Data Mining for Networks

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1. Introduction

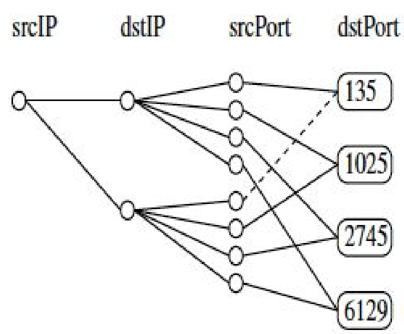
The goal of this project is to perform anomaly detection in IP traffic. The methodology in this case is to build a profile of each IP address as graphlets. With these graphlets, we will then build a model using Support Vector Machine to distinguish normal from malicious end hosts from an annotated trace. The last step will be to try to detect attack in a not annotated trace.

2. Description

In this section, the descriptions to each component of this task will be explained in detail.

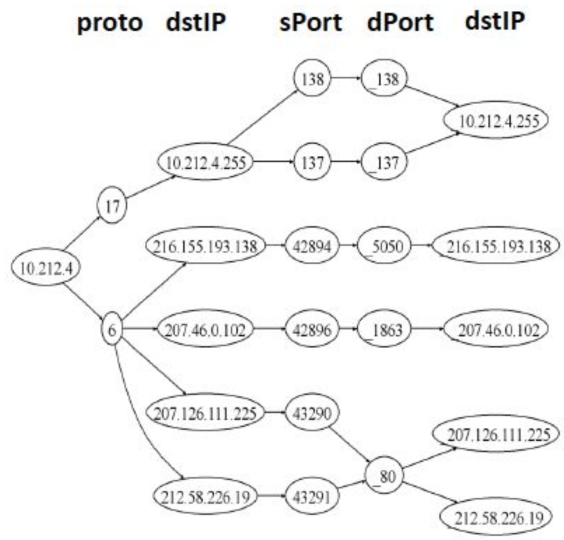
2.1 Graphlets (BLINC)

The graphlets in the initial traffic classification by Karagiannis et al [1] generates graphlets with the four flows srcIP, dstIp, srcPort and dstPort for each source IP.



2.2 Activity Graphlets

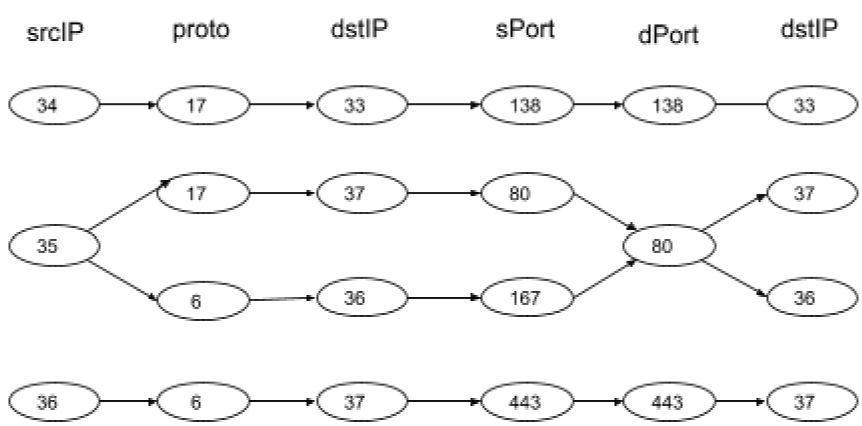
The activity graphlet is the graphlet generated for each source IP address. In the paper "Profiling the end host" it extends the original graphlet proposed in BLINC with an additional information of destination IP (dstIP). The graphlet is now a graph with six columns corresponding to: (srcIP, protocol, dstIP, srcport, dstport, dstIP).



The destination IP will appear twice at the third and sixth column in the graphlet. This method proposed in the paper is to enable us to observe the information heavy fields.

Example:

srcIP	protocol	dstIP	sPort	dPort
12.124.65.34	17	12.124.65.33	138	138
12.124.65.35	17	12.124.65.37	80	80
12.124.65.35	6	12.124.65.36	167	80
12.124.65.36	6	12.124.65.37	443	443



2.3 Significant Nodes

Karagiannis et al [2] observes that there are a nodes with high degrees and many of the activity graphlets only has nodes with one degrees of one as such they proposed methods to identify significant nodes. The term significant nodes is defined as nodes which has either in degrees or out degrees of more than one.

2.4 Profile Graphlets

Building on top of the identification of significant nodes, profile graphlets are introduced as the compact version of activity graphlet. In order to generate the profile graphlets, the Algorithm 4 proposed in the paper is being applied on the activity graphlets.

For all significant nodes

1. *Rank all nodes in activity graphlet according to their maximum in-degree or out-degree: max{indegree, outdegree}*
2. *Remove the highest degree node and all its edges. Insert into profile graphlet.*

As it only retains the ones with the highest degree nodes, we generate a profile graphlet that is a subset of the activity graphlet.

2.5 Random Walk Kernel

The feature space for Random Walk Kernel is defined by

$$V = \sum_{i=0}^{L} A_i \quad where\ A_0\ is\ the\ identity\ matrix,\ A_1 is\ the\ adjacency\ matrix$$

$$L\ the\ length\ of\ the\ random\ walk\ and\ A_i = (A \bullet A \bullet A \bullet \ldots)\ by\ i\ times$$

The adjacency matrix for the directed graph of the profile graphlet will be retrieved. In order to preserve the consistent dimension for the matrix in order to fit an Support Vector Machine algorithm, we use the size of matrix to be n x n where n is the unique number of nodes in the train set.

2.6 Support Vector Machine and Kernel Trick

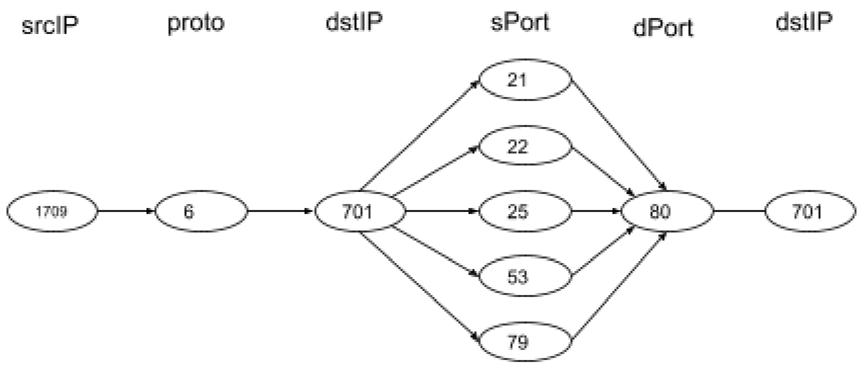
Support Vector Machine (SVM) is a classifier that utilises a technique of separating hyperplane. The algorithm fits the training data such that it returns a model with hyperplanes that best categorizes the sample. The basic implementation of SVM performs a linear separation. The kernel trick transforms data into other dimensions that will provide better division of margin between the different classes of data. Data transformed is still linearly separable in the feature space obtained by a kernel. In this case, the implementation of SVM in *sklearn* library provides other kernels such as *rbf, poly* and *sigmoid*.

3. Methodology

3.1 Building the Anomaly detector

In the set of data in annotated-trace.csv, there is a total of 1059 unique (source IP, label) combinations. Out of the 1059 only 59 are anomalies. In order to better predict the anomalies, we generate graphlets training data such that there are equal number of anomalies and normal graphlets to train the SVM classifier.

In the annotated trace, one such anomaly provided is as shown in the diagram below.



We observe a large amount of influx into a single destination IP and destination port from various different source ports of a single source IP. This kind of attack could correspond to a denial of service attack where it increases the traffic to a single port causing it to unable to handle the load.

3.2 Application on Unannotated Trace

The model trained in 3.1 is then applied to traces that has not been annotated for detection of anomalies.

4. Experimental Results

Model	Run Time
Random Walk + Linear SVM	3m 55s
Random Walk + RBF Kernel SVM	4m 29s

	precision	recall	f1-score	support
0	0.91	1.00	0.95	10
1	1.00	0.93	0.97	15
micro avg	0.96	0.96	0.96	25
macro avg	0.95	0.97	0.96	25
weighted avg	0.96	0.96	0.96	25

Classification Report for Linear SVM

	precision	recall	f1-score	support
0	0.40	1.00	0.57	10
1	0.00	0.00	0.00	15
micro avg	0.40	0.40	0.40	25
macro avg	0.20	0.50	0.29	25
weighted avg	0.16	0.40	0.23	25

Classification Report for RBF Kernel SVM

A kernelized SVM requires higher computation power i.e. greater time complexity in order to perform training as compared to the linear SVM where they are defined by hyperplane equations. As such, we can observe from experimental results that it takes a longer run time for the RBF kernel SVM. We also observe from the classification report that the model fits better on linear SVM than the RBF kernel SVM.

5. Conclusion - Discussion

The research on anomaly detection for web traffic is an ongoing pursuit and the goal is to optimize for true positives. While it is important to accurately determine true positives, it is also important to minimize false positives as it brings a huge impact to the workload of human interference in verification of the positives in the huge traffic that the web has. One of the potential false positives that might occur is when there is a seasonality or specific event to time for example promotional activities on a site and thus causing an influx of traffic or a misplaced redirect link that causes endless loops or increase in traffic could be a false positives that could have been detected. With the advancements of the internet, masking of IP address is a common strategy that has been utilised by many for personal or malicious reasons. In this case, the use of graphlets which divides it on host basis will not pick up the anomalies.

6. References

[1] Thomas Karagiannis, Konstantina Papagiannaki, and Michalis Faloutsos.
BLINC: Multilevel Traffic Classification in the Dark

[2] Thomas Karagiannis, Konstantina Papagiannaki, Nina Taft, and Michalis Faloutsos.
Profiling the End Host.

Anomaly Detection with NetworkX codes

In [2]:

```
import networkx as nx
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

pd.options.display.max_rows=1000
pd.options.display.max_columns=1000
```

Labeled data

In [34]:

```
data = pd.read_csv("annotated-trace.csv", names=['srcIP', 'dstIP', 'proto', 'src
Port', 'dstPort', 'label'])
```

In [3]:

```
data.head()
```

Out[3]:

	srcIP	dstIP	proto	srcPort	dstPort	label
0	214	776	17	21	79	normal
1	933	79	6	21	80	normal
2	139	243	17	53	80	normal
3	920	198	6	80	21	normal
4	100	174	17	20	21	normal

In [32]:

```
# plot function for graph
def plot_graph(g):
    plt.figure(figsize=(20,12))
    pos = nx.spring_layout(g)
    nx.draw_networkx_nodes(g, pos, node_color="plum", node_size = 500)
    nx.draw_networkx_labels(g, pos)
    nx.draw_networkx_edges(g, pos, edgelist=g.edges, arrows=True)
    plt.axis('off')

    plt.show()
```

In [43]:

```
# formatting the data so that the nodes are unique for each column
for k in data.columns:
    data[k] = ["{}:{}".format(k, v) for v in data[k].values]
```

In [6]:

```
# The order for the graphlets generation
data[['srcIP', 'proto', 'dstIP', 'srcPort', 'dstPort', 'dstIP']].head()
```

Out[6]:

	srcIP	proto	dstIP	srcPort	dstPort	dstIP
0	srcIP:214	proto:17	dstIP:776	srcPort:21	dstPort:79	dstIP:776
1	srcIP:933	proto:6	dstIP:79	srcPort:21	dstPort:80	dstIP:79
2	srcIP:139	proto:17	dstIP:243	srcPort:53	dstPort:80	dstIP:243
3	srcIP:920	proto:6	dstIP:198	srcPort:80	dstPort:21	dstIP:198
4	srcIP:100	proto:17	dstIP:174	srcPort:20	dstPort:21	dstIP:174

In [30]:

```
def generate_activity_graphlet(df):
    """
    Given a dataframe representing the data for a graphlet, generate the
    activity graphlet
    """
    g = nx.DiGraph(directed=True)
    cols = ['srcIP', 'proto', 'dstIP', 'srcPort', 'dstPort', 'dstIP']
    for r in df[cols].values:
        for i in range(0, len(cols)-1):
            g.add_edge(r[i], r[i+1])

    return g

def get_neighbouring_node(g, node, orig_node, prof_g, dstNode=None, _type="in",
depth=6):
#     print("node", node, orig_node, dstNode, _type)
    """
    Given the graph, find all the adjacent nodes in the path based on outgoing o
r incoming edges
    """
    if node == orig_node or (orig_node is not None and not orig_node.startswith(
'dstIP') \
                             and dstNode is not None) or depth == 0:
        return prof_g

    if not orig_node:
        orig_node = node

    nodes = g.in_edges(node) if _type == "in" else g.out_edges(node)
    for n in nodes:
        _next = n[0] if _type == "in" else n[1]
        if _next.startswith('dstIP'):
            dstNode = _next

        prof_g.add_edge(n[0], n[1])
        print("depth", depth)
        get_neighbouring_node(g, _next, orig_node, prof_g, dstNode, _type, depth
-1)

    return prof_g

def generate_profile_graphlet(df):
    # generate activity graphlet
    g = nx.DiGraph(directed=True)
    cols = ['srcIP', 'proto', 'dstIP', 'srcPort', 'dstPort', 'dstIP']
    for r in df[cols].values:
        for i in range(0, len(cols)-1):
            g.add_edge(r[i], r[i+1])

    # get significant nodes
    sig_nodes = []
    indegs = g.in_degree()
    outdegs = g.out_degree()
    for node in g.nodes():
        if indegs[node] > 1 or outdegs[node] > 1:
            sig_nodes.append(node)
```

```
    if len(sig_nodes) == 0:
        return None

    prof_g = nx.DiGraph(directed=True)

    # For each significant node, apply the profiling
    # to generate profile graphlet
    for node in sig_nodes:
        n_len = []
        lens = []
        for n in g.neighbors(node):
            num_neighbors = len(list(g.neighbors(n)))
            n_len.append([n, num_neighbors])
            lens.append(num_neighbors)
        lens.sort(reverse=True)
        _max_len = lens[0]

        n_len_cpy = n_len.copy()
        for idx, n in enumerate(n_len_cpy):
            if n[1] != _max_len:
                n_len.remove(n)

        prof_g = get_neighbouring_node(g, node, None, prof_g, None, "in")
        for n in n_len:
            prof_g = get_neighbouring_node(g, n[0], None, prof_g, None, "out")

    return prof_g

def generate_graphlets(data):
    subdf = []

    if 'label' in data.columns:
        # break down the large df into smaller df for each graphlet
        # based on the srcIP and label
        for ip in np.unique(data.srcIP.values):
            for lbl in np.unique(data.label.values):
                d = data[(data.srcIP == ip) & (data.label == lbl)]
                if d.shape[0] > 0:
                    subdf.append(d)

        graphlets = []
        for df in subdf:
            profile_graphlet = generate_profile_graphlet(df)
            label = 1 if df['label'].values[0] == 'label:anomaly' else 0
            if profile_graphlet is not None:
                graphlets.append([profile_graphlet, label])
    else:
        for ip in np.unique(data.srcIP.values):
            d = data[(data.srcIP == ip)]
            if d.shape[0] > 0:
                subdf.append(d)

        graphlets = []
        for df in subdf:
            profile_graphlet = generate_profile_graphlet(df)
            label = 0
            if profile_graphlet is not None:
                graphlets.append([profile_graphlet, label])
```

```
    return graphlets
```

In [42]:

```
data.shape
```

Out[42]:

```
(10070, 6)
```

In [ ]:

```
data[data.label == 'label:anomaly'].sort_values("srcIP")
```

In [44]:

```
negative = data[data.label == 'label:anomaly']
```

In [45]:

```
positive = data[data.label == 'label:normal'].sample(negative.shape[0])
```

In [46]:

```
df = pd.concat([negative, positive], axis=0)
```

In [47]:

```
df.shape
```

Out[47]:

```
(140, 6)
```

In [48]:

```
graphlets = generate_graphlets(df)
```

In [49]:

```
len(graphlets)
```

Out[49]:

```
125
```

In [50]:

```
df.head()
```

Out[50]:

	srcIP	dstIP	proto	srcPort	dstPort	label
14	srcIP:812	dstIP:499	proto:6	srcPort:53	dstPort:14	label:anomaly
195	srcIP:796	dstIP:499	proto:6	srcPort:68	dstPort:22	label:anomaly
249	srcIP:325	dstIP:661	proto:17	srcPort:22	dstPort:20	label:anomaly
385	srcIP:1709	dstIP:791	proto:6	srcPort:21	dstPort:80	label:anomaly
666	srcIP:119	dstIP:661	proto:17	srcPort:22	dstPort:20	label:anomaly

In [37]:

```
keys = np.unique(data[['srcIP', 'dstIP', 'proto', 'srcPort', 'dstPort']].values.
flatten())

def generate_adjacency_matrix(g, keys):
    """
    Generate the adjacency matrix for a graph G with all keys
    """
    all_paths = [p for x in g.nodes() for target in g.nodes() \
                 for p in nx.all_simple_paths(g, x, target, 1)]

    # Generate DF for all the paths to generate the adjacency matrix
    df = pd.DataFrame.from_records(all_paths, columns=['node1', 'node2'])
    df['value'] = 1
    df = df.groupby(['node1', 'node2']).count().reset_index()

    # Existence will be counted as 1 instead of multiple counts
    df['value'] = df['value'].apply(lambda x: 1 if x > 0 else 0)

    # Generate the matrix with df.pivot()
    mat = df.pivot(index='node1', columns='node2', values='value'
                   ).reindex(columns=keys, index=keys).fillna(0)

    return mat
```

In [38]:

```
count = 0
def random_walk(g, L, keys):
    global count
    print(count)
    a0 = np.identity(len(keys))
    a1 = generate_adjacency_matrix(g, keys)

    rw_mat = a0 + a1
    for i in range(1, L):
        mat = a1
        for j in range(i):
            mat = np.dot(mat, a1)
        rw_mat += mat
    count+=1
    return rw_mat.values.flatten().tolist()
```

In [ ]:

```
count = 0
features = [random_walk(g, 4, keys) for g, l in graphlets]
```

In [56]:

```
y = [g[1] for g in graphlets]
```

In [57]:

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(features, y, test_size=0.20,
random_state=42)
```

In [58]:

```
from sklearn import svm

clf = svm.SVC(kernel='linear', verbose=True)
```

In [59]:

```
%timeit clf.fit(X_train, y_train)
```

```
[LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM][LibSVM]3min
55s ± 12.1 s per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

In [60]:

```
from joblib import dump, load

dump(clf, 'svmlinear2.joblib')
```

Out[60]:

```
['svmlinear2.joblib']
```

In [61]:

```
clf_rbf = svm.SVC() # default  rbf
```

In [62]:

```
%timeit clf_rbf.fit(X_train, y_train)
```

```
/Users/sherly/anaconda/lib/python3.6/site-packages/sklearn/svm/base.
py:196: FutureWarning: The default value of gamma will change from
'auto' to 'scale' in version 0.22 to account better for unscaled fea
tures. Set gamma explicitly to 'auto' or 'scale' to avoid this warni
ng.
  "avoid this warning.", FutureWarning)
/Users/sherly/anaconda/lib/python3.6/site-packages/sklearn/svm/base.
py:196: FutureWarning: The default value of gamma will change from
'auto' to 'scale' in version 0.22 to account better for unscaled fea
tures. Set gamma explicitly to 'auto' or 'scale' to avoid this warni
ng.
  "avoid this warning.", FutureWarning)
/Users/sherly/anaconda/lib/python3.6/site-packages/sklearn/svm/base.
py:196: FutureWarning: The default value of gamma will change from
'auto' to 'scale' in version 0.22 to account better for unscaled fea
tures. Set gamma explicitly to 'auto' or 'scale' to avoid this warni
ng.
  "avoid this warning.", FutureWarning)
/Users/sherly/anaconda/lib/python3.6/site-packages/sklearn/svm/base.
py:196: FutureWarning: The default value of gamma will change from
'auto' to 'scale' in version 0.22 to account better for unscaled fea
tures. Set gamma explicitly to 'auto' or 'scale' to avoid this warni
ng.
  "avoid this warning.", FutureWarning)
/Users/sherly/anaconda/lib/python3.6/site-packages/sklearn/svm/base.
py:196: FutureWarning: The default value of gamma will change from
'auto' to 'scale' in version 0.22 to account better for unscaled fea
tures. Set gamma explicitly to 'auto' or 'scale' to avoid this warni
ng.
  "avoid this warning.", FutureWarning)
/Users/sherly/anaconda/lib/python3.6/site-packages/sklearn/svm/base.
py:196: FutureWarning: The default value of gamma will change from
'auto' to 'scale' in version 0.22 to account better for unscaled fea
tures. Set gamma explicitly to 'auto' or 'scale' to avoid this warni
ng.
  "avoid this warning.", FutureWarning)
/Users/sherly/anaconda/lib/python3.6/site-packages/sklearn/svm/base.
py:196: FutureWarning: The default value of gamma will change from
'auto' to 'scale' in version 0.22 to account better for unscaled fea
tures. Set gamma explicitly to 'auto' or 'scale' to avoid this warni
ng.
  "avoid this warning.", FutureWarning)
/Users/sherly/anaconda/lib/python3.6/site-packages/sklearn/svm/base.
py:196: FutureWarning: The default value of gamma will change from
'auto' to 'scale' in version 0.22 to account better for unscaled fea
tures. Set gamma explicitly to 'auto' or 'scale' to avoid this warni
ng.
  "avoid this warning.", FutureWarning)
```

```
4min 29s ± 18.9 s per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

In [63]:

```
dump(clf_rbf, 'svmrbf2.joblib')
```

Out[63]:

```
['svmrbf2.joblib']
```

In [89]:

```
from sklearn.metrics import classification_report, confusion_matrix
```

In [71]:

```
print(classification_report(y_test, clf.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.91      1.00      0.95        10
           1       1.00      0.93      0.97        15

   micro avg       0.96      0.96      0.96        25
   macro avg       0.95      0.97      0.96        25
weighted avg       0.96      0.96      0.96        25
```

In [90]:

```
confusion_matrix(y_test, clf.predict(X_test))
```

Out[90]:

```
array([[10,  0],
       [ 1, 14]])
```

In [72]:

```
print(classification_report(y_test, clf_rbf.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.40      1.00      0.57        10
           1       0.00      0.00      0.00        15

   micro avg       0.40      0.40      0.40        25
   macro avg       0.20      0.50      0.29        25
weighted avg       0.16      0.40      0.23        25


/Users/sherly/anaconda/lib/python3.6/site-packages/sklearn/metrics/c
lassification.py:1143: UndefinedMetricWarning: Precision and F-score
are ill-defined and being set to 0.0 in labels with no predicted sam
ples.
  'precision', 'predicted', average, warn_for)
```

In [92]:

```
confusion_matrix(y_test, clf_rbf.predict(X_test))
```

Out[92]:

```
array([[10,  0],
       [15,  0]])
```

Unlabeled data

In [7]:

```
unlabeled_data = pd.read_csv("not-annotated-trace.csv", names=['srcIP', 'dstIP',
'proto', 'srcPort', 'dstPort'])
```

In [8]:

```
unlabeled_data.shape
```

Out[8]:

```
(10070, 5)
```

In [9]:

```
for k in unlabeled_data.columns:
    unlabeled_data[k] = ["{}:{}".format(k, v) for v in unlabeled_data[k].values]
```

In [10]:

```
ips = np.random.choice(unlabeled_data.srcIP.values, 5)
subset_data = unlabeled_data[unlabeled_data.srcIP.isin(ips)]
```

In [11]:

```
unlabeled_data.head()
```

Out[11]:

	srcIP	dstIP	proto	srcPort	dstPort
0	srcIP:881	dstIP:296	proto:6	srcPort:80	dstPort:25
1	srcIP:799	dstIP:20	proto:6	srcPort:80	dstPort:22
2	srcIP:897	dstIP:790	proto:17	srcPort:80	dstPort:21
3	srcIP:41	dstIP:994	proto:17	srcPort:23	dstPort:53
4	srcIP:361	dstIP:535	proto:6	srcPort:21	dstPort:22

In [24]:

```
ips
```

Out[24]:

```
array(['srcIP:349', 'srcIP:335', 'srcIP:522', 'srcIP:195', 'srcIP:92
4'],
      dtype=object)
```

In [ ]:

```
g = generate_profile_graphlet(subset_data[subset_data.srcIP == 'srcIP:349'])
```

In [33]:

```
plot_graph(g)
```