Machine Learning: Regression of 911 Calls

February 24, 2017 (http://croock.webfactional.com/machine-learning-regression-911-calls/) Lucas KM (http://croock.webfactional.com/author/lukas_km/) Projects (http://croock.webfactional.com/category/projects/)

Welcome to my first Machine Learning project!

This post will be focused on solving the real problem. We will try to predict location and daily quantity of 911 calls in US Montgomery County (PA). Such project could enable help & rescue teams, such as police, fire department and emergency medical services to prepare for upcoming events and better plan their work.

Machine Learning: Regression of 911 Calls

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The (Imaginary) Intro Story

The intro story is totally made up. I create the story to let you dive in into the problem and understand better how Machine Learning can help to solve real-life problems.

You are the Montgomery County Executive. Since the end of 2015, your 911 call center team started to collect data regarding 911 calls in your county. These data contain date, time, location and type of 911 event that occured.

You have promised county citizens that you will improve reaction time of your public safety teams, including fire department, emergency medical services and police. One of the options is to spend more money on new equipment and employ more people, bu the budget in this year is very tight. Also, your rescue team managers complain that people are overworked, and there are many of them that had no vacations for at least two years. So you are looking for another option.

Luckily, you have recently read an interesting article about Machine Learning algorithms that can aid people in making decisions. If your rescue teams could know in more details, where and when they are needed in 2017? That would allow them to plan their shifts better, decide when it is better time to repair their equipment and when they can plan their vacations

Finally, you decide to find a Machine Learning professional and ask him to find solution for your problem.

The Solution

The solution is a Machine Learning Regression model. I have used the scikit-learn implementation of GradientBoostingRegressor as it returned the best results of all of the several regression algorithms I have tested for this problem.

As a result, we can predict the number of 911 calls (events) per each 8 hours in a given day and the general location, according to grid on a map. The model score (R2) is 0.81, so its goodness is significant, at least for our purpose which is really an emergency teams work planning.

The Notebook

Please review the notebook below for details of the solution.

You can also reviev the Notebook on Github (https://github.com/lukaszkm/machinelearningexp/blob/master/Machine_Learning_Regression_911Calls.ipynb).

Machine Learning Notebook – 911 Calls Regression

00. Goal

Goal of this project is the following:

1. predict number of help & rescue (911 calls) events in US (PA) Montgomery County in any arbitrary day of 2017
2. prediction should provide number of events by time of day and by general location
3. prediction should be based on 2016 data
4. we must know the goodness of the prediction
5. some guidance, regarding type of the event would be nice, too.

01. Notebook Intro & Imports

US Montgomery 911 Calls Regression Notebook

- Notebook @author Lukasz KM, lucas.mlexp@gmail.com, http://machinelearningexp.com (http://machinelearningexp.com/)
- Notebook License: Creative Commons CC-BY-SA https://creativecommons.org/licenses/by-sa/4.0/ (https://creativecommons.org/licenses/by-sa/4.0/)
- Dataset source: https://www.kaggle.com/mchirico/montcoalert (https://www.kaggle.com/mchirico/montcoalert)
- Dataset provided by montcoalert.org
- Database released under Open Database License, individual contents under Database Contents License
- Maps source: OpenStreetMap.org
- Maps license: Open Data Commons Open Database License (ODbL).
- Data Description:
- Events Location: Montgomery County, PA, USA
- Timespan: 2015-12-10 to 2017-01-27
- Dataset columns:
    - lat : String variable, Latitude
    - lng: String variable, Longitude
    - desc: String variable, Description of the Emergency Call
    - zip: String variable, Zipcode
    - title: String variable, Title
    - timeStamp: String variable, YYYY-MM-DD HH:MM:SS
    - twp: String variable, Township
    - addr: String variable, Address
    - e: String variable, Dummy variable (always 1 – counter)

Montgomery County, locally also referred to as Montco, is a county located in the Commonwealth of Pennsylvania. As of the 2010 census, the population was 799,874, making it the third-most populous county in Pennsylvania, after Philadelphia and Allegheny Counties, and the 71st most populous in the United States. The county seat is Norristown. Montgomery County is very diverse, ranging from farms and open land in Upper Hanover to densely populated rowhouse streets in Cheltenham.

Source: Wikipedia, https://en.wikipedia.org/wiki/Montgomery_County,_Pennsylvania (https://en.wikipedia.org/wiki/Montgomery_County,_Pennsylvania), Creative Commons Attribution-ShareAlike License

In [3523]:

```
# imports
import math
import numpy as np
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
%matplotlib inline
import seaborn as sns
sns.set()
import sklearn
from __future__ import print_function
from IPython.display import Image
from IPython.display import display
from IPython.display import HTML
from sklearn import metrics
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
from sklearn import preprocessing
import tabletext
from tabletext import to_text
```

02. Load & Preview data

In [3524]:

```
# Load data from disk and preview data
dt1 = pd.read_csv("911.csv")
dt1.head(3)
```

Out[3524]:

	lat	lng	desc	zip	title	timeStamp	twp	addr	e
0	40.297876	-75.581294	REINDEER CT & DEAD END; NEW HANOVER; Station ...	19525.0	EMS: BACK PAINS/INJURY	2015-12-10 17:10:52	NEW HANOVER	REINDEER CT & DEAD END	1
1	40.258061	-75.264680	BRIAR PATH & WHITEMARSH LN; HATFIELD TOWNSHIP...	19446.0	EMS: DIABETIC EMERGENCY	2015-12-10 17:29:21	HATFIELD TOWNSHIP	BRIAR PATH & WHITEMARSH LN	1
2	40.121182	-75.351975	HAWS AVE; NORRISTOWN; 2015-12-10 @ 14:39:21-St...	19401.0	Fire: GAS-ODOR/LEAK	2015-12-10 14:39:21	NORRISTOWN	HAWS AVE	1

03. Feature selection and data cleaning

In [3525]:

```
# restrict data to 2016 to get full year picture (data contain also events from Dec 2015 and Jan 2017
)
# remove unnecessary columns
# we are interested only in accident time, title and geolocation data
# preview limited data
dt1 = dt1[dt1['timeStamp'].str.contains('2016', na = False)]
dt2 = dt1.drop(["desc","addr","e"],axis=1)
print ("Dataset shape :",dt1.shape)
dt2.head(3)
```

```
Dataset shape : (142360, 9)
```

Out[3525]:

	lat	lng	zip	title	timeStamp	twp
7916	40.121354	-75.363829	19401.0	EMS: ASSAULT VICTIM	2016-01-01 00:10:08	NORRISTOWN
7917	40.140505	-75.310874	19401.0	EMS: FALL VICTIM	2016-01-01 00:14:45	EAST NORRITON
7918	40.246837	-75.681381	19464.0	EMS: ABDOMINAL PAINS	2016-01-01 00:20:43	WEST POTTSGROVE

We have around 142 thousands of events in our dataset. That seems to be enough to run our experiment and expect to have a pretty decent result.

In [3526]:

```
# check if we have rows with empty data in the dataset
print ("lat empty count :", dt2['lat'].isnull().sum())
print ("lng empty count :", dt2['lng'].isnull().sum())
print ("zip empty count :", dt2['zip'].isnull().sum())
print ("title empty count :", dt2['title'].isnull().sum())
print ("timeStamp empty count :", dt2['timeStamp'].isnull().sum())
print ("twp empty count :", dt2['twp'].isnull().sum())
```

```
lat empty count : 0
lng empty count : 0
zip empty count : 17865
title empty count : 0
timeStamp empty count : 0
twp empty count : 43
```

In [3527]:

```
# cleaning columns with empty values, we can achieve our goals without them
# it is better to remove columns than get rid of around 18k of events
dt3 = dt2.drop(["zip","twp"],axis=1)
dt3.head(3)
```

Out[3527]:

	lat	lng	title	timeStamp
7916	40.121354	-75.363829	EMS: ASSAULT VICTIM	2016-01-01 00:10:08
7917	40.140505	-75.310874	EMS: FALL VICTIM	2016-01-01 00:14:45
7918	40.246837	-75.681381	EMS: ABDOMINAL PAINS	2016-01-01 00:20:43

In [3528]:

```
# let's check the statistical properties of the numerical data
dt3.describe()
```

Out[3528]:

	lat	lng
count	142360.000000	142360.000000
mean	40.158987	-75.317018
std	0.091876	0.169058
min	30.333596	-95.595595
25%	40.099784	-75.391998
50%	40.144662	-75.304594
75%	40.229008	-75.211735
max	41.167156	-74.993076

In [3529]:

```
# it seems we have some outliers in the geographical data.
# Montgomery County (PA) does not have any locations with min lat 30.333596 or min lng -95.595595.
# there must be some human (data entry operator) mistakes and we need to identify them
outliers = dt3.loc[((dt3['lat'] < 39.00) | (dt3['lat'] > 41.00)) &
                   ((dt3['lng'] < -77.00) | (dt3['lng'] > -74.00))]
print ("Outliers :\n",outliers)
```

```
Outliers :
             lat        lng                        title           timeStamp
25529  32.387090 -86.276106  Traffic: DISABLED VEHICLE -  2016-02-12 18:44:37
66737  30.333596 -95.595595       EMS: CARDIAC EMERGENCY  2016-06-02 13:31:21
```

In [3530]:

```
# we have just a few outliers, removing them will not affect the result. Lets filter out the outliers
dt4 = dt3.loc[((dt3['lat'] > 39.00) & (dt3['lat'] < 41.00)) &
              ((dt3['lng'] > -77.00) & (dt3['lng'] < -74.00))]
# and describe the dataset again to check effect of the cleaning
dt4.describe()
```

Out[3530]:

	lat	lng
count	142352.000000	142352.000000
mean	40.159112	-75.316563
std	0.085606	0.151713
min	39.952584	-75.729789
25%	40.099784	-75.391998
50%	40.144662	-75.304587
75%	40.229008	-75.211735
max	40.479853	-74.993076

04. Features engineering

In [3531]:

```
# we want to get event type from its title
# first we list unique values in title
titles_unique = pd.DataFrame(dt4.title.unique())
titles_unique = titles_unique.sort_values([0],ascending =  True)
print ("Unique titles size :",len(titles_unique))
titles_unique.head(5)
```

```
Unique titles size : 119
```

Out[3531]:

	0
2	EMS: ABDOMINAL PAINS
99	EMS: ACTIVE SHOOTER
43	EMS: ALLERGIC REACTION
3	EMS: ALTERED MENTAL STATUS
73	EMS: AMPUTATION

In [3532]:

```
# as we have more than 100 unique categories of events, let's  modify dataset and assign
# to each event only the master category (the one before the colon)
dt5 = dt4.copy()
dt5['category'],dt5['category2'] = dt5['title'].str.split(':',1).str
dt5 = dt5.drop(['title','category2'],axis = 1)
cat_unique = pd.DataFrame(dt5.category.unique())
cat_unique = cat_unique.sort_values([0],ascending =  True)
cat_unique.head()
```

Out[3532]:

	0
0	EMS
1	Fire
2	Traffic

In [3533]:

```
# We now have the dictionary of the unique categories. We can change strings in dataset to the catego
ry numbers.
# That is necessary as we want to feed the Machine Learning model with this dataset
# and it must contain only numeric values. Here is the mapping:
# 0 = EMS (Emergency Medical Services)
# 1 = FIRE
# 2 =  TRAFFIC
CATEGORIES = {'EMS':0,'Fire':1,'Traffic':2}
dt5['category'].replace(CATEGORIES,inplace=True)
dt5.head(3)
```

Out[3533]:

	lat	lng	timeStamp	category
7916	40.121354	-75.363829	2016-01-01 00:10:08	0
7917	40.140505	-75.310874	2016-01-01 00:14:45	0
7918	40.246837	-75.681381	2016-01-01 00:20:43	0

In [3534]:

```
# now we want to parse timestamp to get more information from it.
# we will extend the dataset with more time related values
# hours_range allows us to split day into several periods, each hours_range long
hours_range = 8
dt6 = dt5
dt6['datetime'] = pd.to_datetime(dt5['timeStamp'])
dt6['year'] = dt5['datetime'].dt.year
dt6['month'] = dt5['datetime'].dt.month
dt6['day'] = dt5['datetime'].dt.day
dt6['day_part'] = np.floor(dt5['datetime'].dt.hour/hours_range)
dt6['day_part'] = dt5.day_part.astype(int)
dt6['dayofweek'] = dt5['datetime'].dt.dayofweek
dt6['week'] = dt5['datetime'].dt.week
#let's describe the dat again
dt6.describe()
```

Out[3534]:

	lat	lng	category	year	month	day	day_part	da
count	142352.000000	142352.000000	142352.000000	142352.0	142352.000000	142352.000000	142352.000000	14
mean	40.159112	-75.316563	0.863212	2016.0	6.534956	15.912105	1.207092	2.9
std	0.085606	0.151713	0.910901	0.0	3.485908	8.769763	0.705224	1.9

min	39.952584	-75.729789	0.000000	2016.0	1.000000	1.000000	0.000000	0.0
25%	40.099784	-75.391998	0.000000	2016.0	4.000000	8.000000	1.000000	1.0
50%	40.144662	-75.304587	1.000000	2016.0	7.000000	16.000000	1.000000	3.0
75%	40.229008	-75.211735	2.000000	2016.0	10.000000	23.000000	2.000000	5.0
max	40.479853	-74.993076	2.000000	2016.0	12.000000	31.000000	2.000000	6.0

In [3535]:

```
# the geo coordinates have limited range
# we want to split the whole location into the geo grid
# epsilon is to extend the upper bound minimally
# to avoid assigning locations at the end of the range to new slot beyond the grid
epsilon = 0.0001
lat_max = dt6['lat'].max() + epsilon
lat_min = dt6['lat'].min()
lat_range = lat_max - lat_min
print ("Latitude min-max: <",lat_min,lat_max,"> | range :",lat_range)
lng_max = dt6['lng'].max() + epsilon
lng_min = dt6['lng'].min()
lng_range = lng_max - lng_min
print ("Longitude min-max: <",lng_min,lng_max,"> | range :",lng_range)
```

```
Latitude min-max: < 39.9525839 40.4799532 > | range : 0.5273693
Longitude min-max: < -75.7297893 -74.9929755 > | range : 0.7368138
```

In [3536]:

```
# Let's then split the area set by these coordinates into an grid
# we will divide the lat and lng range, thus creating grid of rectangles
lat_split = 5 # number of horizontal parts
lng_split = 7 # number of vertical parts
lat_hop = lat_range/lat_split # lat divided to N parts gives us length of one part
print ("Lat hop : ",lat_hop)
lng_hop = lng_range/lng_split # lng divided to N parts gives us length of one part
print ("Lng hop : ",lng_hop)
# now we need to assign coordinates to proper geogrid squares
dt6['lat_grid'] = (np.floor(((dt6['lat']-lat_min)/lat_hop)))
dt6['lng_grid'] = (np.floor(((dt6['lng']-lng_min)/lng_hop)))
dt6.lat_grid = dt6.lat_grid.astype(int)
dt6.lng_grid = dt6.lng_grid.astype(int)
dt7 = dt6.drop(['lat','lng'],axis = 1)
dt7 = dt6
dt7.head(3)
```

```
Lat hop :  0.10547386
Lng hop :  0.105259114286
```

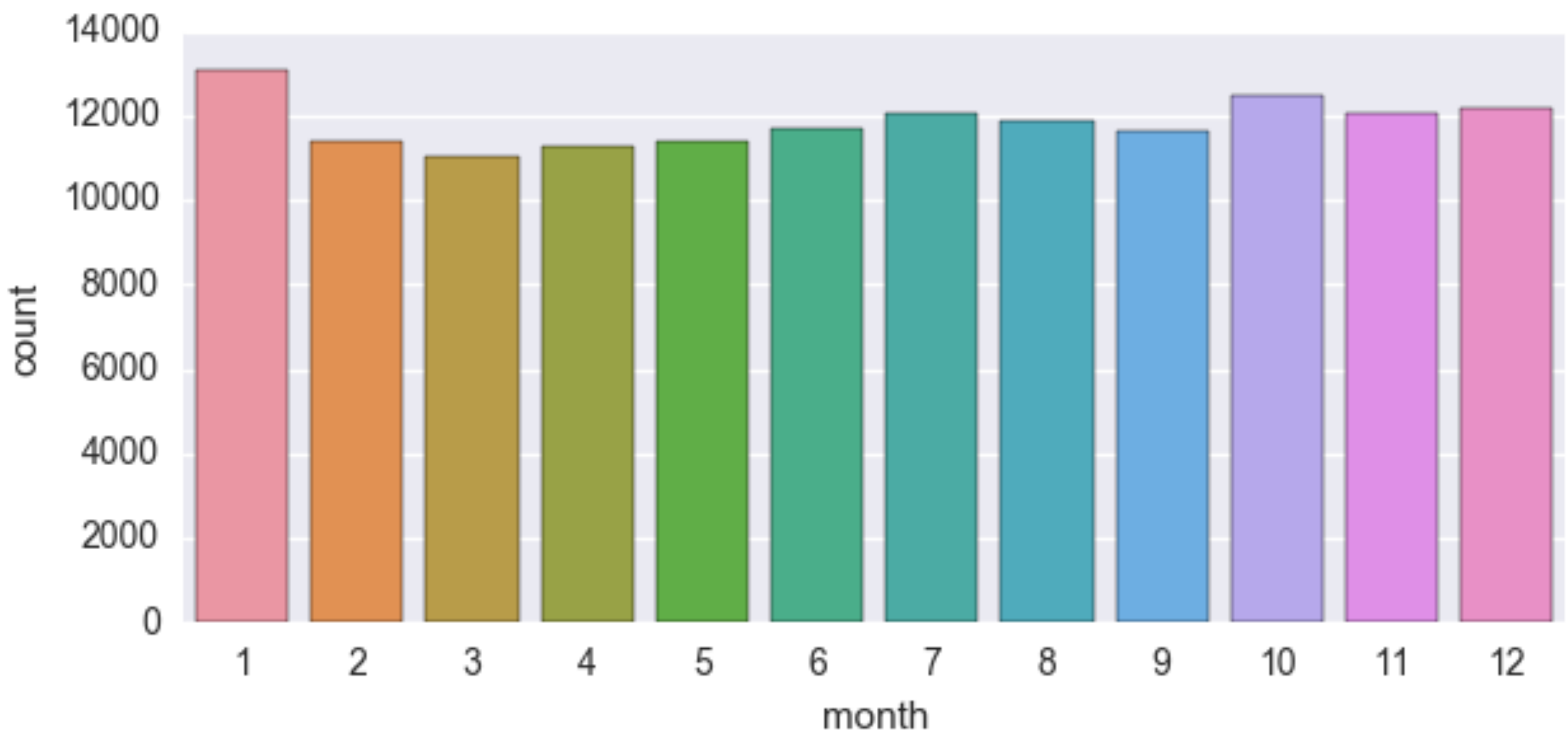
Out[3536]:

	lat	lng	timeStamp	category	datetime	year	month	day	day_part	dayofweek	week
7916	40.121354	-75.363829	2016-01-01 00:10:08	0	2016-01-01 00:10:08	2016	1	1	0	4	53
7917	40.140505	-75.310874	2016-01-01 00:14:45	0	2016-01-01 00:14:45	2016	1	1	0	4	53
7918	40.246837	-75.681381	2016-01-01 00:20:43	0	2016-01-01 00:20:43	2016	1	1	0	4	53

05. Visualize data

In [3537]:

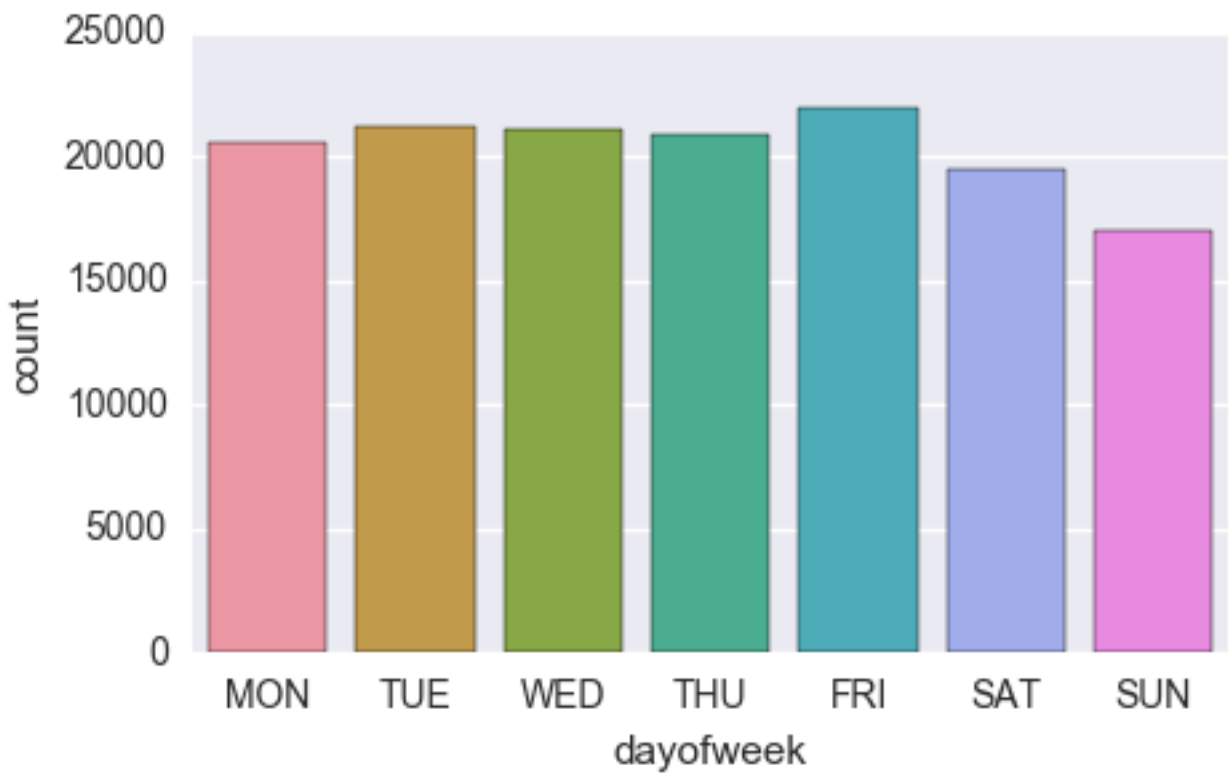
```
# let's check number of events per month
fig, ax = plt.subplots(figsize=(7,3))
ax = sns.countplot(x="month", data=dt7,ax=ax)
```



October-January is definetely the worst period, probably due to the weather. Also, vacation period has higher number of events.

In [3538]:

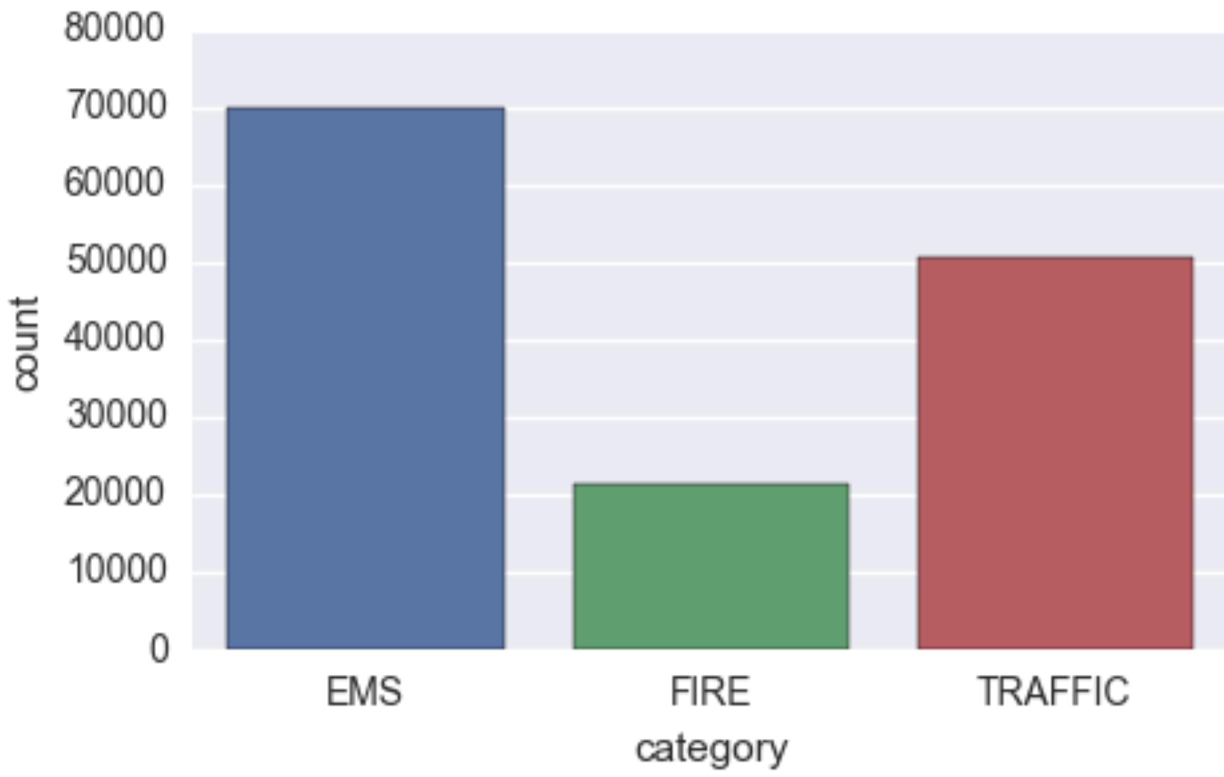
```
# let's check number of events per day of the week
fig, ax = plt.subplots(figsize=(5,3))
ax = sns.countplot(x="dayofweek", data=dt7)
ax.axes.set_xticklabels(["MON", "TUE","WED","THU","FRI","SAT","SUN"])
pass
```



Friday is definetely the leader in this pack. Start of the weekend – that explains a lot.

In [3539]:

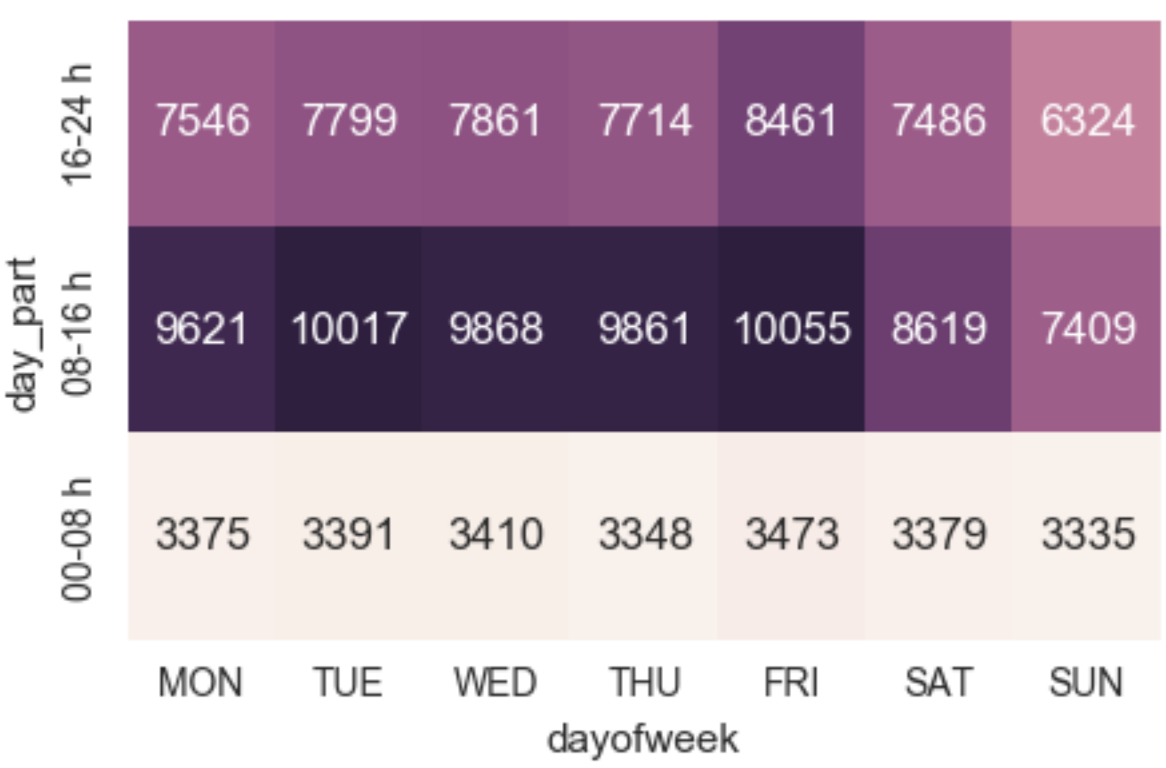
```
#let's see the size of each category (class)
# 0 = EMS (Emergency Medical Services), 1 = FIRE, 2 =  TRAFFIC
fig, ax = plt.subplots(figsize=(5,3))
ax = sns.countplot(x="category", data=dt7)
ax.axes.set_xticklabels(["EMS","FIRE","TRAFFIC"])
pass
```



EMS conditions are the majority of all events, followed by traffic (mostly car accidents).

In [3540]:

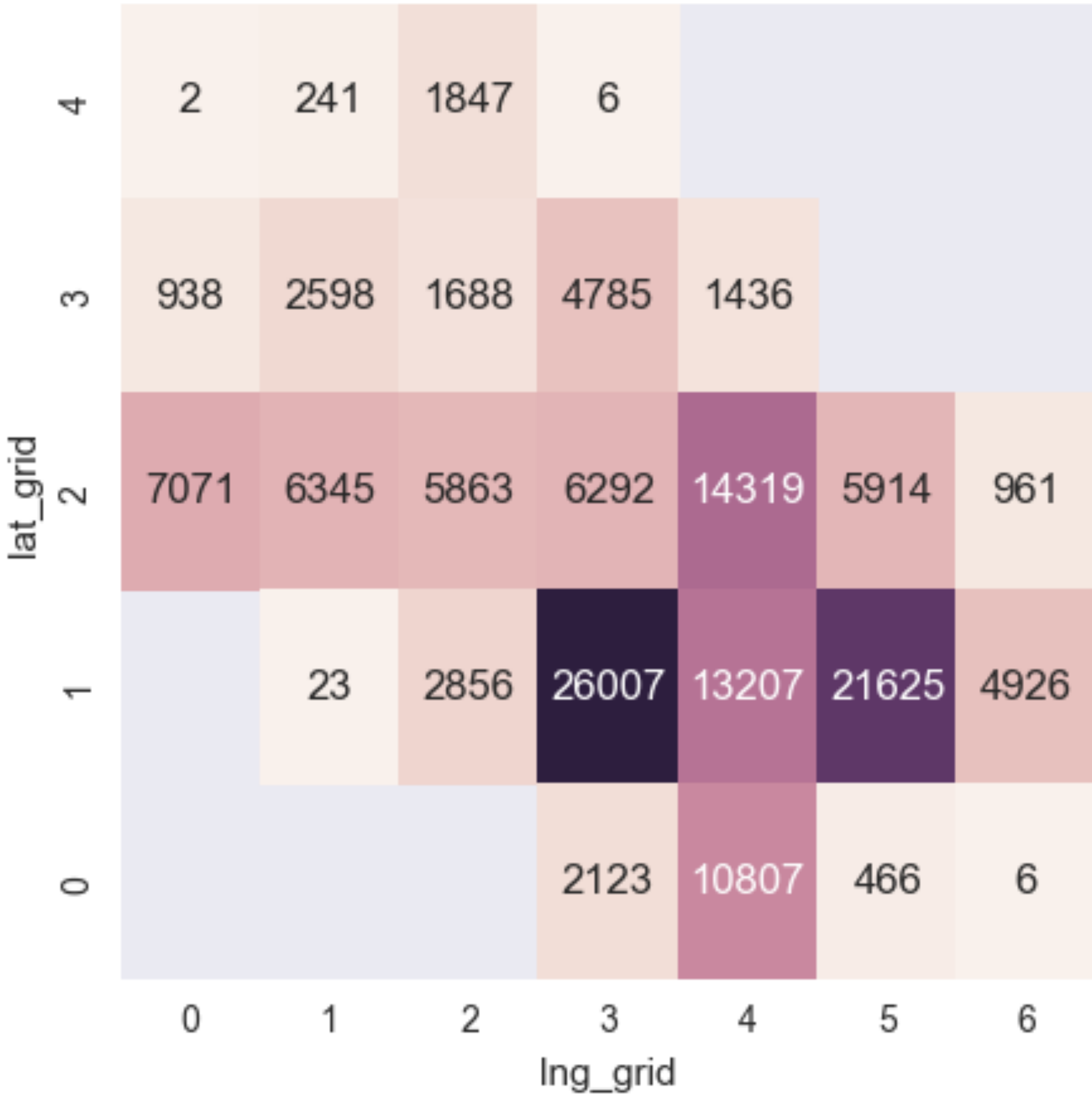
```
# lets check the time impact on the events
dt_timegrid = dt7.groupby(['dayofweek','day_part']).size().reset_index(name='count')
dt_timeheatmap = dt_timegrid.pivot(index='day_part', columns='dayofweek', values='count')
# generate heatmap
fig, ax = plt.subplots(figsize=(5,3))
ax = sns.heatmap(dt_timeheatmap,annot=True, fmt="d",cbar=False)
ax.invert_yaxis()
ax.axes.set_yticklabels(["16-24 h","08-16 h","00-08 h"])
ax.axes.set_xticklabels(["MON", "TUE","WED","THU","FRI","SAT","SUN"])
pass
```



Luckily, events in the middle of the day dominates the whole 24h. That is also the time when most of the emergency teams operate with full performance.

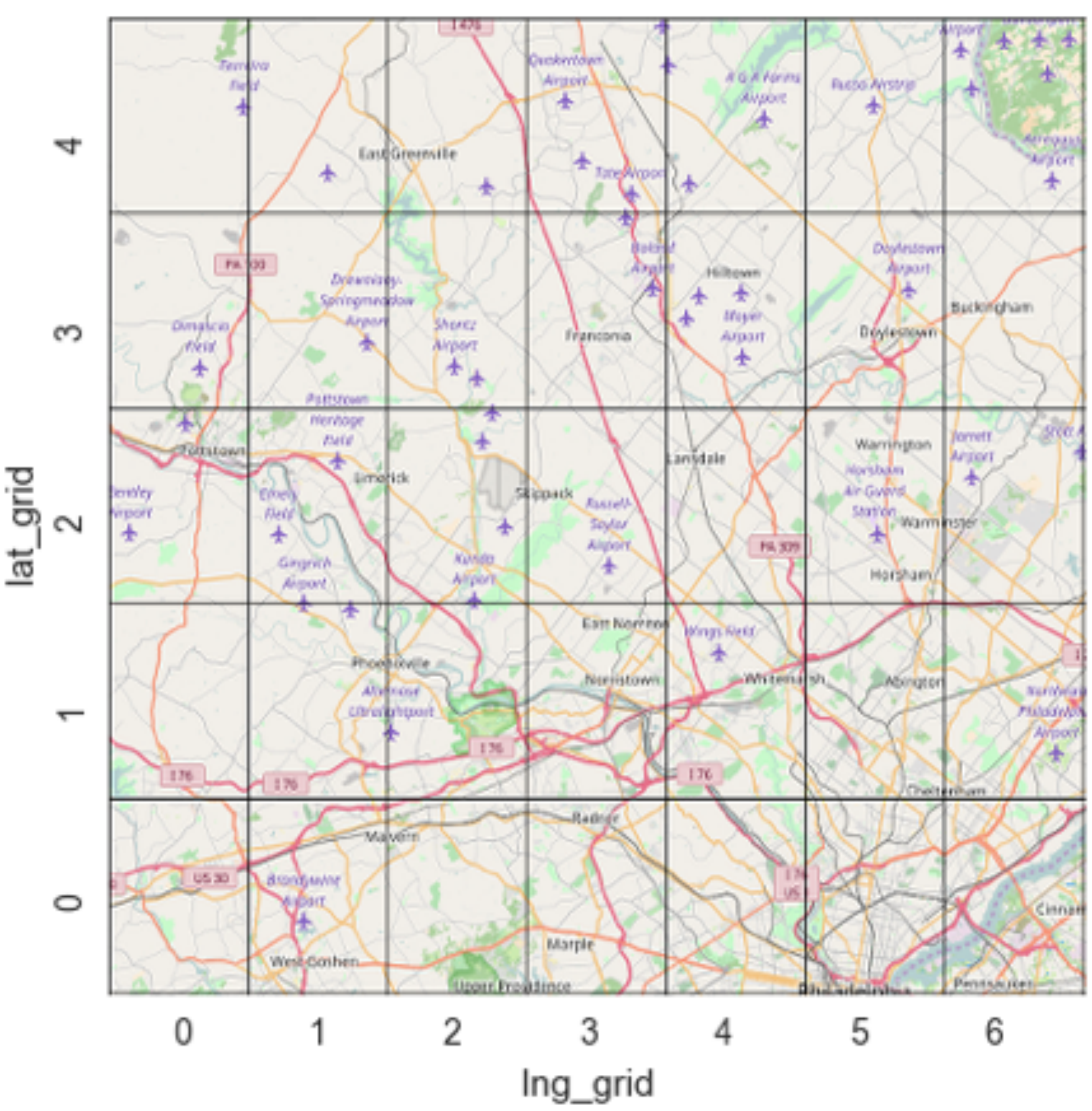
In [3541]:

```
# now we can visualize our data on the geogrid.
dt_geogrid = dt7.groupby(['lat_grid','lng_grid']).size().reset_index(name='count')
dt_geoheatmap = dt_geogrid.pivot(index='lat_grid',columns='lng_grid', values='count')
# generate heatmap
fig, ax = plt.subplots(figsize=(5,5))
ax = sns.heatmap(dt_geoheatmap,annot=True,fmt=".0f",cbar=False)
ax.invert_yaxis()
sns.plt.show()
print ("Longitude min-max: <",lng_min,lng_max,"> | range :",lng_range)
print ("Latitude min-max: <",lat_min,lat_max,"> | range :",lat_range)
#draw reference map
print ("\nUS PA Montgomery County Reference map")
print ("Map source: OpenStreetMap.org, Map license: Open Data Commons Open Database License (ODbL).")
img = Image(filename = "montco-map-grid.png", width=480, height=480)
display(img)
# save plots locally
```




```
Longitude min-max: < -75.7297893 -74.9929755 > | range : 0.7368138
Latitude min-max: < 39.9525839 40.4799532 > | range : 0.5273693

US PA Montgomery County Reference map
Map source: OpenStreetMap.org, Map license: Open Data Commons Open Database License (ODbL).
```



In [3542]:

```
# reorganize table to have mor intuitive order of the features
final_columns = ["month","week","dayofweek","day","day_part","lat_grid","lng_grid","category"]
dt7 = dt6[final_columns]
dt7.head(3)
```

Out[3542]:

	month	week	dayofweek	day	day_part	lat_grid	lng_grid	category
7916	1	53	4	1	0	1	3	0
7917	1	53	4	1	0	1	3	0

7918	1	53	4	1	0	2	0	0

In [3543]:

```
# let's describe the data again
dt7.describe()
```

Out[3543]:

	month	week	dayofweek	day	day_part	lat_grid	lng_grid
count	142352.000000	142352.000000	142352.000000	142352.000000	142352.000000	142352.000000	142352.00000
mean	6.534956	26.685407	2.908551	15.912105	1.207092	1.439341	3.412759
std	3.485908	15.239628	1.953423	8.769763	0.705224	0.826899	1.455951
min	1.000000	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000
25%	4.000000	13.000000	1.000000	8.000000	1.000000	1.000000	3.000000
50%	7.000000	27.000000	3.000000	16.000000	1.000000	1.000000	4.000000
75%	10.000000	40.000000	5.000000	23.000000	2.000000	2.000000	4.000000
max	12.000000	53.000000	6.000000	31.000000	2.000000	4.000000	6.000000

06. Model data for Machine Learning regression

In [3544]:

```
# create separate datasets for categories and group them by all parameters to get count of events for
a given group
groupby_list = ['month','week','dayofweek','day','day_part','lat_grid','lng_grid']
dt_cat = dict() # holder for subdatasets with categories.
for item in CATEGORIES:
    dt_temp = dt7.loc[(dt7['category'] == CATEGORIES[item])]
    dt_cat[item] =  dt_temp.groupby(groupby_list).size().reset_index(name='count')
dt_cat['ALL'] = dt7.groupby(groupby_list).size().reset_index(name='count') # All data, without catego
ry grouping
dt_cat['ALL'].head(3)
```

Out[3544]:

	month	week	dayofweek	day	day_part	lat_grid	lng_grid	count
0	1	1	0	4	0	0	3	1
1	1	1	0	4	0	0	4	2
2	1	1	0	4	0	0	5	1

In [3545]:

```
dt_cat['ALL'].describe()
```

Out[3545]:

	month	week	dayofweek	day	day_part	lat_grid	lng_grid	cour
count	19396.000000	19396.000000	19396.000000	19396.000000	19396.000000	19396.000000	19396.000000	1939
mean	6.507166	26.634306	2.990462	15.783667	1.056197	1.801609	3.053671	7.339
std	3.466914	15.164158	1.988070	8.815254	0.797869	1.049303	1.681422	7.945
min	1.000000	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000	1.000
25%	3.000000	13.000000	1.000000	8.000000	0.000000	1.000000	2.000000	2.000

50%	7.000000	27.000000	3.000000	16.000000	1.000000	2.000000	3.000000	4.00
75%	10.000000	40.000000	5.000000	23.000000	2.000000	3.000000	4.000000	9.00
max	12.000000	53.000000	6.000000	31.000000	2.000000	4.000000	6.000000	91.0

In [3546]:

```
# let's now create a function that will split data into train and test sets and run regresion algorit
hm on the data

def run_regression(name,input_dt):
    X = input_dt.iloc[:,[0,1,2,3,4,5,6]]
    Y = input_dt.iloc[:,[7]]
    Y = Y.values.reshape(len(X))
    validation_size = 0.20
    seed = 7
    X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size = validation_size,random_state
= seed)
    model = GradientBoostingRegressor(n_estimators=200,
                                      learning_rate=0.1, max_depth=5, random_state=0, loss='ls', warm
_start =  True)
    model.fit(X_train,Y_train)
    return name,model,r2_score(Y_test, model.predict(X_test))

# run model for all categories and put results into the table.
# also save trained models for later use
results_table = [["CATEGORY","R2 SCORE"]]
trained_models = dict() # holder for trained models
for item in dt_cat:
    results = run_regression(item,dt_cat[item])
    results_table.append([item,results[2]])
    trained_models[item] =  results[1]

print (to_text(results_table))
```

CATEGORY	R2 SCORE
Fire	0.324846254407
ALL	0.811930416054
Traffic	0.594352576961
EMS	0.754139525183

07. Predict events for a single day in 2017

In [3547]:

```
# we will use trained GradientBoostingRegressor model to estimate 911 calls
# in a single day of 2017, based on the 2016 year data
# we need to generate list containing all time slots in a single day and "active" geogrid locations
# the selected date will be 19 May 2017 (arbitrary date)
# note we cannot use all geogrid locations as not for all we have the data
# and model will not be able to predict anything meaningful for them
# the county map does not cover the whole grid.
# So we will use the previous dt_geogrid variable to get "active" locations
singleday_dt = []
# record structure is month,week,dayofweek,day,day_part,lat_grid,lng_grid
row_base = [5,20,4,19] #base row with date 19 May 2017, Wednesday. Change it to get another day.
for day_idx in range(24/hours_range):
    for idx,row in dt_geogrid.iterrows():
        singleday_dt.append(row_base+[day_idx,row['lat_grid'],row['lng_grid']])
singleday_dt = pd.DataFrame(singleday_dt,columns=final_columns[:7])
singleday_dt.head(3)
```

Out[3547]:

	month	week	dayofweek	day	day_part	lat_grid	lng_grid
0	5	20	4	19	0	0	3
1	5	20	4	19	0	0	4
2	5	20	4	19	0	0	5

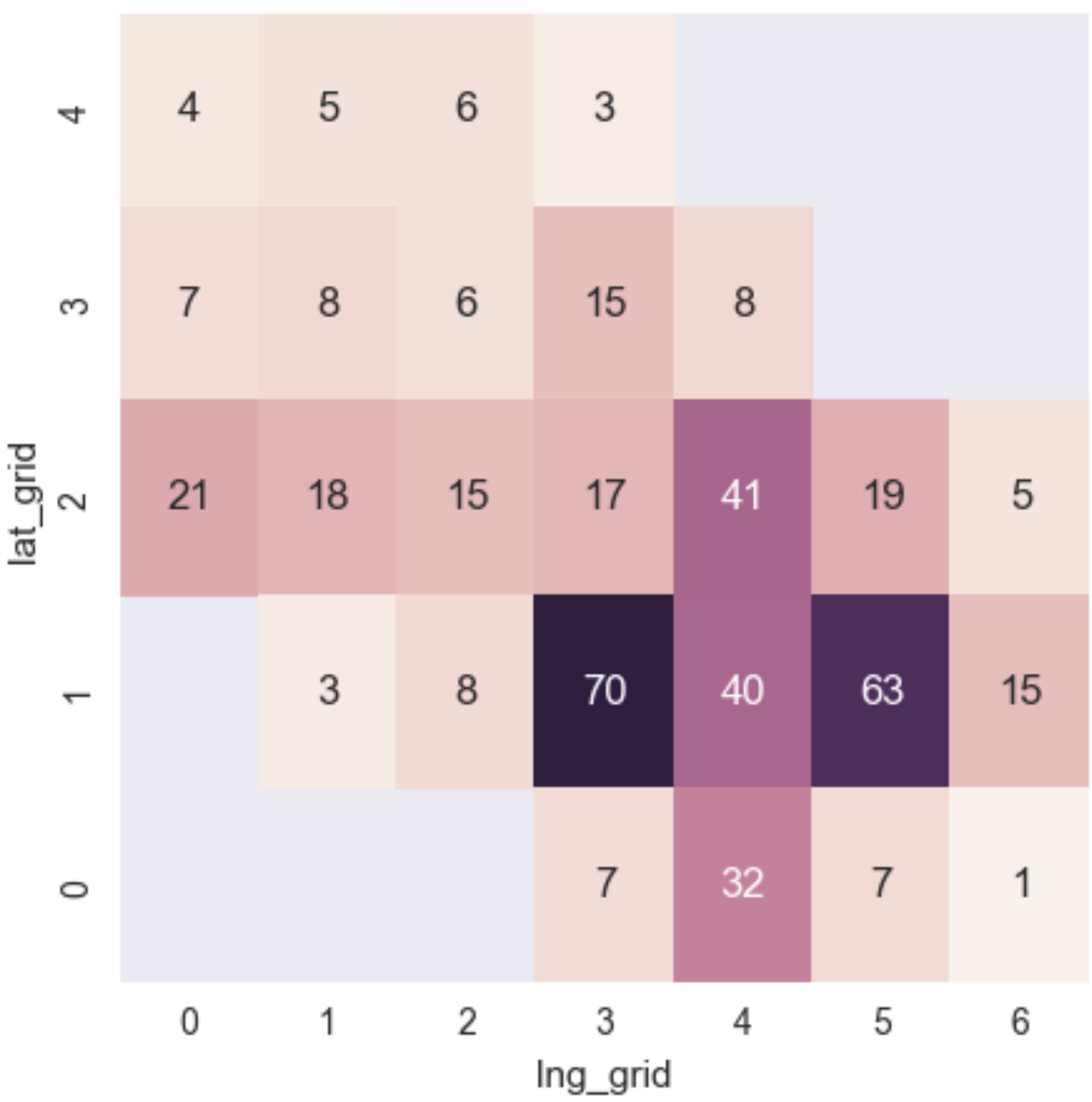
In [3548]:

```
# we will pass generated data to scikit-learn model predict method to see the result
predictions_all = trained_models['ALL'].predict(singleday_dt)
singleday_dt_full = singleday_dt
singleday_dt_full['events'] = predictions_all
print ("Total number of 911 events in selected day is : ", round(singleday_dt_full['events'].sum()))
```

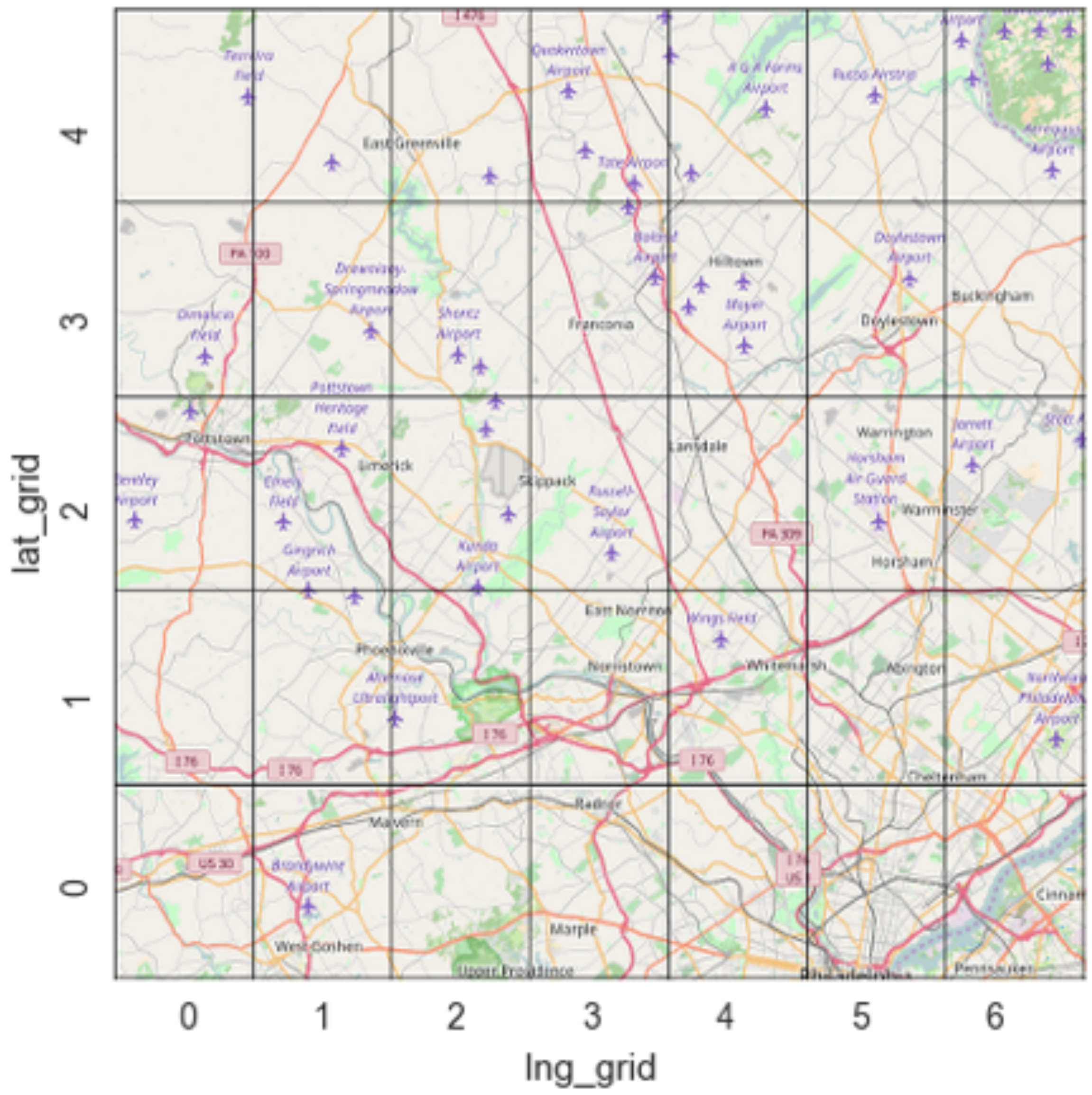
```
Total number of 911 events in selected day is :  448.0
```

In [3549]:

```
# now we can visualize our data for 19 May 2017 on the map.
dt_geogrid = singleday_dt_full.groupby(['lat_grid','lng_grid']).agg({'events': np.sum}).reset_index()
dt_geoheatmap = dt_geogrid.pivot(index='lat_grid', columns='lng_grid', values='events')
# generate heatmap
fig, ax = plt.subplots(figsize=(5,5))
ax = sns.heatmap(dt_geoheatmap,annot=True,fmt=".0f",cbar=False)
ax.invert_yaxis()
sns.plt.show()
fig = ax.get_figure()
fig.savefig("6.png")
print ("US PA Montgomery County Reference map")
print ("Map source: OpenStreetMap.org, Map license: Open Data Commons Open Database License (ODbL).")
img = Image(filename = "montco-map-grid.png", width=480, height=480)
display(img)
```

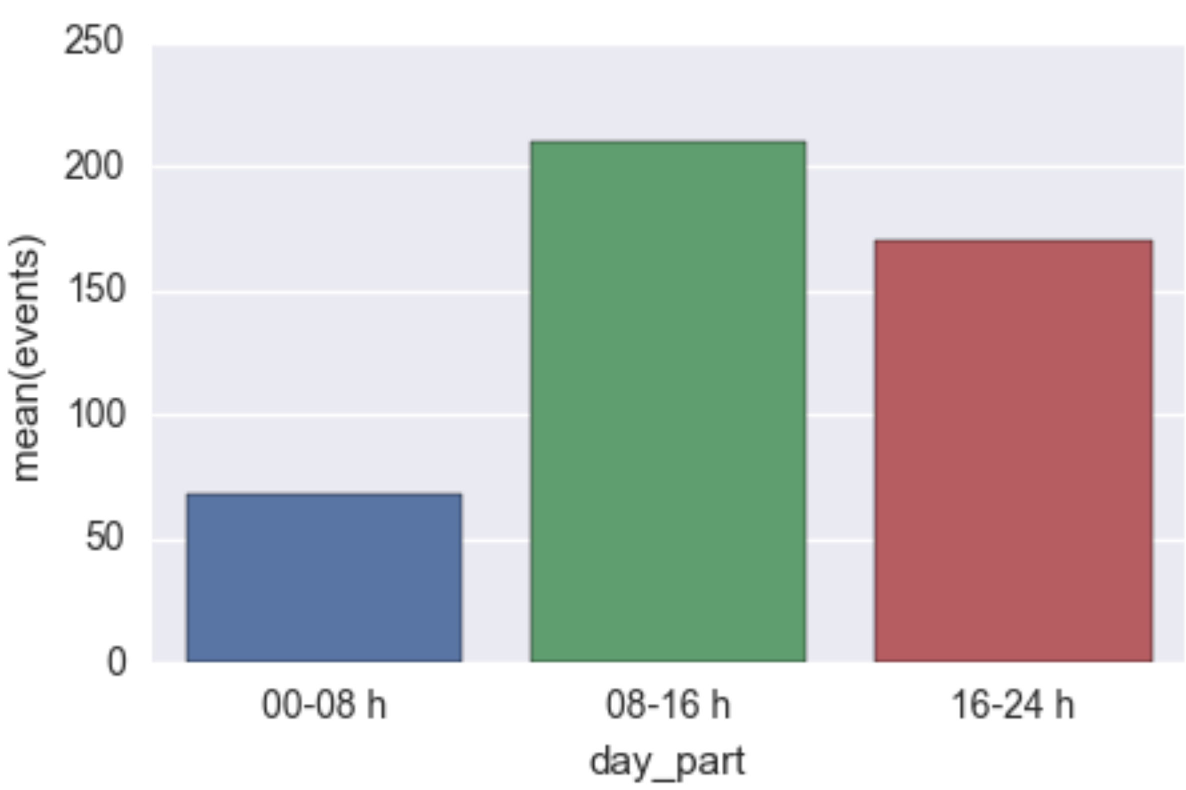



```
US PA Montgomery County Reference map
Map source: OpenStreetMap.org, Map license: Open Data Commons Open Database License (ODbL).
```



In [3550]:

```
data_timeevents = singleday_dt_full.groupby(['day_part']).agg({'events': np.sum}).reset_index()
fig, ax = plt.subplots(figsize=(5,3))
ax = sns.barplot(x="day_part", y="events", data=data_timeevents)
ax.axes.set_yticklabels(["16-24 h","08-16 h","00-08 h"])
pass
```



08. Summary

Let's check whether we have achieved our goals:

1. predict number of help & rescue (911) events in US (PA) Montgomery County in arbitrary day of 2017
   - PASSED, we can predict data for any day using our trained model.
2. prediction should provide number of events by time of day and by general location
   - PASSED, we can get prediction per time of day and per geolocation grid
3. prediction should be based on 2016 data
   - PASSED, model is trained on 2016 data
4. we must know the goodness of the prediction
   - PASSED, The overall goodness (R2 score) for 2017 is 0.81
5. some guidance, regarding type of the event would be nice, too.
   - PARTIALLY PASSED. We know general relation between number of events in each category. So we know that most of events is in EMS category, followed by Traffic. Fire events are the last. However, the prediction goodness for categories is too low to use it (is acceptable for for EMS where equals 0.75 , but for FIRE is just 0.32. Seems that fire events are quite hard to predict).

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My name is Lucas and I am an Senior IT Business Anayst with over 10 years of experience in IT system development and integration. I have worked for several large international companies from industries such as: IT, finance, insurance, telecommunications, pharmacy and gambling. I took part in multiple IT projects, ranging from small budgets (hundreds thousands of US dollars) to large (multiple millions of US dollars). A year ago (in 2016), encouraged by a friend, I completed Andrew Ng Machine Learning course on Coursera and I got fascinated by this subject. So I decided to master it. Feel free to contact me via my Email address: lucas.mlexp@gmail.com / Linkedin profile: https://www.linkedin.com/in/lukaszmruk / Twitter account: https://twitter.com/ml_exp

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