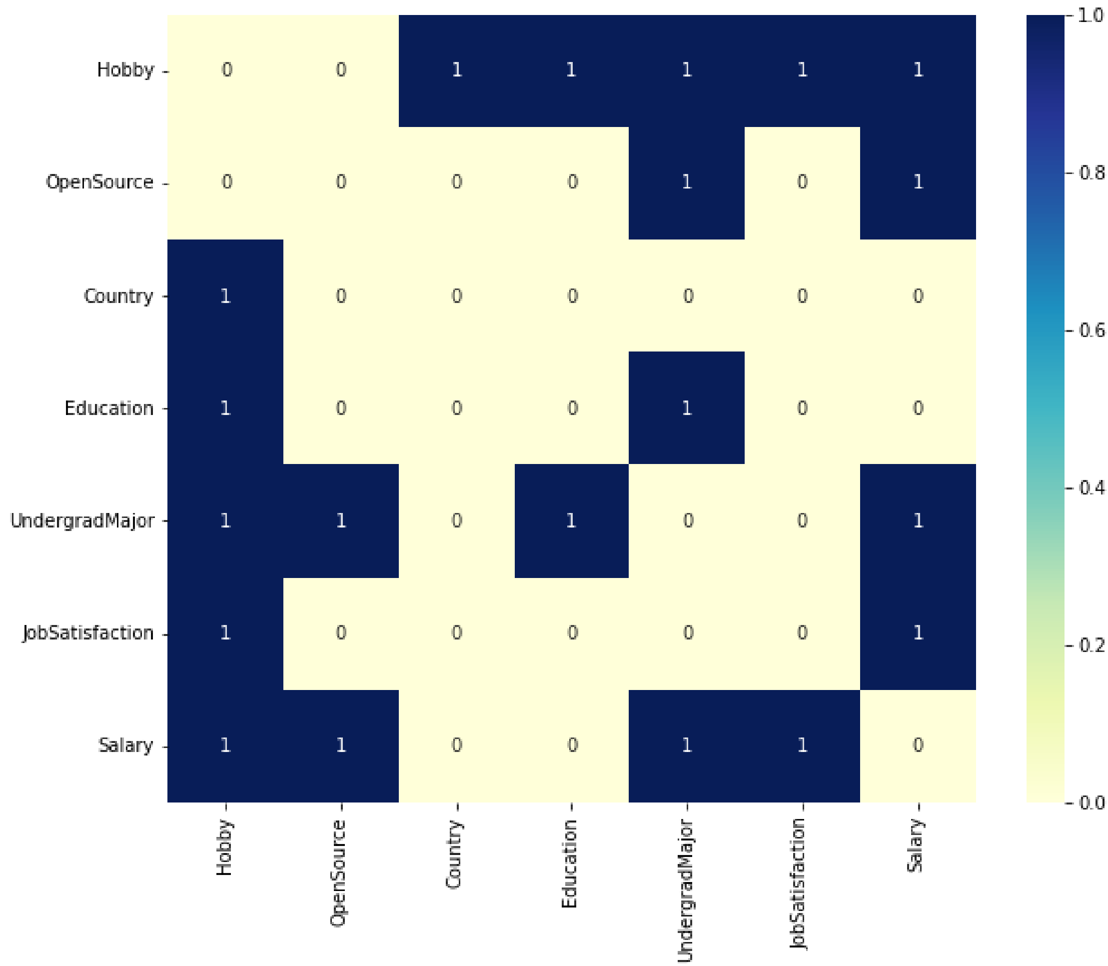
[ ]: <AxesSubplot:>



As we can see the *Employment* column could make the **BN** too complicated and also doesn't really seem signicative enough, so we decided to drop it and recompute the Contingency matrix.

[ ]:
```
data = data.drop('Employment', axis=1)
chi2Mat=chi2_contingency_mat(data,5e-3)
labels = list(data.columns)
plt.figure(figsize=(10,8))
sns.heatmap(chi2Mat,annot=True, xticklabels=labels,␣
↪yticklabels=labels,cmap="YlGnBu")
```

[ ]: <AxesSubplot:>



1.5 Graph Plotting

- Function used to Compute a Graph Table starting from a computed χ^2 matrix.

[ ]:
```
def compute_graph_table(data, chi2Mat):

    graph_table = pd.DataFrame()


    source = []
    target=[]

    a=1
    for i in range(data.columns.size):
        for j in range(a, data.columns.size):
            if chi2Mat[i][j]==0:
                source.append(data.columns[i])
```

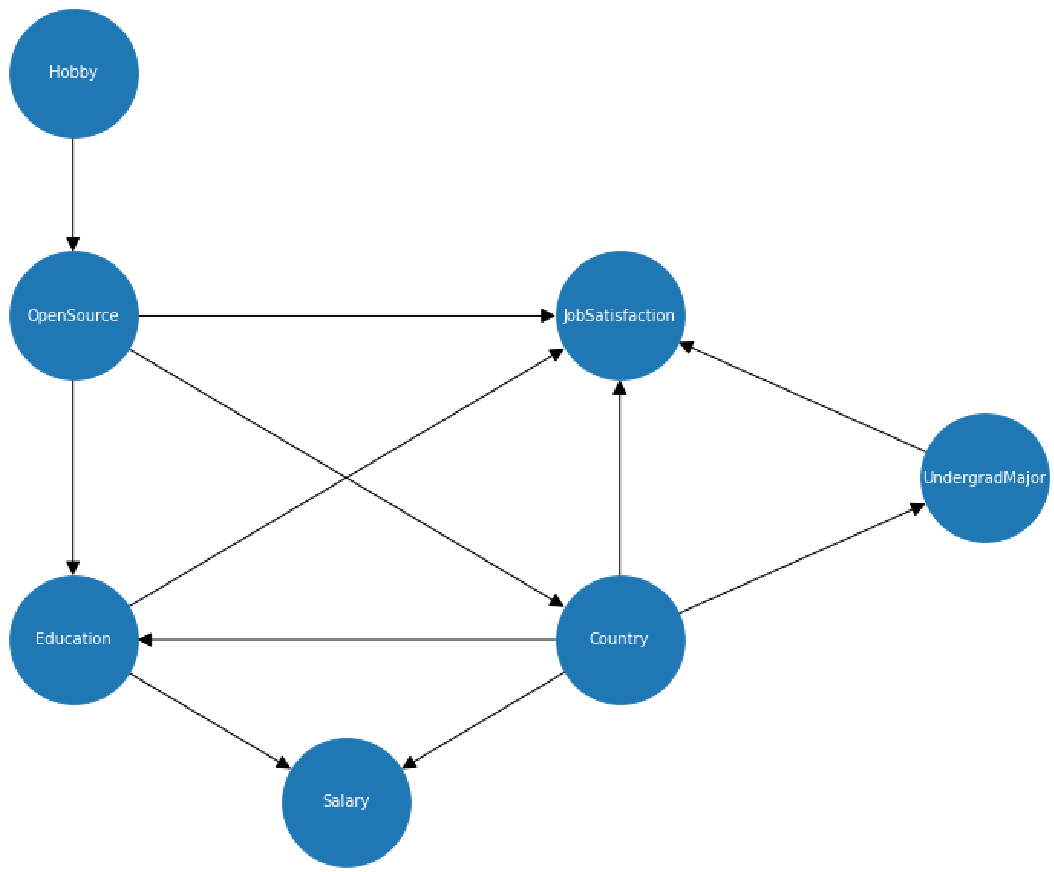
```
                target.append(data.columns[j])
        a=a+1

    type=['Unidirected' for i in range(len(source))]
    weight=[None for i in range(len(source))]
    graph_table['Source']=source
    graph_table['Target']=target
    graph_table['Type']=type
    graph_table['weight']=weight
    return graph_table
```

Computed Graph Table:

[ ]:
```
graph_table = compute_graph_table(data, chi2Mat)
graph_table
```

[ ]:
```
            Source           Target         Type weight
0            Hobby       OpenSource  Unidirected   None
1       OpenSource          Country  Unidirected   None
2       OpenSource        Education  Unidirected   None
3       OpenSource  JobSatisfaction  Unidirected   None
4          Country        Education  Unidirected   None
5          Country   UndergradMajor  Unidirected   None
6          Country  JobSatisfaction  Unidirected   None
7          Country           Salary  Unidirected   None
8        Education  JobSatisfaction  Unidirected   None
9        Education           Salary  Unidirected   None
10  UndergradMajor  JobSatisfaction  Unidirected   None
```

[ ]:
```
import networkx as nx

G = nx.from_pandas_edgelist(graph_table, source='Source',␣
 ↪target='Target',create_using=nx.DiGraph())
pos={'Hobby':(0.5,10),
     'JobSatisfaction':(2,7),
     'OpenSource':(0.5,7),
     'Education':(0.5,3),
     'Country':(2,3),
     'Salary':(1.25,1),
     'UndergradMajor':(3,5)
 }
plt.figure(figsize=(10,8))

nx.draw(G, arrows=True, with_labels=True, node_size=7000, arrowsize=20,␣
 ↪pos=pos, font_size=10, font_color='white')
# print(G.edges())
```



1.6 Markov Blanket Plotting

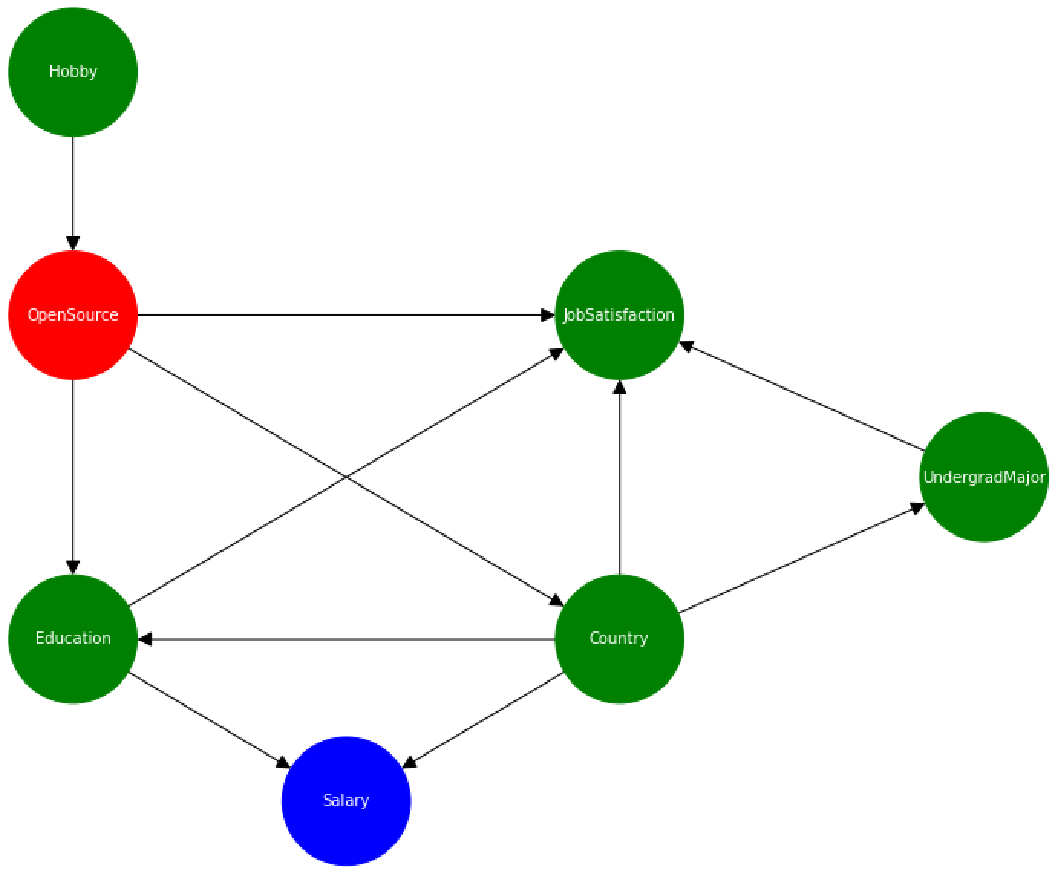
- Function to compute a Markov Blanked given a Graph and a Node.
- Function that Plots the Markov Blanket of a Node:
  - **Red**: Node We are Interested in.
  - **Green**: Markov Blanket Set of Nodes.
  - **Blue**: Set of nodes which are not part of the Markov Blanket.

[ ]:
```
#Function to extract the Markov Blanket of a Node from the Graph
def get_mb(graph, node):
    mb = set()
    parents = [i for i in graph.predecessors(node)]
    mb.update(parents)
    sons = [i for i in graph.successors(node)]
    mb.update(sons)
    sons_parents=[]
    for s in sons:
        sons_parents.extend([i for i in graph.predecessors(s) if i != node])
```

```
    mb.update(sons_parents)
    return mb

#Markov Blanket Plotting Function
def plot_mb(G, mb, node):
    pos={'Hobby':(0.5,10),
      'JobSatisfaction':(2,7),
      'OpenSource':(0.5,7),
      'Education':(0.5,3),
      'Country':(2,3),
      'Salary':(1.25,1),
      'UndergradMajor':(3,5)
    }
    plt.figure(figsize=(10,8))
    color_map=[]
    for n in G:
        if n in mb:
            color_map.append('green')
        elif n == node:
            color_map.append('red')
        else:
            color_map.append('blue')
    nx.draw(G, arrows=True,node_color=color_map, with_labels=True,␣
 ↪node_size=7000, arrowsize=20, pos=pos, font_size=10, font_color='white')
```

Markov Blanket of the OpenSource Node

[ ]:
```
mb=get_mb(G, 'OpenSource')
plot_mb(G, mb, 'OpenSource')

plt.show()
```



1.7 Bayesian Network Model (PGMPY library)

This function computes the Graph Edges using the Upper triangular part of the χ^2 matrix as an adjacency Table.

[ ]:
```
def getEdges(mat,names=[]):
    result=[]
    l,_=mat.shape
    for i in range(l):
        for j in range(i+1,l):
            if mat[i,j]==0:
                if len(names)>0:
                    result.append((names[i],names[j]))
                else: result.append((i,j))
    return result
```

1.7.1 Maximum likelihood

Model Creation using a **Maximum Likelihood Estimator** to compute the Probability Tables.

- **Maximum likelihood estimation (MLE)** is a method of estimating the parameters of an assumed probability distribution, given some observed data.
- This is achieved by maximizing a likelihood function so that, under the assumed statistical model, the observed data is most probable.

Given the **Likelihood** of a function:

$L_n(\theta) = L_n(\theta; y) = f_n(y; \theta)$

where $y = \{y_1, y_2, ...\}$ is a set of random variables.

MLE aims at maximizing $\hat{\theta}$ using the following formula:

$\hat{\theta} = arg_{\theta \in \Theta} max \hat{L_n}(\theta; y)$

[ ]:
```python
from pgmpy.models import BayesianNetwork
from pgmpy.estimators import MaximumLikelihoodEstimator

edges=getEdges(chi2Mat,names=data.columns)
model= BayesianNetwork(edges)
model.fit(data, estimator=MaximumLikelihoodEstimator)
for cpd in model.get_cpds():
    print(cpd)
```

```
+------------+----------+
| Hobby(No)  | 0.199923 |
+------------+----------+
| Hobby(Yes) | 0.800077 |
+------------+----------+
+-----------------+--------------------+---------------------+
| Hobby           | Hobby(No)          | Hobby(Yes)          |
+-----------------+--------------------+---------------------+
| OpenSource(No)  | 0.7966101694915254 | 0.49800223749400674 |
+-----------------+--------------------+---------------------+
| OpenSource(Yes) | 0.2033898305084746 | 0.5019977625059933  |
+-----------------+--------------------+---------------------+
+-------------------------+---------------------+---------------------+
| OpenSource              | OpenSource(No)      | OpenSource(Yes)     |
+-------------------------+---------------------+---------------------+
| Country(India)          | 0.20440215522182736 | 0.24486845909222318 |
+-------------------------+---------------------+---------------------+
| Country(United Kingdom) | 0.17872291642783447 | 0.16536571263370917 |
+-------------------------+---------------------+---------------------+
| Country(United States)  | 0.6168749283503382  | 0.5897658282740676  |
+-------------------------+---------------------+---------------------+
+---------------------+-----+------------------------+
| Country             | … | Country(United States) |
+---------------------+-----+------------------------+
| OpenSource          | … | OpenSource(Yes)        |
+---------------------+-----+------------------------+
```

Education(Bachelor)	…	0.7134803921568628
Education(Master)	…	0.24215686274509804
Education(Ph.D)	…	0.04436274509803922

Country	…	Country(United States)
Education	…	Education(Ph.D)
OpenSource	…	OpenSource(Yes)
UndergradMajor	…	UndergradMajor(STEM)
JobSatisfaction(0)	…	0.05806451612903226
JobSatisfaction(1)	…	0.05806451612903226
JobSatisfaction(2)	…	0.08387096774193549
JobSatisfaction(3)	…	0.025806451612903226
JobSatisfaction(4)	…	0.08387096774193549
JobSatisfaction(5)	…	0.3741935483870968
JobSatisfaction(6)	…	0.3161290322580645

Country	…	Country(United States)
UndergradMajor(NOT_STEM)	…	0.15759433463693057
UndergradMajor(STEM)	…	0.8424056653630695

Country	…	Country(United States)
Education	…	Education(Ph.D)
Salary(0-250.000)	…	0.9244712990936556
Salary(1.000.000+)	…	0.027190332326283987
Salary(250.000-1.000.000)	…	0.04833836858006042

1.7.2 Model Independencies

[ ]:
```
model.get_independencies()
```

[ ]:
```
(Education   Hobby | OpenSource)
(Education   UndergradMajor | Country)
(Education   Hobby | OpenSource, JobSatisfaction)
(Education   Hobby | OpenSource, UndergradMajor)
(Education   Hobby | OpenSource, Salary)
(Education   Hobby, UndergradMajor | OpenSource, Country)
(Education   UndergradMajor | Hobby, Country)
(Education   UndergradMajor | Salary, Country)
(Education   UndergradMajor | OpenSource, Hobby, Country)
(Education   Hobby | OpenSource, JobSatisfaction, UndergradMajor)
(Education   Hobby | OpenSource, Salary, JobSatisfaction)
(Education   Hobby | OpenSource, JobSatisfaction, Country)
(Education   Hobby | OpenSource, Salary, UndergradMajor)
(Education   Hobby | OpenSource, Country, UndergradMajor)
(Education   Hobby, UndergradMajor | OpenSource, Salary, Country)
(Education   UndergradMajor | Salary, Hobby, Country)
(Education   UndergradMajor | OpenSource, Salary, Hobby, Country)
(Education   Hobby | OpenSource, Salary, JobSatisfaction, UndergradMajor)
(Education   Hobby | OpenSource, JobSatisfaction, Country, UndergradMajor)
(Education   Hobby | OpenSource, Salary, JobSatisfaction, Country)
(Education   Hobby | OpenSource, Salary, Country, UndergradMajor)
(Education   Hobby | OpenSource, JobSatisfaction, Country, UndergradMajor,
Salary)
(OpenSource   UndergradMajor | Country)
(OpenSource   Salary, UndergradMajor | Education, Country)
(OpenSource   UndergradMajor | Hobby, Country)
(OpenSource   UndergradMajor | Salary, Country)
(OpenSource   Salary, UndergradMajor | Education, Hobby, Country)
(OpenSource   Salary | Education, JobSatisfaction, Country)
(OpenSource   Salary | Education, Country, UndergradMajor)
(OpenSource   UndergradMajor | Education, Salary, Country)
(OpenSource   UndergradMajor | Salary, Hobby, Country)
(OpenSource   Salary | Education, Hobby, Country, JobSatisfaction)
(OpenSource   Salary | Education, Hobby, Country, UndergradMajor)
(OpenSource   UndergradMajor | Education, Salary, Hobby, Country)
(OpenSource   Salary | Education, JobSatisfaction, Country, UndergradMajor)
(OpenSource   Salary | Education, Hobby, JobSatisfaction, Country,
UndergradMajor)
(JobSatisfaction   Hobby | OpenSource)
(JobSatisfaction   Hobby | Education, OpenSource)
(JobSatisfaction   Salary | Education, Country)
(JobSatisfaction   Hobby | OpenSource, UndergradMajor)
(JobSatisfaction   Hobby | OpenSource, Salary)
```

(JobSatisfaction Hobby | OpenSource, Country)
(JobSatisfaction Hobby | Education, OpenSource, UndergradMajor)
(JobSatisfaction Hobby | Education, OpenSource, Salary)
(JobSatisfaction Salary, Hobby | Education, OpenSource, Country)
(JobSatisfaction Salary | Education, Hobby, Country)
(JobSatisfaction Salary | Education, Country, UndergradMajor)
(JobSatisfaction Hobby | OpenSource, Salary, UndergradMajor)
(JobSatisfaction Hobby | OpenSource, Country, UndergradMajor)
(JobSatisfaction Hobby | OpenSource, Salary, Country)
(JobSatisfaction Salary | Education, OpenSource, Hobby, Country)
(JobSatisfaction Hobby | Education, OpenSource, Salary, UndergradMajor)
(JobSatisfaction Salary, Hobby | Education, OpenSource, Country,
UndergradMajor)
(JobSatisfaction Hobby | Education, OpenSource, Salary, Country)
(JobSatisfaction Salary | Education, Hobby, Country, UndergradMajor)
(JobSatisfaction Hobby | OpenSource, Salary, Country, UndergradMajor)
(JobSatisfaction Salary | Education, OpenSource, Hobby, Country,
UndergradMajor)
(JobSatisfaction Hobby | Education, OpenSource, Country, UndergradMajor,
Salary)
(Hobby Education, JobSatisfaction, UndergradMajor, Salary, Country |
OpenSource)
(Hobby UndergradMajor | Country)
(Hobby UndergradMajor, Salary, JobSatisfaction, Country | Education,
OpenSource)
(Hobby Salary, UndergradMajor | Education, Country)
(Hobby Education, Salary, UndergradMajor, Country | OpenSource,
JobSatisfaction)
(Hobby Education, Salary, JobSatisfaction, Country | OpenSource,
UndergradMajor)
(Hobby Education, JobSatisfaction, UndergradMajor, Country | OpenSource,
Salary)
(Hobby Education, Salary, JobSatisfaction, UndergradMajor | OpenSource,
Country)
(Hobby UndergradMajor | Salary, Country)
(Hobby UndergradMajor, Salary, Country | Education, OpenSource,
JobSatisfaction)
(Hobby Salary, JobSatisfaction, Country | Education, OpenSource,
UndergradMajor)
(Hobby UndergradMajor, JobSatisfaction, Country | Education, OpenSource,
Salary)
(Hobby Salary, JobSatisfaction, UndergradMajor | Education, OpenSource,
Country)
(Hobby Salary | Education, JobSatisfaction, Country)
(Hobby Salary | Education, Country, UndergradMajor)
(Hobby UndergradMajor | Education, Salary, Country)
(Hobby Education, Salary, Country | OpenSource, JobSatisfaction,

```
UndergradMajor)
(Hobby  Education, UndergradMajor, Country | OpenSource, Salary,
JobSatisfaction)
(Hobby  Education, Salary, UndergradMajor | OpenSource, JobSatisfaction,
Country)
(Hobby  Education, JobSatisfaction, Country | OpenSource, Salary,
UndergradMajor)
(Hobby  Education, Salary, JobSatisfaction | OpenSource, Country,
UndergradMajor)
(Hobby  Education, JobSatisfaction, UndergradMajor | OpenSource, Salary,
Country)
(Hobby  Salary, Country | Education, OpenSource, JobSatisfaction,
UndergradMajor)
(Hobby  UndergradMajor, Country | Education, OpenSource, JobSatisfaction,
Salary)
(Hobby  Salary, UndergradMajor | Education, OpenSource, JobSatisfaction,
Country)
(Hobby  JobSatisfaction, Country | Education, OpenSource, Salary,
UndergradMajor)
(Hobby  Salary, JobSatisfaction | Education, OpenSource, Country,
UndergradMajor)
(Hobby  JobSatisfaction, UndergradMajor | Education, OpenSource, Salary,
Country)
(Hobby  Salary | Education, JobSatisfaction, Country, UndergradMajor)
(Hobby  Education, Country | OpenSource, Salary, JobSatisfaction,
UndergradMajor)
(Hobby  Education, Salary | OpenSource, JobSatisfaction, Country,
UndergradMajor)
(Hobby  Education, UndergradMajor | OpenSource, Salary, JobSatisfaction,
Country)
(Hobby  Education, JobSatisfaction | OpenSource, Salary, Country,
UndergradMajor)
(Hobby  Country | Education, OpenSource, JobSatisfaction, UndergradMajor,
Salary)
(Hobby  Salary | Education, OpenSource, JobSatisfaction, Country,
UndergradMajor)
(Hobby  UndergradMajor | Education, OpenSource, JobSatisfaction, Country,
Salary)
(Hobby  JobSatisfaction | Education, OpenSource, Country, UndergradMajor,
Salary)
(Hobby  Education | OpenSource, JobSatisfaction, Country, UndergradMajor,
Salary)
(Country  Hobby | OpenSource)
(Country  Hobby | Education, OpenSource)
(Country  Hobby | OpenSource, JobSatisfaction)
(Country  Hobby | OpenSource, UndergradMajor)
(Country  Hobby | OpenSource, Salary)
```

```
(Country   Hobby | Education, OpenSource, JobSatisfaction)
(Country   Hobby | Education, OpenSource, UndergradMajor)
(Country   Hobby | Education, OpenSource, Salary)
(Country   Hobby | OpenSource, JobSatisfaction, UndergradMajor)
(Country   Hobby | OpenSource, Salary, JobSatisfaction)
(Country   Hobby | OpenSource, Salary, UndergradMajor)
(Country   Hobby | Education, OpenSource, JobSatisfaction, UndergradMajor)
(Country   Hobby | Education, OpenSource, JobSatisfaction, Salary)
(Country   Hobby | Education, OpenSource, Salary, UndergradMajor)
(Country   Hobby | OpenSource, Salary, JobSatisfaction, UndergradMajor)
(Country   Hobby | Education, OpenSource, JobSatisfaction, UndergradMajor,
Salary)
(UndergradMajor   Hobby | OpenSource)
(UndergradMajor   Education, OpenSource, Hobby, Salary | Country)
(UndergradMajor   Hobby | Education, OpenSource)
(UndergradMajor   OpenSource, Salary, Hobby | Education, Country)
(UndergradMajor   Hobby | OpenSource, JobSatisfaction)
(UndergradMajor   Education, Salary, Hobby | OpenSource, Country)
(UndergradMajor   Hobby | OpenSource, Salary)
(UndergradMajor   Education, OpenSource, Salary | Hobby, Country)
(UndergradMajor   Education, OpenSource, Hobby | Salary, Country)
(UndergradMajor   Hobby | Education, OpenSource, JobSatisfaction)
(UndergradMajor   Salary, Hobby | Education, OpenSource, Country)
(UndergradMajor   Hobby | Education, OpenSource, Salary)
(UndergradMajor   OpenSource, Salary | Education, Hobby, Country)
(UndergradMajor   Salary | Education, JobSatisfaction, Country)
(UndergradMajor   OpenSource, Hobby | Education, Salary, Country)
(UndergradMajor   Education, Salary | OpenSource, Hobby, Country)
(UndergradMajor   Hobby | OpenSource, JobSatisfaction, Country)
(UndergradMajor   Hobby | OpenSource, Salary, JobSatisfaction)
(UndergradMajor   Education, Hobby | OpenSource, Salary, Country)
(UndergradMajor   Education, OpenSource | Salary, Hobby, Country)
(UndergradMajor   Salary | Education, OpenSource, Hobby, Country)
(UndergradMajor   Salary, Hobby | Education, OpenSource, JobSatisfaction,
Country)
(UndergradMajor   Hobby | Education, OpenSource, JobSatisfaction, Salary)
(UndergradMajor   Hobby | Education, OpenSource, Salary, Country)
(UndergradMajor   Salary | Education, Hobby, Country, JobSatisfaction)
(UndergradMajor   OpenSource | Education, Salary, Hobby, Country)
(UndergradMajor   Education | OpenSource, Salary, Hobby, Country)
(UndergradMajor   Hobby | OpenSource, Salary, JobSatisfaction, Country)
(UndergradMajor   Salary | Education, OpenSource, Hobby, JobSatisfaction,
Country)
(UndergradMajor   Hobby | Education, OpenSource, JobSatisfaction, Country,
Salary)
(Salary   Hobby | OpenSource)
(Salary   UndergradMajor | Country)
```

```
(Salary   Hobby | Education, OpenSource)
(Salary   OpenSource, JobSatisfaction, Hobby, UndergradMajor | Education,
Country)
(Salary   Hobby | OpenSource, JobSatisfaction)
(Salary   Hobby, UndergradMajor | OpenSource, Country)
(Salary   Hobby | OpenSource, UndergradMajor)
(Salary   UndergradMajor | Hobby, Country)
(Salary   Hobby | Education, OpenSource, JobSatisfaction)
(Salary   JobSatisfaction, Hobby, UndergradMajor | Education, OpenSource,
Country)
(Salary   Hobby | Education, OpenSource, UndergradMajor)
(Salary   OpenSource, JobSatisfaction, UndergradMajor | Education, Hobby,
Country)
(Salary   OpenSource, Hobby, UndergradMajor | Education, JobSatisfaction,
Country)
(Salary   OpenSource, Hobby, JobSatisfaction | Education, UndergradMajor,
Country)
(Salary   UndergradMajor | OpenSource, Hobby, Country)
(Salary   Hobby | OpenSource, JobSatisfaction, Country)
(Salary   Hobby | OpenSource, JobSatisfaction, UndergradMajor)
(Salary   Hobby | OpenSource, UndergradMajor, Country)
(Salary   JobSatisfaction, UndergradMajor | Education, OpenSource, Hobby,
Country)
(Salary   Hobby, UndergradMajor | Education, OpenSource, JobSatisfaction,
Country)
(Salary   Hobby | Education, OpenSource, JobSatisfaction, UndergradMajor)
(Salary   Hobby, JobSatisfaction | Education, OpenSource, UndergradMajor,
Country)
(Salary   OpenSource, UndergradMajor | Education, Hobby, Country,
JobSatisfaction)
(Salary   OpenSource, JobSatisfaction | Education, Hobby, UndergradMajor,
Country)
(Salary   OpenSource, Hobby | Education, JobSatisfaction, UndergradMajor,
Country)
(Salary   Hobby | OpenSource, JobSatisfaction, UndergradMajor, Country)
(Salary   UndergradMajor | Education, OpenSource, Hobby, JobSatisfaction,
Country)
(Salary   JobSatisfaction | Education, OpenSource, Hobby, UndergradMajor,
Country)
(Salary   Hobby | Education, OpenSource, JobSatisfaction, UndergradMajor,
Country)
(Salary   OpenSource | Education, Hobby, JobSatisfaction, UndergradMajor,
Country)
```

1.8 Flows of probabilistic influence

Definition (active two-edge trail): If influence can flow from X to Y via Z, the trail $X \rightleftharpoons Z \rightleftharpoons Y$ is active.

For influence to flow from nodes X_1 to X_n, it needs to flow through every single node on the trail. This is true if and only if every two-edge trail $X_{i-1} \rightleftharpoons X_i \rightleftharpoons X_{i+1}$ along the trail allows influence to flow.

Definition (active trail): let Z be a subset of observed variables. The trail $X_{i-1} \rightleftharpoons X_i \rightleftharpoons X_{i+1}$ is active given Z if - $\forall X_{i-1} \rightarrow X_i \leftarrow X_{i+1}$, X_i or one of its descendants are in Z - no other node along the trail is in Z

[ ]:
```
print(model.active_trail_nodes(['JobSatisfaction'])['JobSatisfaction'])
print(model.
 ↪active_trail_nodes(['JobSatisfaction'],['OpenSource'])['JobSatisfaction'])
```

```
{'Education', 'OpenSource', 'JobSatisfaction', 'Hobby', 'Country',
'UndergradMajor', 'Salary'}
{'Education', 'JobSatisfaction', 'Country', 'UndergradMajor', 'Salary'}
```

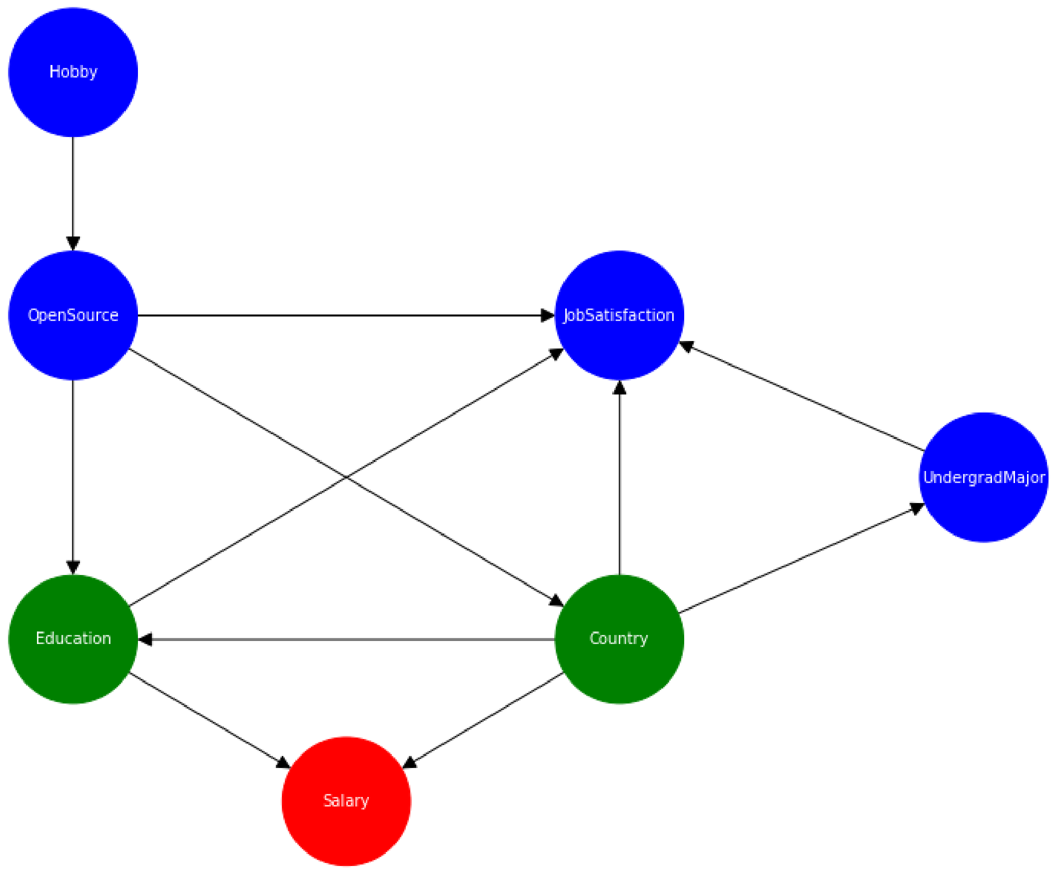
You can see how the presence of *OpenSource* in the evidence 'blocks' the trail between *JobSatisfaction* and *Hobby*.

1.9 Markov Blanket Notes

All information about a random variable in a **Bayesian network** is contained within this set of nodes (parents, children, and parents of children).

If we observe all of these variables (giving an **evidence**), then our node is independent of all other nodes within the network.

[ ]:
```
plot_mb(G, model.get_markov_blanket('Salary'), 'Salary')
```



As we can see asking the BN the probability of having a certain *Salary* given its **Markov Blanket** is the same as adding evidence to other nodes that aren't part of it.

This means that ***Salary*** is independent to other nodes given its **Markov Blanket**.

1.10 Variable Elimination

Variable Elimination is an exact inference algorithm which consists in computing a probability by repeatedly applying two basic factor operations: product and marginalization.

- In a Bayesian network, a *factor* correspond to a conditional probability distribution.
- **Pointwise product** of factors f_1 and f_2 :

$$f_1(x_1, .., x_j, y_1, .., y_k) \times f_2(y_1, .., y_k, z_1, .., z_l) = f(x_1, .., x_j, y_1, .., y_k, z_1, .., z_l)$$

- **Summing out** a variable from a product of factors:
  1. move any constant factors outside the summation

2. add up submatrices in pointwise product of remaining factors

$$\sum_X f_1 \times ... \times f_k = f_1 \times ... \times f_i \sum_X f_{i+1} \times ... \times f_k$$
$$= f_1 \times ... \times f_i \times f_{\bar{X}}$$

The VE algorithm loops over the variables of the network and eliminates them following an ordering O. For each varibale X_i (ordered according to O): 1. multiply all factors ϕ_i containing X_i 2. sum out X_i to obtain a new factor τ 3. replace the factors ϕ_i with τ

Any ordering yields a valid algorithm. However, different orderings may **drammatically alter the running time of the VE algorithm**, and the search for the best ordering is a **NP_hard** problem.

Now we will show two different queries made on the BN putting in evidence what an **irrelevant variable** is. A variable is irrelevant to the query if the **sum over it is equal to 1**.

Th. Y is irrelevant if **d-separated** from X by E.

In the previous picture, we have shown the Markov Blanket of *Salary*, which is formed by its ancestors *Country* and *Education*. Now we'll make two different queries: - *P(Salary|Country='India',Education='Bachelor')* - *P(Salary|Country='India',Education='Bachelor',OpenSource='Yes')*

And we are expecting the outcomes to be equal, since *OpenSource* is d-separated from *Salary* by *Country* and *Education*, thus irrelevant to the query.

[ ]:
```
%%capture
from pgmpy.inference import VariableElimination
inference = VariableElimination(model)

pSalary1 = inference.query(['Salary'],{'Country':'India','Education':
↪'Bachelor'})

pSalary2 = inference.query(['Salary'],{'Country':'India','Education':
↪'Bachelor','OpenSource':'Yes'})
```

[ ]:
```
print("P(Salary | Country=India, Education=Bachelor)")
print(pSalary1)
print("\nP(Salary | Country=India, Education=Bachelor, OpenSource=Yes)")
print(pSalary2)
```

```
P(Salary | Country=India, Education=Bachelor)
+--------------------------+---------------+
| Salary                   |   phi(Salary) |
+==========================+===============+
| Salary(0-250.000)        |        0.9836 |
+--------------------------+---------------+
| Salary(1.000.000+)       |        0.0008 |
+--------------------------+---------------+
| Salary(250.000-1.000.000) |        0.0156 |
```

```
+---------------------------+---------------+

P(Salary | Country=India, Education=Bachelor, OpenSource=Yes)
+---------------------------+---------------+
| Salary                    |   phi(Salary) |
+===========================+===============+
| Salary(0-250.000)         |        0.9836 |
+---------------------------+---------------+
| Salary(1.000.000+)        |        0.0008 |
+---------------------------+---------------+
| Salary(250.000-1.000.000) |        0.0156 |
+---------------------------+---------------+
```

As expected, the two CPDs are **exactly the same**.

1.11 Comparison between Exact and Approximate Methods

We wil now make a comparison between Exact Inference Methods and Approximate Inference ones.

First of all, we define a function that, given in input our model, an evidence, a sample size and the exact probabilities (computed using *Variable Elimination*), returns as results probabilities and absolutes error w.r.t. the exact computed on the samples obtained from two different sampling methods: - **Rejection Sampling:** randomly generates samples rejecting the ones where the evidence is false - **Likelihood Weighting:** in addition to every sample, produces a weight representing the probability that a sample would not be rejected

[ ]:
```
# Now switch to sampling methods
from pgmpy.factors.discrete import State
from pgmpy.sampling import BayesianModelSampling

def run_experiment(model,sample_size,evidence,p_exact):
    # Sample
    def prob_LW(samples,variable):
        result={}
        values=samples[variable].unique()
        for value in values:
            result[value]=round(np.
 ↪sum(samples[samples[variable]==value]['_weight'])/np.
 ↪sum(samples['_weight']),2)
        return result

    def prob_RS(samples,variable):
        result={}
        values=samples[variable].unique()
        tot=len(samples[variable])
        for value in values:
            result[value]=len(samples[samples[variable]==value])/tot
        return result
```

```
    def absolute_error(exact_value,approx_value):
        return np.absolute(exact_value-approx_value)

    evidence2 = [State(key,val) for key,val in evidence.items()]
    inference_sampling=BayesianModelSampling(model)
    samples_LW = inference_sampling.likelihood_weighted_sample(evidence =␣
↪evidence2, size=sample_size)
    samples_RS = inference_sampling.rejection_sample(evidence=evidence2,␣
↪size=sample_size)

    ## Statistics
    variables=[str(node) for node in model.nodes if str(node) not in evidence.
↪keys()]
    p_LW={}
    p_RS={}
    absolute_error_LW={}
    absolute_error_RS={}

    for variable in variables:

        p_LW[variable]=prob_LW(samples_LW,variable)
        p_RS[variable]=prob_RS(samples_RS,variable)

        values=samples_LW[variable].unique()
        # exec('absolute_error_LW[variable]={value:
↪absolute_error(p_exact[variable].get_value(%s=value),p_LW[variable][value])␣
↪for value in values}'%variable,locals())
        absolute_error_LW[variable]={value:absolute_error(p_exact[variable].
↪get_value(**{variable:value}),p_LW[variable][value]) for value in values}

        values=samples_RS[variable].unique()
        # exec('absolute_error_RS[variable]={value:
↪absolute_error(p_exact[variable].get_value(%s=value),p_RS[variable][value])␣
↪for value in values}'%variable,locals())
        absolute_error_RS[variable]={value:absolute_error(p_exact[variable].
↪get_value(**{variable:value}),p_RS[variable][value]) for value in values}

    # Return results
    return p_LW,p_RS,absolute_error_LW,absolute_error_RS
```

Then we run a number of experiments using an increasing sample size.

[ ]:
```
%%capture
evidence = {'Country':'India','Education':'Bachelor'}
starting_size_=1 # from 10 sample points
final_size=5     # to 10^5 sample points
experiments=20 # 8 experiments
```

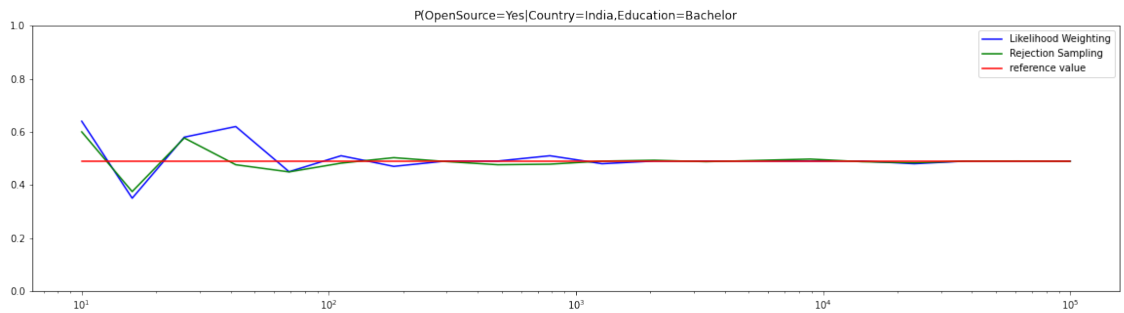
```
result=[]
inference_exact=VariableElimination(model)

variables=[str(node) for node in model.nodes if str(node) not in evidence.
 ↪keys()]
p_exact={variable:inference_exact.query([variable],evidence) for variable in␣
 ↪variables}

for size in np.logspace(starting_size_, final_size, num=experiments,␣
 ↪dtype='<i8'):
  ␣
 ↪p_LW,p_RS,absolute_error_LW,absolute_error_RS=run_experiment(model,size,evidence,p_exact)
    result.append({
        'sample_size':size,
        'p_exact':p_exact,
        'p_LW':p_LW,
        'p_RS':p_RS,
        'e_LW':absolute_error_LW,
        'e_RS':absolute_error_RS
    })
```

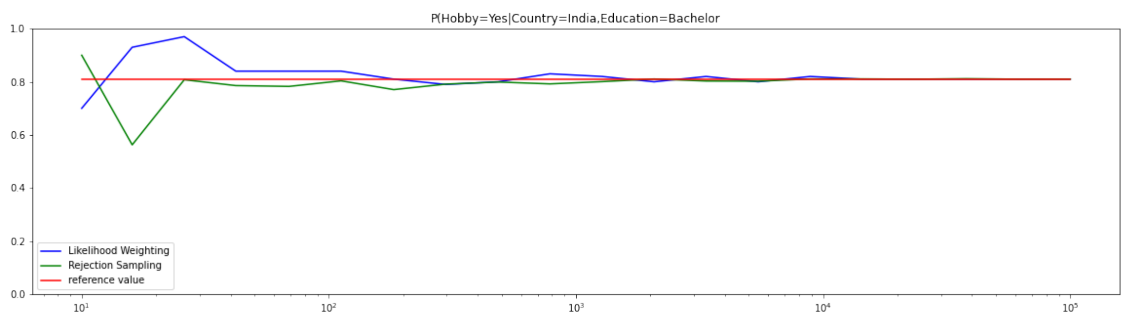
These two function simply plot respectively the probability and the error wrt the exact probability for a given variable assuming a certain value.

```
[ ]: def plot_prob(results,p_exact,evidence,**variables):

    sample_size=[r['sample_size'] for r in results]

    for var,val in variables.items():
        p_LW=[r['p_LW'][var][val] for r in results]
        p_RS=[r['p_RS'][var][val] for r in results]
        p=p_exact[var].get_value(**{var:val})

        plt.figure(figsize=(20,5))
        plt.subplot()
        plt.ylim(0,1)
        plt.title('P({}={}|{}'.format(var,val,','.join([str(k)+"="+str(v) for␣
 ↪k,v in evidence.items()])))
        LWCplot, = plt.semilogx(sample_size,p_LW,'b',label="Likelihood␣
 ↪Weighting")
        RSCplot, = plt.semilogx(sample_size,p_RS,'g',label="Rejection Sampling")
        VECplot, = plt.semilogx(sample_size,p*np.
 ↪ones(len(results)),'r',label="reference value")
        plt.legend(handles=[LWCplot,RSCplot,VECplot])
        plt.show()

def plot_error(results,evidence,**variables):
```

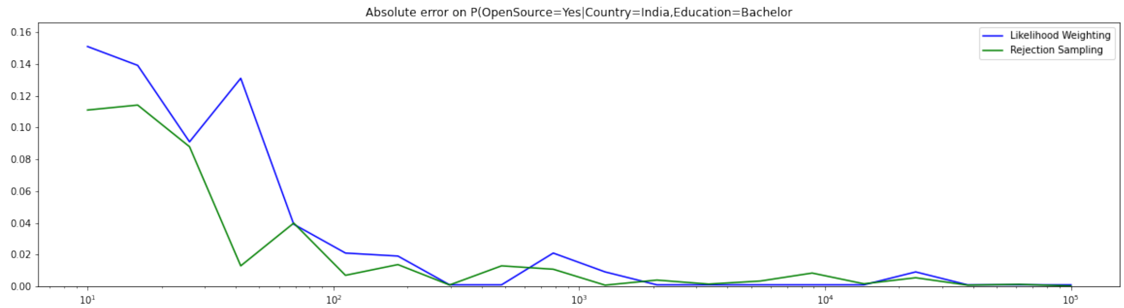
```
    # evidence=p_exact['Hobby'].get_evidence()
    # print(evidence)
    sample_size=[r['sample_size'] for r in results]

    for var,val in variables.items():
        e_LW=[r['e_LW'][var][val] for r in results]
        e_RS=[r['e_RS'][var][val] for r in results]

        plt.figure(figsize=(20,5))
        plt.subplot()
        plt.ylim(0,np.max(e_LW+e_RS)+0.1*np.max(e_LW+e_RS))
        plt.title('Absolute error on P({}={}|{}'.format(var,val,','.
↪join([str(k)+"="+str(v) for k,v in evidence.items()])))
        LWCplot, = plt.semilogx(sample_size,e_LW,'b',label="Likelihood␣
↪Weighting")
        RSCplot, = plt.semilogx(sample_size,e_RS,'g',label="Rejection Sampling")
        plt.legend(handles=[LWCplot,RSCplot])
        plt.show()
```

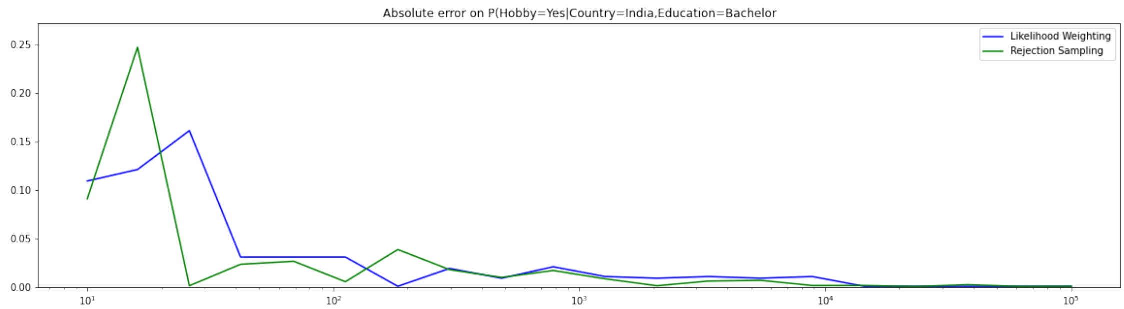
[ ]:
```
plot_prob(result,p_exact,evidence,OpenSource='Yes',Hobby='Yes')
```





[ ]:
```
plot_error(result,evidence,OpenSource='Yes',Hobby='Yes')
```





As expected, as the sample size increases, the accuracy of the probability computed using sampling methods approximate the exact one.

1.12 Final Considerations

1.12.1 To conclude we'll show some Interesting Queries that can be formulated using the BN we built.

*Given a **Country** what's the probability of having a **NON-STEM Degree**?*

[ ]:
```
# %%capture

for country in ['India', 'United Kingdom', 'United States']:

    p_country_um = inference.query(['UndergradMajor'], {'Country':country})
    print(country)
    print(p_country_um)
```

```
Finding Elimination Order: : : 0it [00:00, ?it/s]
0it [00:00, ?it/s]

India
+-------------------------+----------------------+
| UndergradMajor          |   phi(UndergradMajor) |
+=========================+======================+
| UndergradMajor(NOT_STEM) |              0.0129 |
```

```
+-------------------------+-----------------------+
| UndergradMajor(STEM)    |                0.9871 |
+-------------------------+-----------------------+

Finding Elimination Order: : : 0it [00:00, ?it/s]
0it [00:00, ?it/s]

United Kingdom
+-------------------------+-----------------------+
| UndergradMajor          |   phi(UndergradMajor) |
+=========================+=======================+
| UndergradMajor(NOT_STEM) |                0.0844 |
+-------------------------+-----------------------+
| UndergradMajor(STEM)    |                0.9156 |
+-------------------------+-----------------------+

Finding Elimination Order: : : 0it [00:00, ?it/s]
0it [00:00, ?it/s]

United States
+-------------------------+-----------------------+
| UndergradMajor          |   phi(UndergradMajor) |
+=========================+=======================+
| UndergradMajor(NOT_STEM) |                0.1576 |
+-------------------------+-----------------------+
| UndergradMajor(STEM)    |                0.8424 |
+-------------------------+-----------------------+
```

There's a certain **bias towards STEM degrees** since the Dataset comes from a Stack Overflow Dataset and the Website is usually aimed at people which deal with IT concepts.

As we can see **Indian entries** are more prone to having pursued a **STEM degree**.

On the other hand, entries from the **USA** are more inclined to **Humanities Majors compared to the other countries.**

This point is quite interesting because it shows that people from the **United States** with a **NON-STEM Background** are more **engaged in programming** (Given The Dataset Website of Reference) than people from the other two countries.

*Given a **Country** what's the probability distribution of Bachelor's, Master's degres and Ph.Ds?*

[ ]:
```
for country in ['India', 'United Kingdom', 'United States']:
    print(country)
    p_country_ed = inference.query(['Education'], {'Country':country})
    print(p_country_ed)
```

```
India

Finding Elimination Order: : 100%|      | 2/2 [00:00<?, ?it/s]
Eliminating: OpenSource: 100%|      | 2/2 [00:00<00:00, 235.08it/s]
```

```
+---------------------+-------------------+
| Education           |   phi(Education)  |
+=====================+===================+
| Education(Bachelor) |            0.7363 |
+---------------------+-------------------+
| Education(Master)   |            0.2614 |
+---------------------+-------------------+
| Education(Ph.D)     |            0.0023 |
+---------------------+-------------------+
United Kingdom

Finding Elimination Order: : 100%|      | 2/2 [00:00<00:00, 4032.98it/s]
Eliminating: OpenSource: 100%|      | 2/2 [00:00<?, ?it/s]

+---------------------+-------------------+
| Education           |   phi(Education)  |
+=====================+===================+
| Education(Bachelor) |            0.6337 |
+---------------------+-------------------+
| Education(Master)   |            0.2986 |
+---------------------+-------------------+
| Education(Ph.D)     |            0.0677 |
+---------------------+-------------------+
United States

Finding Elimination Order: : 100%|      | 2/2 [00:00<?, ?it/s]
Eliminating: OpenSource: 100%|      | 2/2 [00:00<00:00, 227.05it/s]

+---------------------+-------------------+
| Education           |   phi(Education)  |
+=====================+===================+
| Education(Bachelor) |            0.7406 |
+---------------------+-------------------+
| Education(Master)   |            0.2244 |
+---------------------+-------------------+
| Education(Ph.D)     |            0.0350 |
+---------------------+-------------------+
```

People from the **UK** are more likely to have a **Master's degree** while in the US most entries own Just a Bachelor's.

Also **UK** has the highest number of **Ph.D** entries.

Job Satisfaction Index comparison between People with a Lower Income based on wether they consider Coding a Hobby or not.

[ ]:
```
%%capture
p_js_h_y = inference.query(['JobSatisfaction'], {'Hobby':'Yes', 'Salary':'0-250.
 ↪000'})
```

```
p_js_h_n = inference.query(['JobSatisfaction'], {'Hobby':'No', 'Salary':'0-250.
  ↪000'})
```

P(JobSatisfaction|Hobby=Yes,Salary=0-250.000)

```
[ ]: print(p_js_h_y)
```

```
+--------------------+------------------------+
| JobSatisfaction    |   phi(JobSatisfaction) |
+====================+========================+
| JobSatisfaction(0) |                 0.0334 |
+--------------------+------------------------+
| JobSatisfaction(1) |                 0.0929 |
+--------------------+------------------------+
| JobSatisfaction(2) |                 0.1029 |
+--------------------+------------------------+
| JobSatisfaction(3) |                 0.0583 |
+--------------------+------------------------+
| JobSatisfaction(4) |                 0.1336 |
+--------------------+------------------------+
| JobSatisfaction(5) |                 0.3749 |
+--------------------+------------------------+
| JobSatisfaction(6) |                 0.2041 |
+--------------------+------------------------+
```

P(JobSatisfaction|Hobby=No,Salary=0-250.000)

```
[ ]: print(p_js_h_n)
```

```
+--------------------+------------------------+
| JobSatisfaction    |   phi(JobSatisfaction) |
+====================+========================+
| JobSatisfaction(0) |                 0.0351 |
+--------------------+------------------------+
| JobSatisfaction(1) |                 0.0961 |
+--------------------+------------------------+
| JobSatisfaction(2) |                 0.1085 |
+--------------------+------------------------+
| JobSatisfaction(3) |                 0.0580 |
+--------------------+------------------------+
| JobSatisfaction(4) |                 0.1371 |
+--------------------+------------------------+
| JobSatisfaction(5) |                 0.3732 |
+--------------------+------------------------+
| JobSatisfaction(6) |                 0.1921 |
+--------------------+------------------------+
```

As we can see results are quite similar.

Proportionally entries who **consider Coding a Hobby** are **slightly more probable to be**

Extremely Satisfied with their Job.

1.12.2 Data Augmentation Example

This Bayesian Network could be quite useful in a Data Augmentation context.

For example we might want to generate n new British Entries which consider Coding a hobby and are moderately satisfied with their job.

This can be useful in the context of balancing the number of entries in the Dataset for further Analysis.

The Network can be used to generate the non-specified attributes using queries to obtain new parameters.

$P(EveryOtherAttribute|Country = UnitedKingdom, Hobby = Yes)$

[ ]:
```
%%capture
inference_sampling=BayesianModelSampling(model)
evidence = [State(key, val) for key,val in {'Country':'United Kingdom', 'Hobby':
↪'Yes'}.items()]
samples = inference_sampling.rejection_sample(evidence=evidence, size=30)
```

[ ]:
```
samples
```

[ ]:
```
   Hobby OpenSource        Country Education  JobSatisfaction UndergradMajor  \
0    Yes         No  United Kingdom    Master                6           STEM
1    Yes        Yes  United Kingdom    Master                6           STEM
2    Yes         No  United Kingdom    Master                5           STEM
3    Yes         No  United Kingdom      Ph.D                6           STEM
4    Yes        Yes  United Kingdom  Bachelor                1           STEM
5    Yes         No  United Kingdom  Bachelor                5       NOT_STEM
6    Yes         No  United Kingdom    Master                5           STEM
7    Yes         No  United Kingdom    Master                6       NOT_STEM
8    Yes        Yes  United Kingdom  Bachelor                4           STEM
9    Yes         No  United Kingdom  Bachelor                0           STEM
10   Yes         No  United Kingdom      Ph.D                5           STEM
11   Yes        Yes  United Kingdom  Bachelor                5           STEM
12   Yes         No  United Kingdom      Ph.D                6           STEM
13   Yes         No  United Kingdom  Bachelor                5           STEM
14   Yes        Yes  United Kingdom    Master                4           STEM
15   Yes        Yes  United Kingdom      Ph.D                2           STEM
16   Yes        Yes  United Kingdom    Master                4           STEM
17   Yes        Yes  United Kingdom  Bachelor                2           STEM
18   Yes        Yes  United Kingdom  Bachelor                3           STEM
19   Yes        Yes  United Kingdom  Bachelor                6           STEM
20   Yes         No  United Kingdom  Bachelor                5           STEM
21   Yes         No  United Kingdom  Bachelor                5           STEM
22   Yes        Yes  United Kingdom  Bachelor                2           STEM
23   Yes         No  United Kingdom    Master                2       NOT_STEM
```

24	Yes	No	United Kingdom	Master	6	STEM
25	Yes	No	United Kingdom	Bachelor	0	STEM
26	Yes	No	United Kingdom	Bachelor	5	STEM
27	Yes	No	United Kingdom	Bachelor	2	STEM
28	Yes	Yes	United Kingdom	Bachelor	5	STEM
29	Yes	Yes	United Kingdom	Bachelor	5	STEM

	Salary
0	0-250.000
1	0-250.000
2	0-250.000
3	0-250.000
4	0-250.000
5	250.000-1.000.000
6	0-250.000
7	0-250.000
8	250.000-1.000.000
9	0-250.000
10	250.000-1.000.000
11	0-250.000
12	0-250.000
13	0-250.000
14	0-250.000
15	0-250.000
16	0-250.000
17	250.000-1.000.000
18	0-250.000
19	0-250.000
20	0-250.000
21	0-250.000
22	0-250.000
23	0-250.000
24	0-250.000
25	0-250.000
26	250.000-1.000.000
27	0-250.000
28	0-250.000
29	0-250.000