Cynet

Info: See <https://arxiv.org/abs/1406.6651> for theoretical background

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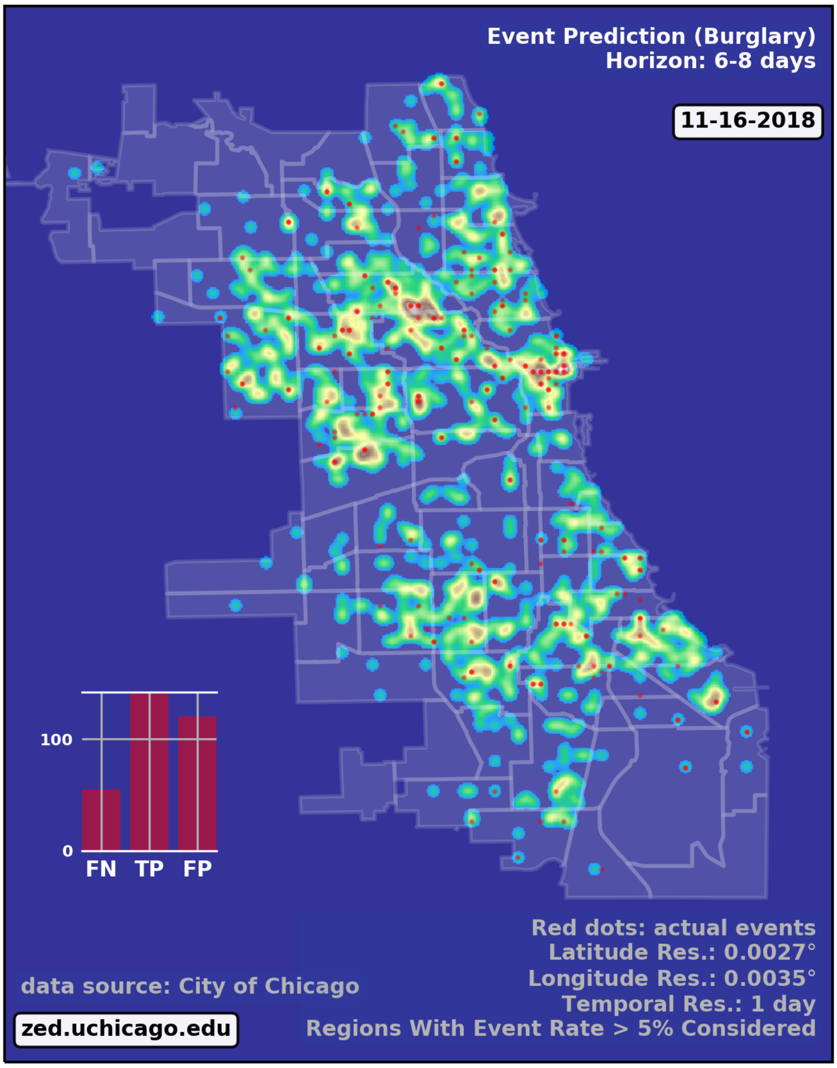
Description: Implementation of the Deep Granger net inference algorithm, described in https://arxiv.org/abs/1406.6651, for learning spatio-temporal stochastic processes (*point processes*). **cynet** learns a network of generative local models, without assuming any specific model structure.

Introduction:

Cynet is a python wrapper for a C++ implementation of the Deep Granger network inference algorithm. This package seeks to assist in the parsing of raw data into appropriate formats and then building predictive models from them. This document will go through an example of how to use this package with the Chicago crime dataset to build and evaluate predictive models. We use these predictions to draw an example of predictive heatmaps.



Dataset:

<https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-present/ijzp-q8t2>

Chicago Boundaries shape files:

<https://data.cityofchicago.org/Facilities-Geographic-Boundaries/Boundaries-Community-Areas-current-/cauq-8yn6>

Installaion:

```
pip install cynet
```

Contents:

1. Processing raw data into xGenESeSS friendly format.
2. Generating models using xGenESeSS.
3. Running Cynet binary to get predictions log files and statistics.
4. Generating prediction csvs.
5. Using predictions to generate predictive heat maps.
6. Perturb data for exploration.

Section 1: Processing raw data into xGenESeSS friendly format.

The goal of this section is to show how to turn the raw Chicago crime data into a format appropriate for xGenESeSS.

1.1: The Crime dataset.

The Chicago crime dataset is a large csv which can be downloaded from the link above. It is frequently updated and contains reported crime events from 2001 to present. There are about 6.8 million rows, one for each recorded event. There are 22 different columns, one for a different variable. For our purposes, the important variables are:

- Date: Contains the date and time at which the event took place.
- Primary Type: the type of the crime. Includes but not limited to: Battery, Assault, Theft, Criminal Damage, Burglary, Motor Vehicle Theft.
- Arrest: Inidicates if an arrest was made.
- Latitude: Latitude coordinate of the event.
- Longitude: Longitude coordinate of the event.

We will use these above variables to help parse the data into the appropriate format.

1.2: The desired file formats and time series table.

To generate the Xgenesis models, we need three types of files. These three files constitutes a time series table. Each row in the table will describe a tile in our grid. Tiles are defined by coordinate boundaries and a variable type. That is, tiles with the same latitude and longitude boundaries but with different variables will count as separate tiles in this table. The column headers in this case will be time slices. The time slices in our example will be days. Each value in the table will be an integer describing the number of events that took place at that particular tile, within that particular time slice.

Files and examples:

Column file. The columns (time slices) in our table. In this example, they are one day long.

```
2014-01-01T00:00:00.000000000
2014-01-02T00:00:00.000000000
2014-01-03T00:00:00.000000000
2014-01-04T00:00:00.000000000
2014-01-05T00:00:00.000000000
...
```

Coordinate file. The rows (tiles) in our table:

```
42.0196#42.02236#-87.66784#-87.66432#VAR
42.0196#42.02236#-87.66784#-87.66432#BURGLARY-THEFT-MOTOR_VEHICLE_THEFT
42.0196#42.02236#-87.66784#-87.66432#HOMICIDE-ASSAULT-BATTERY
41.74874#41.75151#-87.57286#-87.56935#VAR
41.74874#41.75151#-87.57286#-87.56935#BURGLARY-THEFT-MOTOR_VEHICLE_THEFT
41.74874#41.75151#-87.57286#-87.56935#HOMICIDE-ASSAULT-BATTERY
...
```

Csv file. The actual timeseries:

```
0 1 1 0 2 0 1 ...
0 0 0 1 0 2 0 ...
0 1 1 0 0 0 1 ...
0 0 0 1 1 2 0 ...
...
```

If these examples are taken together, then the table implies that for the the tile **42.0196#42.02236#-87.66784#-87.66432#VAR**, 0 events took place on 1/1/2014, 1 on 1/2/2014, 1 on 1/3/2014, 0 on 1/4/2014, 2 on 1/5/2014, etc.

1.3: Intermediate Time Series Tables.

Here we begin processing the csv into the desired formats. The spatioTemporal

class is used for this. This step will take a bit of time to run. We will fit the data from 2001 to 2018. We will group the various types in the **Primary Type** column into three groups. For each of these groups, we will produce an intermediate timeseries table. In these csv files, the columns are the dates and the rows will start with a tile followed by the time series on that tile.

```python
import numpy as np
EPS = 200

grid={'Latitude':np.around(np.linspace(41.5,42.05,EPS),decimals=5),
      'Longitude':np.around(np.linspace(-87.9,-87.2,EPS),decimals=5),
      'Eps':EPS}

tiles=list([[grid['Latitude'][i],grid['Latitude'][i+1],grid['Longitude'][j], grid['Longitude'][j+1]]
            for i in np.arange(len(grid['Latitude'])-1)
            for j in np.arange(len(grid['Longitude'])-1)])
```

tiles is generated using **grid** and **EPS**. In grid, we define the latitude longitude boundaries of Chicago. We divide the boundaries into sections based on EPS. Then coordinates are paired up to made a list of list (**tiles**). Each inner list is in the format [latitude 1, latitude 2, longitude 1, longitude 2] and represents the boundaries for a tile. Note that **EPS** will dictate how finely the grid is divided and thus controls the number of tiles. Please feel free to lower EPS to a lower integer to decrease run time.

```
import cynet.cynet as cn

STOREFILE='crime.p'
CSVFILE='crime.csv'

S0=cn.spatioTemporal(log_file=CSVFILE,
                     log_store=STOREFILE,
                     types=[['BURGLARY','THEFT','MOTOR VEHICLE THEFT']],
                     value_limits=None,
                     grid=tiles,
                     init_date='2001-01-01',
                     end_date='2018-12-31',
                     freq='D',
                     EVENT='Primary Type',
                     threshold=0.05)
S0.fit(csvPREF='CRIME-')
```

CSVFILE refers to the crime csv data file downloaded from the Chicago database. **STOREFILE** is where we will store the database as a pickle file incase it needs to be recalled. In the **S0** class, the following arguments are used.

EVENT: which indicates the column name in the dataframe with which we will use to select events.

types: list of list which defines the groups to be selected for. We only have one group here. Every event which falls into the specifed categories ('BURGLARY','THEFT','MOTOR VEHICLE THEFT') will be selected. Other categories are not counted.

value_limits: Only for numerical categories. Set to none here.

init_date and **end_date:** the date range of selection data.

freq: how large the time slices are. 'D' indicates one day.

threshold: A very important variable. It is not very interesting to predict areas in which there are not much crime. Hence, we are using this variable throw out tiles in which less than five percent of the time slices have an event. That is, we keep only tiles where there was an event in at least five percent of the days.

```
tiles=S0.getGrid()

with open("tiles.txt", "wb") as tiles_pickle:
    pickle.dump(tiles,tiles_pickle)
```

After throwing out the tiles which had lower than five percent event rate, we retrieve those tiles that are left over with getGrid(). We store them as a pickle for later use.

In sum, the script (**Script 1**) that will be run is

```
import cynet.cynet as cn
import numpy as np
import pickle
```

```
EPS = 200
STOREFILE='crime.p'
CSVFILE='crime.csv'

grid={'Latitude':np.around(np.linspace(41.5,42.05,EPS),decimals=5),
      'Longitude':np.around(np.linspace(-87.9,-87.2,EPS),decimals=5),
      'Eps':EPS}

tiles=list([[grid['Latitude'][i],grid['Latitude'][i+1],grid['Longitude'][j], grid['Longitude'][j+1]]
            for i in np.arange(len(grid['Latitude'])-1)
            for j in np.arange(len(grid['Longitude'])-1)])


S0=cn.spatioTemporal(log_file=CSVFILE,
                     log_store=STOREFILE,
                     types=[['BURGLARY','THEFT','MOTOR VEHICLE THEFT']],
                     value_limits=None,
                     grid=tiles,
                     init_date='2001-01-01',
                     end_date='2018-12-31',
                     freq='D',
                     EVENT='Primary Type',
                     threshold=0.05)
S0.fit(csvPREF='CRIME-')
tiles=S0.getGrid()

with open("tiles.txt", "wb") as tiles_pickle:
    pickle.dump(tiles,tiles_pickle)
```

Script 1 creates tiles.txt, crime.p, and CRIME-BURGLARY-THEFT-MOTOR_VEHICLE_THEFT.csv. This csv is the intermediate time series table mentioned above. However, it is only one of them. We will create two more.

Script 2

```
import cynet.cynet as cn
import pickle

STOREFILE='crime.p'
CSVFILE='crime.csv'

with open("tiles.txt", "rb") as tiles_pickle:
    tiles = pickle.load(tiles_pickle)

S01=cn.spatioTemporal(log_store=STOREFILE,
                     types=[['HOMICIDE','ASSAULT','BATTERY']],
                     value_limits=None,
                     grid=tiles,
                     init_date='2001-01-01',
                     end_date='2018-12-31',
                     freq='D',threshold=0.05)
S01.fit(csvPREF='CRIME-')
```

This is very much like **Script 1** with the only difference being that it loads in the previously stored tiles. This will produce another intermediate time series table for another group of categories. The csv is called CRIME-HOMICIDE-ASSAULT-BATTERY.csv We do not change the tiles with get grid as that will make the tiles used for all three scripts to be different.

Script 3:

```
import cynet.cynet as cn
import pickle
```

```
STOREFILE='crime.p'
CSVFILE='crime.csv'

with open("tiles.txt", "rb") as tiles_pickle:
    tiles = pickle.load(tiles_pickle)

S2=cn.spatioTemporal(log_store=STOREFILE,
                     types=None,
                     value_limits=[0,1],
                     grid=tiles,
                     init_date='2001-01-01',
                     end_date='2018-12-31',
                     freq='D', EVENT='Arrest',
                     threshold=0.05)
S2.fit(csvPREF='ARREST')
```

This script is slightly different from the last two. By leaving types as None, all of the categories in "Primary Type" will be counted. Instead, we filter by the "Arrest" column. This time, we are creating a time series table whose tiles had a crime which resulted in an arrest in at least five percent of the days. The CSV created here will called ARREST.csv.

The three intermediate time series tables we have now are:

- CRIME-BURGLARY-THEFT-MOTOR_VEHICLE_THEFT.csv (Nonviolent Crimes)
- CRIME-HOMICIDE-ASSAULT-BATTERY.csv (Violent Crimes)
- ARREST.csv (All Categories)

As explained above, the columns in these csvs will be dates. Each row will be will be a tile followed by that tile's timeseries. The tiles will look like so:

- 41.65477#41.65754#-87.61508#-87.61156#CRIME-BURGLARY-THEFT-MOTOR_VEHICLE_THEFT
- 41.65477#41.65754#-87.61508#-87.61156#HOMICIDE-ASSAULT-BATTERY
- 41.65477#41.65754#-87.61508#-87.61156#VAR

In the first two we combine the names of the category and use that as the type name of the tile. In the ARREST csv, we use "VAR" to indicate that any category in "Primary Type" counted. Lastly, the scripts are run separately because each can have high run time depending on how large **EPS** is.

1.4: Generating the coordinate, column, and csv files.

Now it is time to generate the file formats appropriate for xGenESeSS. We will use the date range 2015-01-01 - 2017-12-31 as our training data. The period 2017-12-31 - 2018-12-31 will be our out of sample data. We will store the three desired files in a folder named 'triplets'. The out of sample data we store in a folder called 'split'.

Script 4:

```
import cynet.cynet as cn

CSVfile = ['ARREST.csv','CRIME-BURGLARY-THEFT-MOTOR_VEHICLE_THEFT.csv','CRIME-HOMICIDE-ASSAULT-BATTERY.csv']
begin = '2015-01-01'
end = '2017-12-31'
extended_end = '2018-12-31'
```

```
name = 'triplet/' + 'CRIME-'+'_' + begin + '_' + end

#Generates desired triplets.
cn.readTS(CSVfile,csvNAME=name,BEG=begin,END=end)

#Generates files which contains in sample and out of sample data.
cn.splitTS(CSVfile, BEG = begin, END = extended_end, dirname = './split', prefix = begin + '_' + extended_end)
```

We combine all the csvs produced in the last step. Recall that their columns, the dates, are all the same. The number of tiles in each file may be different, but they do not necessarily need to be the same. We take each of the csvs and stack them on top of each other. This table is pulled apart into the three files described in section 1.1. All tile names will go into a .coords file. The dates will go into a .columns file. Lastly, the time series for each tile will go into a .csv file.

The three files will be:

- CRIME-_2016-01-01_2018-12-31.csv
- CRIME-_2016-01-01_2018-12-31.coordss
- CRIME-_2016-01-01_2018-12-31.columns

We will discuss the split files that were placed into the split folder later.

Section 2: Creating the xGenESeSS models.

2.1 xGenESeSS and settings.

With the three files constituting the time series table prepared, it is time to produce xGenESeSS models. Doing so will require the **xGenESeSS binary**. There are many variables that can be set with in this process. We use a yaml file, **config.yaml**, to have our settings in one place.

```
#YAML Configuration

# path to file which has the rowwise multiline time series data
TS_PATH: './CRIME-_2015-01-01_2017-12-31.csv'

# path to file with name of the variables
NAME_PATH: './CRIME-_2015-01-01_2017-12-31.coords'

# path to log file for xgenesess inference
LOG_PATH: 'log.txt'

# xgenesses run parameters (these are not hyperparameters, Beg is 0, End is whatever tempral memory is)
END: 60
BEG: 0

# number of restarts (20 is good)
NUM: 2

# partition sequence (we can specify different partition for each time series. XgenESeSS already has this capability)
PARTITION:
- 0.5

# number of models to use in prediction (using cynet binary)
model_nums:
- 85

# prediction horizons to test in unit of temporal quantization (using cynet binary)
horizons:
- 7
```

```yaml
# length of run using cynet (generally length of individual ts in split folder)

RUNLEN: 1460

#Periods to predict for
FLEX_TAIL_LEN: 365

# path to split series

DATA_PATH: '../split/2015-01-01_2018-12-31'

# path to models
FILEPATH: 'models/'

# glob string that matches all the model.json files.
MODEL_GLOB: 'models/*model.json'

# number of processors to use for post process models
NUMPROC: 10

# path to where result files are stored
RESPATH: './models/*model*res'

# path to XgenESeSS binary
XgenESeSS: '../bin/XgenESeSS'

# do we run XgenESeSS binary locally, or do we produce a list of commands to be run via phnx
RUN_LOCAL: 0

# max distance cutoff in render network
MAX_DIST: 3

# min distance cutoff in render network
MIN_DIST: 0.1

# max gamma cutoff in render network
MAX_GAMMA: 0.95

# min gamma cutoff in render network
MIN_GAMMA: 0.25

# colormap in render network
COLORMAP: 'Reds'
```

2.2: Generating xGenESeSS commands.

The important settings for this step are:

- TS_PATH
- NAME_PATH
- LOG_PATH
- END and BEG
- NUM
- PARTITION
- RUN_LOCAL

Cynet provides a class that will generate a file which will generate the commands which will need to be run.

Script 5:

```python
import cynet.cynet as cn
import yaml

with open('config.yaml','r') as fh:
    settings_dict = yaml.load(fh)

TS_PATH=settings_dict['TS_PATH']
NAME_PATH=settings_dict['NAME_PATH']
LOG_PATH=settings_dict['LOG_PATH']
```

```
FILEPATH=settings_dict['FILEPATH']
END=settings_dict['END']
BEG=settings_dict['BEG']
NUM=settings_dict['NUM']
PARTITION=settings_dict['PARTITION']
XgenESeSS=settings_dict['XgenESeSS']
RUN_LOCAL=settings_dict['RUN_LOCAL']

XG = cn.xgModels(TS_PATH,NAME_PATH, LOG_PATH,FILEPATH, BEG, END, NUM, PARTITION, XgenESeSS,RUN_LOCAL)
XG.run(workers=4)
```

Before running **Script 5**, create a directory named **payload2015_2017** and place the command, the three files in the triplets folder and script 5 in it. Your directories should look like so.

```
..
|-- bin/
|    |-- XgenESeSS
|-- split/
|    |-- many split files
|-- payload2015_2017/
     | -- CRIME-_2015-01-01_2017-12-31.columns
     | -- CRIME-_2015-01-01_2017-12-31.coords
     | -- CRIME-_2015-01-01_2017-12-31.csv
     | -- script5.py
     | -- config.yaml
```

Script 5 calls in the required settings and generates a **program_calls.txt** containing all the XGenESeSS commands that need to be called. There will be one command for every tile in our timeseries table. Alternatively, if RUN_LOCAL is set to True, XG.run() will run the commands locally instead. This is generally not recommended unless EPS was set to something very small.

One of the commands should look like this. xGenESeSS command for tile 1592.

```
../bin/XgenESeSS -f ./CRIME-_2015-01-01_2017-12-31.csv -k "  :1592 "  -B 0
-E 60 -n 2 -p 0.5 -S -N ./CRIME-_2015-01-01_2017-12-31.coords -l models/1592log.txt
-m -g 0.01 -G 10000 -v 0 -A .5 -q -w models/1592
```

Section 2.3: Running the commands.

Whether you run the commands locally or on a computing cluster, the directory needs to be set up properly. For the settings above, our directory looks like this.

```
..
|-- bin/
|    |-- XgenESeSS
|-- payload2015_2017/
     | -- CRIME-_2015-01-01_2017-12-31.columns
     | -- CRIME-_2015-01-01_2017-12-31.coords
     | -- CRIME-_2015-01-01_2017-12-31.csv
     | -- models/
     | -- script5.py
     | -- config.yaml
```

Running all of the xGenESeSS commands listed in program_calls.txt will output *model.json files inside the models directory. One model file will appear for each tile. If you are running on the Uchicago computing cluster, the following settings work well.

```
USER UserID
MAX_PARALLEL_JOBS 100
```

```
INTERVAL 60
PARTITION broadwl
RUNTIME 1
QOS normal
MEM 10G
NODES 1
TPC 28
RUNTIME_LIMIT 35
```

Section 3: Running Cynet to get prediction log files and statistics.

3.1: Split files.

Once the model json files have been produced, it is time to run the cynet binary. There were files produced by **Script 4** in section 1.4 that outputted to a folder called split. We set their prefix to be a combination of the beginning and end dates As a result, the name of each file is their date range combined with the tile name. Below is an example.

```
2015-01-01_2018-12-3142.01633#42.02755#-87.67143#-87.65714#HOMICIDE-ASSAULT-BATTERY
```

The contents of these files are simply that tile's time series within the data range. We currently have these split files set to be one year longer, in length, compared to the training data. The training data was dated 01/01/2015 - 12/31/2017. Three years or 1195 days (365 times 3). The split files are dated 01/01/2015 - 12/31/2018. This four years or 1460 days (365 * 4). Hence, the split file contains the time series of the training, in sample period, and the out of sample data (the year of 2018). **RUNLEN** will be the length of the split files, 1460. **FLEX_TAIL_LEN** will be the length of the out of sample data, 365. **DATA_PATH** is the path from the working directory to the split folder combined with the date prefix. **See the yaml configuration above.**

With the working directory being **payload2015_2017/,** the directory tree in this example looks like this.

```
..
|-- bin/
|   |-- XgenESeSS
|-- payload2015_2017/
|     | -- CRIME-_2015-01-01_2017-12-31.columns
|     | -- CRIME-_2015-01-01_2017-12-31.coords
|     | -- CRIME-_2015-01-01_2017-12-31.csv
|     | -- models/
|          | -- *model.json (multiple)
|--split/
   | -- 2015-01-01_2018-12-31* (multiple)
```

3.2: Cynet Log files.

Cynet takes the model json files and split files to create log files. A log file is produced for each tile. The names of these log files will contain its tile number, the number of models used in generating its **predicted time series,** and the source variable type used to make the predictions.

```
9modeluse85models#HOMICIDE-ASSAULT-BATTERY.log
```

This is in the format (tile number)modeluse(number of predictor tiles used)models#(source variable).log

Inside the log files is, in order, information on the target tile of the predictions, the number of the time slice (day), if an event actually happened, probability threshold of non-event, and probability threshold of event.

```
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 7 0 0.793203 0.206797
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 8 0 0.791338 0.208662
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 9 1 0.793203 0.206797
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 10 1 0.791795 0.208205
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 11 0 0.782952 0.217048
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 12 0 0.788287 0.211713
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 13 0 0.787275 0.212725
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 14 0 0.786255 0.213745
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 15 0 0.790431 0.209569
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 16 0 0.797401 0.202599
...
```

We are using variables to predict one another. In the above, we are Using the variable **HOMICIDE-ASSAULT-BATTERY**, the source, to predict **VAR**, the target.

3.3: Running cynet to generate log files.

To create these log files from model json and split files, cynet uses the run_parallel function.

Script 6

```python
import cynet.cynet as cn
import yaml
import glob

with open('config.yaml','r') as fh:
    settings_dict = yaml.load(fh)

model_nums = settings_dict['model_nums']
MODEL_GLOB = settings_dict['MODEL_GLOB']
horizon = settings_dict['horizons'][0]
DATA_PATH = settings_dict['DATA_PATH']
RUNLEN = settings_dict['RUNLEN']
RESPATH = settings_dict['RESPATH']
FLEX_TAIL_LEN = settings_dict['FLEX_TAIL_LEN']
VARNAME=list(set([i.split('#')[-1] for i in glob.glob(DATA_PATH+"*")]))+['ALL']

cn.run_pipeline(MODEL_GLOB,model_nums, horizon, DATA_PATH, RUNLEN, VARNAME, RESPATH,\
    FLEX_TAIL_LEN=FLEX_TAIL_LEN,cores=4,gamma=True)
```

Once again, load in necessary parameters from the yaml configuration file. The cores argument defines the number of cpus that will be used to run cynet in parallel. We can sort the models by gamma or distance. Distance is the distance between the source and target tiles. **VARNAME** is a list of the different variable types of the tiles and ALL. These will be the sources in the predictions. ALL indicates that all model types are being used in the prediction.The log files will be placed in the models folder, at least in this example.

3.4: tpr, fpr, and auc statistics.

Aside from the cynet log files produced in the designated directory(**models/**), **res** or result csvs are also placed into the directory. Recall that we are using different variable types to predict each other. For example, we use:

- VAR to predict HOMICIDE-ASSAULT-BATTERY
- HOMICIDE-ASSAULT-BATTERY to predict BURGLARY-THEFT-MOTOR_VEHICLE_THEFT
- ALL to predict VAR

and so on. In these result files are auc (area under curve), tpr (true positive rate), and fpr (false positive rate) statistics on the model's preformance.

```
loc_id,lattgt1,lattgt2,lontgt1,lontgt2,varsrc,vartgt,num_models,auc,tpr,fpr,horizon
models/9model,41.67688,41.67965,-87.64322,-87.6397,VAR,VAR,85,0.802666,0.518072,0.403226,7
models/9model,41.67688,41.67965,-87.64322,-87.6397,HOMICIDE-ASSAULT-BATTERY,VAR,85,0.770124,0.494382,0.453488,7
models/9model,41.67688,41.67965,-87.64322,-87.6397,BURGLARY-THEFT-MOTOR_VEHICLE_THEFT,VAR,85,0.767714,0.333333,0.397661,7
models/9model,41.67688,41.67965,-87.64322,-87.6397,ALL,VAR,85,0.80817,0.487805,0.338624,7
```

The **loc_id** gives the name of the model file. **varsrc** is the variable of the source of the predictions. **vartgt** is the the variable type of the tile for which the prediction is being made. Note that **vartgt** is all the same, VAR. This is the result file for one tile, and predictions are coming in from other tiles. Hence, the third(including the header) line of the above result file contains statistics on the performance of the predictions made by all tiles using the variable HOMICIDE-ASSAULT-BATTERY (source). These predictions are made for events at the tile given by the boundaries the longitude and latitude parameters plus the VAR variable.

The result files for every tile is combined into a single csv called **all_res.csv** and placed into the working directory by **run_pipeline()**.

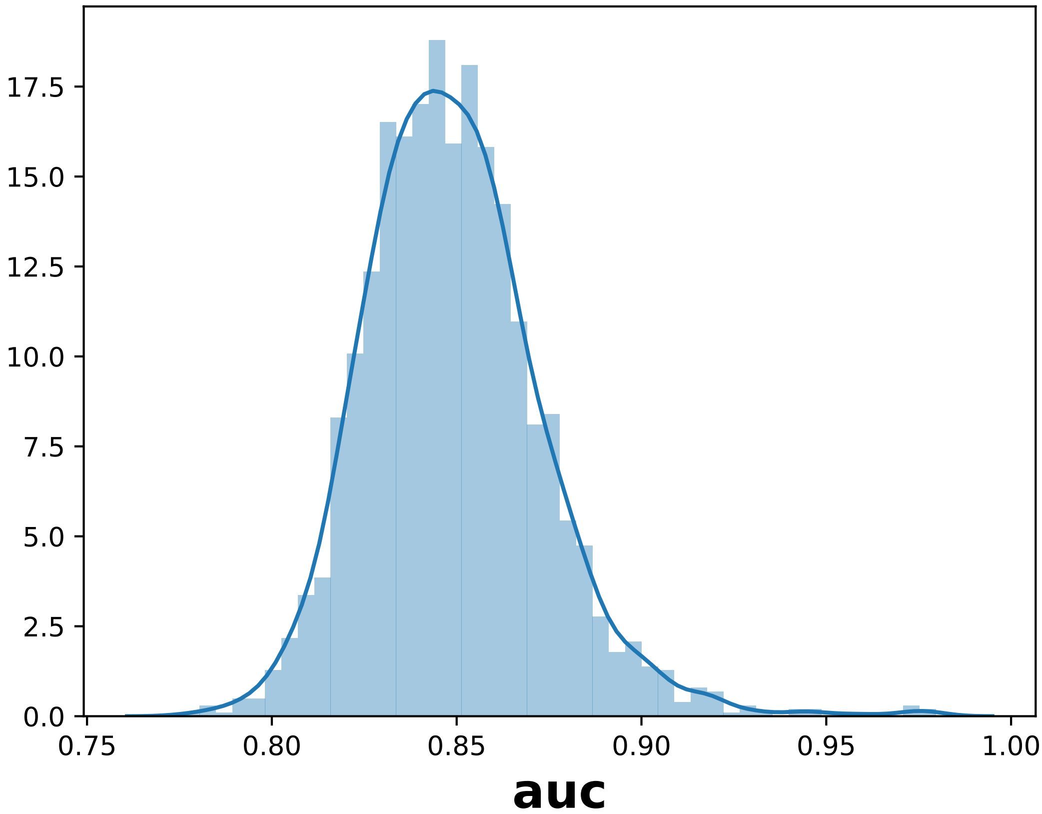
3.5: Plotting statistics

Plotting the statistics is done once **all_res.csv** is produced. We provide a simple script.

Script 7

```
import cynet.cynet as cn

    VARNAMES=['BURGLARY-THEFT-MOTOR_VEHICLE_THEFT','HOMICIDE-ASSAULT-BATTERY','VAR']

    cn.get_var('res_all.csv',['lattgt1','lattgt2','lontgt1','lontgt2','vartgt'],varname='auc',VARNAMES=VARNAMES)
    cn.get_var('res_all.csv',['lattgt1','lattgt2','lontgt1','lontgt2','vartgt'],varname='tpr',VARNAMES=VARNAMES)
    cn.get_var('res_all.csv',['lattgt1','lattgt2','lontgt1','lontgt2','vartgt'],varname='fpr',VARNAMES=VARNAMES)
    cn.get_var('res_all.csv',['lattgt1','lattgt2','lontgt1','lontgt2'],varname='tpr',VARNAMES=VARNAMES)
    cn.get_var('res_all.csv',['lattgt1','lattgt2','lontgt1','lontgt2'],varname='auc',VARNAMES=VARNAMES)
    cn.get_var('res_all.csv',['lattgt1','lattgt2','lontgt1','lontgt2'],varname='fpr',VARNAMES=VARNAMES)
```

This produces various plots. It should be obvious what each plot is. The auc is included below.



Section 4: Generating prediction csvs.

4.1: The flexroc binary.

The flexroc binary is one of the cynet package's tools for calculating auc, tpr, and fpr statistics. Recall that in each of the log files, there is a series of positive event probabilities. One probability is given for each day. Example from section 3.2.

```
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 7 0 0.793203 0.206797
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 8 0 0.791338 0.208662
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 9 1 0.793203 0.206797
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 10 1 0.791795 0.208205
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 11 0 0.782952 0.217048
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 12 0 0.788287 0.211713
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 13 0 0.787275 0.212725
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 14 0 0.786255 0.213745
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 15 0 0.790431 0.209569
----> 41.67688#41.67965#-87.66432#-87.6608#VAR 16 0 0.797401 0.202599
...
```

The positive event probabilities are in the last column. Suppose we were to choose a threshold for these probabilities. On days where the probability is higher than this threshold, then, we would say there is a predicted event. On days where the probability is lower than this threshold, then a non event is predicted for that day. One can imagine that if the threshold is fixed very low, then more events will be predicted. In this case, we will capture more of the actual events, but will have more false positives. On the other hand, if the threshold is set very high, then fewer events will be predicted and we will have more false negatives. |

The **flexroc** binary allows us to specify a desired true positive rate,tpr, or false positive rate,fpr. It takes the log file and returns the threshold that should be used to achieve either the desired tpr or fpr. We can then use that threshold to map the positive event probabilities into a series of actual events.

4.2: Prediction csvs.

Aside from mapping the series of probabilities into predictions, we would also like to transform the cynet log files into a more manageable forms. We'd like to generate csvs which contain the information in the log files as well as the mapped event series.

```
lat1,lat2,lon1,lon2,target,day,actual_event,negative_event,positive_event,predictions,source,threshold
41.67688,41.67965,-87.64322,-87.6397,VAR,7,0,0.780455,0.219545,1,BURGLARY-THEFT-MOTOR_VEHICLE_THEFT,0.1207
41.67688,41.67965,-87.64322,-87.6397,VAR,8,0,0.776299,0.223701,1,BURGLARY-THEFT-MOTOR_VEHICLE_THEFT,0.1207
41.67688,41.67965,-87.64322,-87.6397,VAR,9,0,0.80419,0.19581,1,BURGLARY-THEFT-MOTOR_VEHICLE_THEFT,0.1207
41.67688,41.67965,-87.64322,-87.6397,VAR,10,0,0.783441,0.216559,1,BURGLARY-THEFT-MOTOR_VEHICLE_THEFT,0.1207
41.67688,41.67965,-87.64322,-87.6397,VAR,11,1,0.734133,0.265867,1,BURGLARY-THEFT-MOTOR_VEHICLE_THEFT,0.1207
41.67688,41.67965,-87.64322,-87.6397,VAR,12,0,0.830888,0.169112,1,BURGLARY-THEFT-MOTOR_VEHICLE_THEFT,0.1207
41.67688,41.67965,-87.64322,-87.6397,VAR,13,1,0.810834,0.189166,1,BURGLARY-THEFT-MOTOR_VEHICLE_THEFT,0.1207
41.67688,41.67965,-87.64322,-87.6397,VAR,14,0,0.803271,0.196729,1,BURGLARY-THEFT-MOTOR_VEHICLE_THEFT,0.1207
41.67688,41.67965,-87.64322,-87.6397,VAR,15,0,0.777034,0.222966,1,BURGLARY-THEFT-MOTOR_VEHICLE_THEFT,0.1207
41.67688,41.67965,-87.64322,-87.6397,VAR,16,0,0.789064,0.210936,1,BURGLARY-THEFT-MOTOR_VEHICLE_THEFT,0.1207
...
```

Note that the threshold used for the mapping is also given.

4.3: Running flexroc.

Cynet provides a wrapper function for the flexroc binary, **flexroc_only_parallel**. It takes a specified tpr or fpr. It applies flexroc to desired log files, and for each log file returns the threshold necessary to achieve the desired rate. This implies that the threshold will likely be different between log files.

Script 8

```python
import cynet.cynet as cn
import yaml

with open('config.yaml','r') as fh:
    settings_dict = yaml.load(fh)
FLEX_TAIL_LEN = settings_dict['FLEX_TAIL_LEN']

cn.flexroc_only_parallel('models/*.log',tpr_threshold=0.85,fpr_threshold=None,FLEX_TAIL_LEN=FLEX_TAIL_LEN, cores=4)
```

As, described, **flexroc_only_parallel** will apply flexroc to all the log files matched by the glob string **models/*.log**. The desired tpr is set to 0.85, whereas the desired fpr is set to none. Again, only one can be chosen. **FLEX_TAIL_LEN** is retrieved from the yaml configuration and is 365 in this example. The required threshold for each log file is acquired and then applied to their probability series. The resulting event series and all the information in the log file is transferred in a csv file. A csv is created for each log file and will also be placed in the same directory as the log files.

Section 5: Using predictions to generate predictive heat maps.

5.1: Combining the csvs.

We now have a csv for every tile. In this example, the csvs should have been placed in the models/ directory. The names of these files contain quite a bit of information.

```
4572modeluse85models#ALL#BURGLARY-THEFT-MOTOR_VEHICLE_THEFT.csv
```

The above format implies that the tile number is 4572, the number of models used in prediction is 85, the source used to generate the predictions is **ALL** and the target predicted event is **BURGLARY-THEFT-MOTOR_VEHICLE_THEFT**. The contents of these csvs have already been described in section 4.2. |

Imagine if we were do combine all csvs with **ALL** as the source. We would then have a single csv which contains all predictions on all tiles whose source was **ALL**. We could then use pandas to select for the target. In this example, we will generate a predictive heat map which uses **ALL** as the source and **BURGLARY-THEFT-MOTOR_VEHICLE_THEFT**. One can of course use other variables as the source or target.

Script 9

```python
import cynet.cynet as cn

mapper=cn.mapped_events('models/*85models#ALL#*.csv')
mapper.concat_dataframes('85modelsALL.csv')
```

The above script simply, combines all csvs matching the path **models/*85models#ALL#*.csv** and outputs them as the concentenated csv **85modelsALL.csv**.

5.2: The heatmap settings.

We will use another yaml file to set our configurations. Call it **config2.yaml**.

```yaml
#Heatmap configurations

#The variable which we use as the predictor of our events.
source: 'ALL'

#The types of events to be predicted. Only one used here, but can be more.
types:
  - 'BURGLARY-THEFT-MOTOR_VEHICLE_THEFT'
```

```
#The grace we allow ourselves. One day in this case.
grace: 1

#A setting used in the previous scripts. Used for generating our initial grid.
EPS: 200

#Boundaries of Chicago
lat_min: 41.575
lat_max: 42.05
lon_min: -87.87
lon_max: -87.5

#The day number we are trying to predict on.
day: 1415

#Database
predictions_csv: '85modelsALL.csv'

#Shapefiles used. For drawing Chicago boundaries.
shapefiles: 'shapefiles/geo_export_437d164b-0f27-49ac-9a3c-587a85d9f3b1'

#Defines numer of tiles in our heatmap. Lower means more tiles. Will need to play around with this.
radius: 0.006

# How detailed our heatmap is. Lower means more detailed.
detail: 0.0007

#Intensity threshold
min_intensity: 0.006
```

Most of the above settings should be self-explanatory. **grace** is to give us some room in our predictions. That is, if we are able to predict an event within an error of 1 day, then we count that as a correct prediction. The **day** on which we are predicting events for is numbered 1415. The count starts from our beginning of our training period, 01-01-2015. The training period lasted until 12-31-2017, or 1095 days (3 years x 365 days). Therefore, day 1415 is 320 days beyond the training period. It is approximately, 11-16-2018. **shapefiles** is the path to files used to draw the boundaries of Chicago. The link is listed at the start of this document.

We are drawing a diffusion heatmap. Hence, variables such as **radius** and **detail** are necessary to define the grid in which we place the events in. Once we have placed our predictions on the grid, we calculate the intensity of events in an area. We will use the **min_intensity** to determine if we are predicting events in that area. If the calculated intensity of the area is higher than **min_intensity**, then we are predicting events.

5.3: Drawing the heatmap.

Now we draw the heatmap.

Script 10

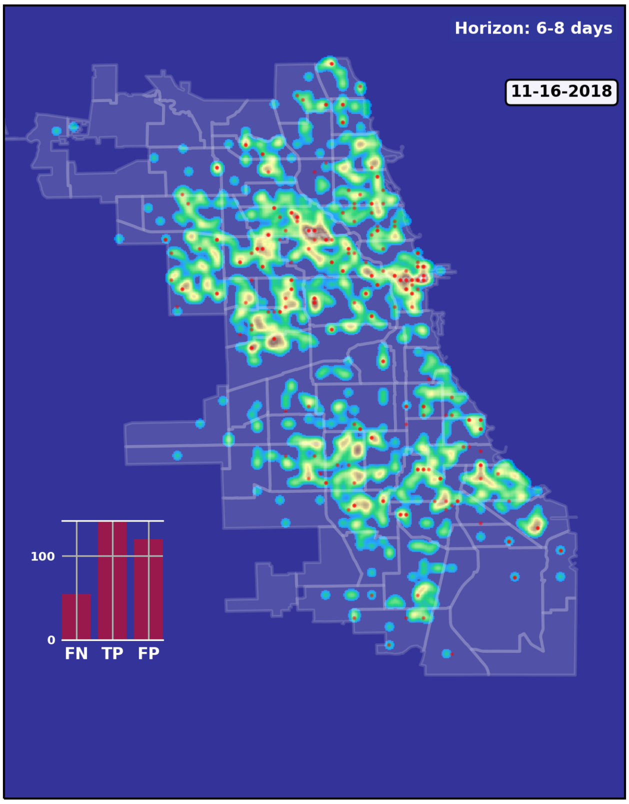
```
import viscynet.viscynet as viz
import numpy as np
import pandas as pd
import yaml

with open('config2.yaml','r') as fh:
    settings_dict = yaml.load(fh)

source = settings_dict['source']
types = settings_dict['types']
grace = settings_dict['grace']
EPS = settings_dict['EPS']
lat_min = settings_dict['lat_min']
```

```python
lat_max = settings_dict['lat_max']
lon_min = settings_dict['lon_min']
lon_max = settings_dict['lon_max']
day = settings_dict['day']
csv = settings_dict['predictions_csv']
shapefiles = settings_dict['shapefiles']
radius = settings_dict['radius']
detail = settings_dict['detail']
min_intensity = settings_dict['min_intensity']

df = pd.read_csv(csv)
dt,fp,fn,tp,df_gnd_augmented,lon_mesh,lat_mesh,intensity = \
viz.get_prediction(df,day,lat_min,
        lat_max,lon_min,lon_max,source,
        types,startdate="12/31/2017",offset=1095,
        radius=radius,detail=detail,
        Z=min_intensity,SINGLE=False)

viz.getFigure(day,dt,fp,fn,tp,df_gnd_augmented,lon_mesh,lat_mesh,
          intensity,
          fname=shapefiles,cmap='terrain',
          save=True,PREFIX='Burglary')
```

Most of the above script is loading in settings. **get_prediction** takes the predictions csvs and makes the calculations necessary to produce information necessary for the heatmap.

- dt: the date string.
- fp: false positives.
- fn: false negatives.
- tp: true positives.
- df_gnd_augmented. A dataframe consisting of the events that actually happened today.
- lon_mesh and lat_mesh: boundaries of diffusion grid.
- intensity: series of intensities calculated for each section of our heatmap.

getFigure consumes this information and produces the heatmap.



Comments:

Red dots indicate the events the actually happened. This heatmap looks different from the one at the beginning of the document. This is because we altered the getFigure function to add more information. Feel free to look change the **getFigure** function in the **viscynet** file to do the same to your own heatmap. It should be pretty easy for the reader to run the above script 10 in a loop to produce a series of heatmaps and string them into a heatmap movie.

Section 6: Perturb data for exploration.

Recall that we are using one type of event to predict for others. Ex: **HOMICIDE-ASSAULT-BATTERY** predicts **BURGLARY-THEFT-MOTOR_VEHICLE_THEFT** or vice-versa. It may also be the case that we are using one type of event to predict for that same type. Ex: **VAR** predicts **VAR**.

What would happen if crimes in one of these categories were to increase or decrease? How would that affect the dynamics of crime in Chicago? Since we have already trained the models, we can answer this and similar questions simply by altering the data and feeding them into the models again.

6.1: Setting up new split files.

The trained models are not going to change. However, the split files, which represents the data fed into the models, are going to change. In this example, we will increase (or perturb) the occurrences of **BURGLARY-THEFT-MOTOR_VEHICLE_THEFT** crime events by ten percent and observe the change in predictions made by the models.

Recall our directory setup.

```
..
|-- bin/
|     |-- XgenESeSS
|-- payload2015_2017/
|     |-- other files
|     |-- models/
|           |-- *model.json (multiple) + other files
```

```
|--split/
     |-- 2015-01-01_2018-12-31* (multiple)
```

Create a new directory called **split_burg_10p/** adjacent to the old split directory. This is where we will place the perturbed data. Also create a new payload directory named **perturbed_payload2015_2017** adjacent to the old payload folder. Also create a models directory within, similar to the old payload directory. Remember to move the model files, (*model.json files) to the new models folder. **DO NOT** move other files from the old models directory. Only move the original models generated from xGenESeSS which end in **model.json**.

```
..
|-- bin/
|    |-- XgenESeSS
|-- payload2015_2017/
|    |-- other files
|    |-- models/
|         |-- other files that not matching *model.json
|-- perturbed_payload2015_2017/
|    |-- other files
|    |-- models/
|         |-- *model.json (multiple)
|
|--split/
|    |-- 2015-01-01_2018-12-31* (multiple)
|--split_burg_10p/
```

Now we change the data (split files). Recall that the names of the split files indicate the date range, the tile, and the type.

Ex: 2015-01-01_2018-12-3142.01633#42.02755#-87.7#-87.68571#BURGLARY-THEFT-MOTOR_VEHICLE_THEFT

The date range is 2015/01/01 to 2018/12/31. The boundaries of the tile are given by 42.01633, 42.02755, -87.7, -87.68571 (lat1,lat2,lon1,lon2). The type is **BURGLARY-THEFT-MOTOR_VEHICLE_THEFT**. We are only concerned with split files matching the 2015/01/01 to 2018/12/31 date range. Furthermore, we are only looking to increase nonviolent crimes, **BURGLARY-THEFT-MOTOR_VEHICLE_THEFT**. Thus we will keep file types **VAR** and **HOMICIDE-ASSAULT-BATTERY** the same.

With that said, copy the files corresponding to the types that we will not change into the new split folder. Like so:

```
cp split/2015-01-01_2018-12-31*VAR split_burg_10p/
cp split/2015-01-01_2018-12-31*HOMICIDE-ASSAULT-BATTERY split_burg_10p/
```

Now we have the data which are not being changed in the proper place. For the data we will change, use the following script.

Script 11

```python
import cynet.cynet as cn

cn.alter_splitfiles('split/2015*BURGLARY-THEFT-MOTOR_VEHICLE_THEFT','split_burg_10p/', theta=0.1)
```

The **alter_splitfiles** function looks for files matching the first argument, then perturbs them. Each file is a series of numbers indicating the number of crime incidents that occurred on a certain day. Whenever it encounters a 0, a day where there was no crime, it will change it to a 1 with a probability of theta. Since the split files consists of mostly 0's, it is similar to increasing crime by 10 percent. The new split files are placed into the directory designated by the second argument.

```
..
|-- bin/
|     |-- XgenESeSS
|-- payload2015_2017/
|     |-- other files
|     |-- models/
|          |-- other files that not matching *model.json
|-- perturbed_payload2015_2017/
|     |-- other files
|     |-- models/
|          |-- *model.json (multiple)
|
|--split/
|     |-- 2015-01-01_2018-12-31* (multiple)
|--split_burg_10p/
|     |-- 2015-01-01_2018-12-31* (multiple. perturbed and non-perturbed)
```

6.2: Rerunning cynet for new prediction csvs.

Everything is in place to rerun cynet for the new csvs. We now work in the **perturbed_payload2015_2017/** directory. The last thing we need to change is one setting in our configuration yaml file. Here is the previous configuration yaml but with one setting changed.

```yaml
#YAML Configuration

# path to file which has the rowwise multiline time series data
TS_PATH: './CRIME-_2015-01-01_2017-12-31.csv'

# path to file with name of the variables
NAME_PATH: './CRIME-_2015-01-01_2017-12-31.coords'

# path to log file for xgenesess inference
LOG_PATH: 'log.txt'

# xgenesses run parameters (these are not hyperparameters, Beg is 0, End is whatever tempral memory is)
END: 60
BEG: 0

# number of restarts (20 is good)
NUM: 2

# partition sequence (we can specify different partition for each time series. XgenESeSS already has this capability)
PARTITION:
- 0.5

# number of models to use in prediction (using cynet binary)
model_nums:
- 85
```

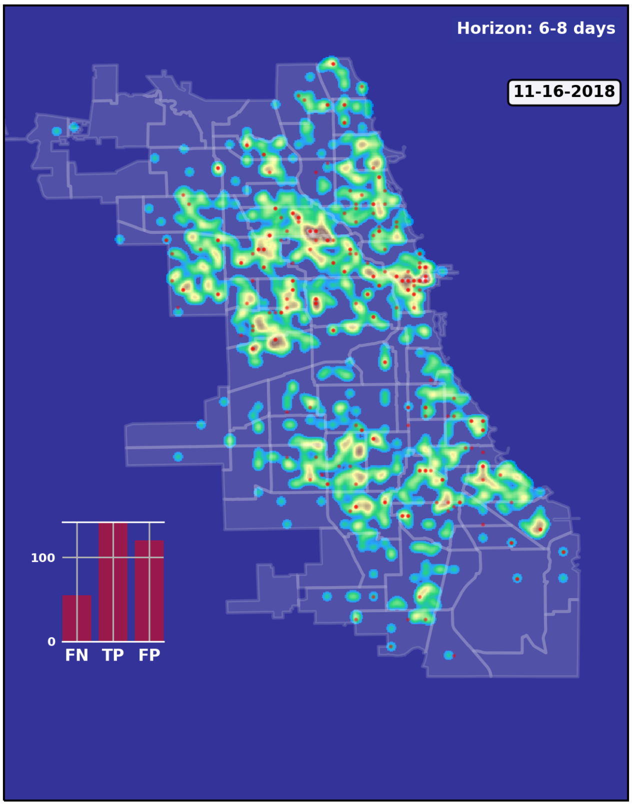
```yaml
# prediction horizons to test in unit of temporal quantization (using cynet binary)
horizons:
- 7

# length of run using cynet (generally length of individual ts in split folder)

RUNLEN: 1460

#Periods to predict for
FLEX_TAIL_LEN: 365

# path to split series

DATA_PATH: '../split_burg_10p/2015-01-01_2018-12-31'

# path to models
FILEPATH: 'models/'

# glob string that matches all the model.json files.
MODEL_GLOB: 'models/*model.json'

# number of processors to use for post process models
NUMPROC: 10

# path to where result files are stored
RESPATH: './models/*model*res'

# path to XgenESeSS binary
XgenESeSS: '../bin/XgenESeSS'

# do we run XgenESeSS binary locally, or do we produce a list of commands to be run via phnx
RUN_LOCAL: 0

# max distance cutoff in render network
MAX_DIST: 3

# min distance cutoff in render network
MIN_DIST: 0.1

# max gamma cutoff in render network
MAX_GAMMA: 0.95

# min gamma cutoff in render network
MIN_GAMMA: 0.25

# colormap in render network
COLORMAP: 'Reds'
```

Notice that only the **DATA_PATH** setting is changed. It now points to the new split folder. Rerunning cynet to get the new csvs should be familiar. It only involves running scripts 6 and 8 again. This needs to be done in the **perturbed_payload2015_2017/** directory. In the end, the csvs will appear in the **models/** directory as before.

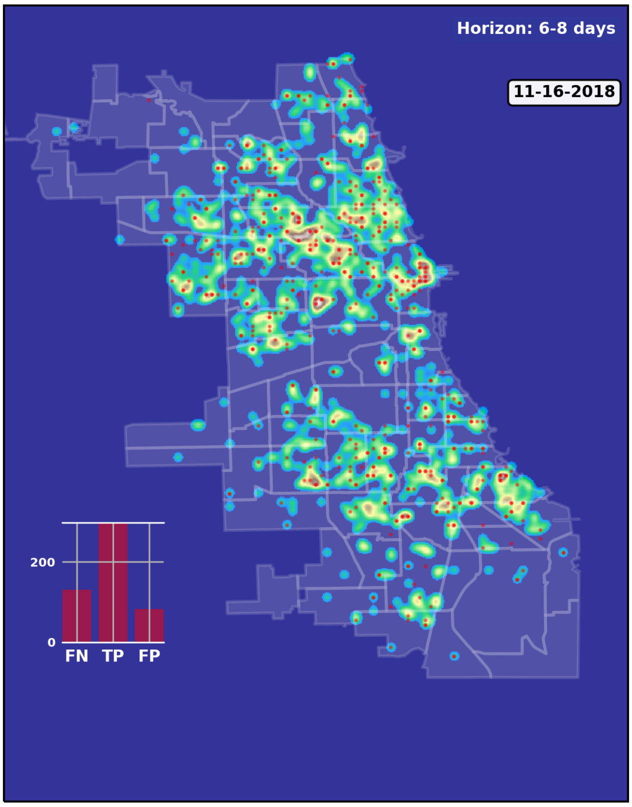
6.3: Using the new predictions.

We leave it to the reader to play around with different perturbations. We only demonstrated how to perturb one variable with a theta of 0.1. It should be clear how to do so with other variables and different thetas. The following is a predictions heatmap produced in the exact same manner. This uses the new prediction csvs from the perturbed data. Recall that this is using **ALL** to predict the type we perturbed, **BURGLARY-THEFT-MOTOR_VEHICLE_THEFT**. Below is the original heatmap and the one made from perturbed data.

Original



Peruturbed



Comments:

One should be able to see that the insensity of crime predictions in certain have increased significantly. There are many interesting results that can be found between the interaction of crime types in Chicago.