Before you turn in the homework, make sure everything runs as expected. To do so, select **Kernel →Restart & Run All** in the toolbar above. Remember to submit both on **DataHub** and **Gradescope**.

Please fill in your name and include a list of your collaborators below.

In [1]:
```
NAME = "Benjamin Liu"
COLLABORATORS = ""
```

Project 2: NYC Taxi Rides

Part 3: NYC Accidents Data

In the real world, data isn't always nicely bundled in one file; data can be sourced from many places with many formats. Now we will use NYC accident data to try to improve our set of features.

In this part of the project, you'll do some EDA over the combined data set. We'll do a lot of the coding work for you, but there will be a few coding subtasks for you to complete on your own, as well as many results to interpret.

Note

If your kernel dies unexpectedly, make sure you have shutdown all other notebooks. Each notebook uses valuable memory which we will need for this part of the project.

Imports

Let us start by loading the Python libraries and custom tools we will use in this part.

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import zipfile
import os
from pathlib import Path

sns.set(style="whitegrid", palette="muted")

plt.rcParams['figure.figsize'] = (12, 9)
plt.rcParams['font.size'] = 12

%matplotlib inline
```

Downloading the Data

We will use the `fetch_and_cache` utility to download the dataset.

In [3]:
```
# Download and cache urls and get the file objects.
from utils import fetch_and_cache
data_url = 'https://github.com/DS-100/fa18/raw/gh-pages/assets/datasets/collisio
file_name = 'collisions.zip'
dest_path = fetch_and_cache(data_url=data_url, file=file_name)

print(f'Located at {dest_path}')
```

```
Using version already downloaded: Sun Nov 25 04:22:44 2018
MD5 hash of file: a445b925d24f319cb60bd3ace6e4172b
Located at data/collisions.zip
```

We will store the taxi data locally before loading it.

In [4]:
```
collisions_zip = zipfile.ZipFile(dest_path, 'r')

#Extract zip files
collisions_dir = Path('data/collisions')
collisions_zip.extractall(collisions_dir)
```

Loading and Formatting Data

The following code loads the collisions data into a Pandas DataFrame.

In [5]:
```
# Run this cell to load the collisions data.
skiprows = None
collisions = pd.read_csv(collisions_dir/'collisions_2016.csv', index_col='UNIQUE
                         parse_dates={'DATETIME':["DATE","TIME"]}, skiprows=skip
collisions['TIME'] = pd.to_datetime(collisions['DATETIME']).dt.hour
collisions['DATE'] = pd.to_datetime(collisions['DATETIME']).dt.date
collisions = collisions.dropna(subset=['LATITUDE', 'LONGITUDE'])
collisions = collisions[collisions['LATITUDE'] <= 40.85]
collisions = collisions[collisions['LATITUDE'] >= 40.63]
collisions = collisions[collisions['LONGITUDE'] <= -73.65]
collisions = collisions[collisions['LONGITUDE'] >= -74.03]
collisions.info()
```

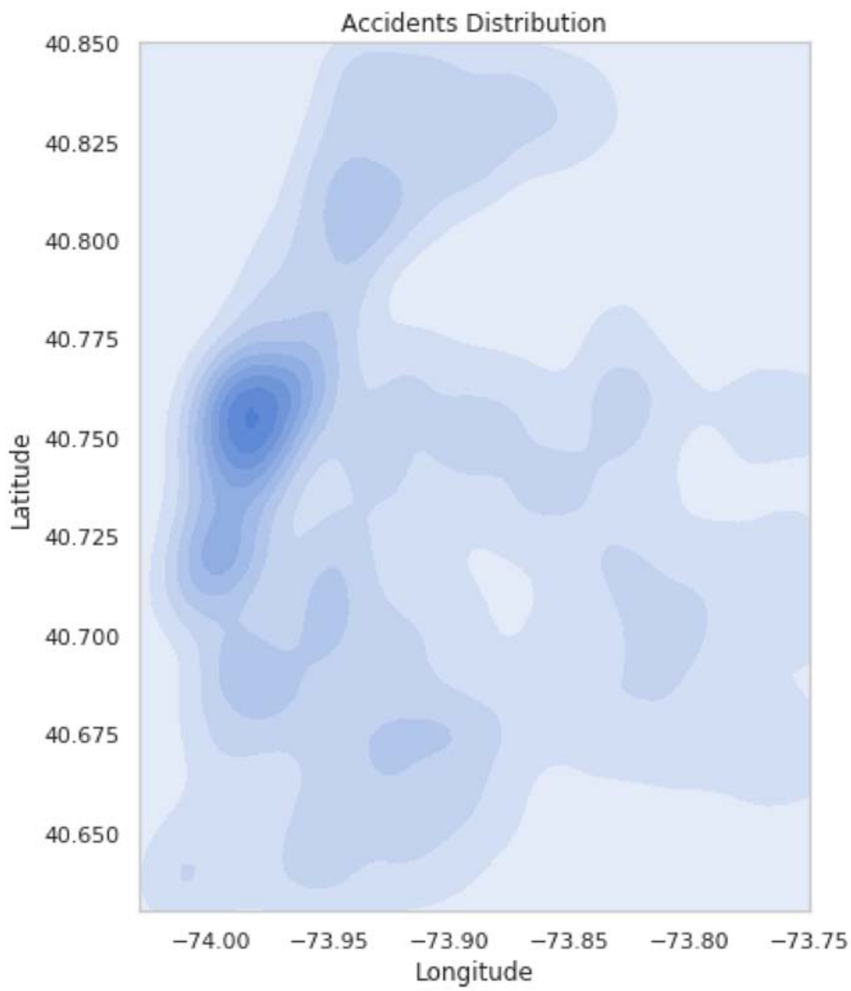
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 116691 entries, 3589202 to 3363795
Data columns (total 30 columns):
DATETIME                         116691 non-null datetime64[ns]
Unnamed: 0                       116691 non-null int64
BOROUGH                          100532 non-null object
ZIP CODE                         100513 non-null float64
LATITUDE                         116691 non-null float64
LONGITUDE                        116691 non-null float64
LOCATION                         116691 non-null object
ON STREET NAME                   95914 non-null object
CROSS STREET NAME                95757 non-null object
OFF STREET NAME                  61545 non-null object
NUMBER OF PERSONS INJURED        116691 non-null int64
NUMBER OF PERSONS KILLED         116691 non-null int64
NUMBER OF PEDESTRIANS INJURED    116691 non-null int64
NUMBER OF PEDESTRIANS KILLED     116691 non-null int64
NUMBER OF CYCLIST INJURED        116691 non-null int64
NUMBER OF CYCLIST KILLED         116691 non-null int64
NUMBER OF MOTORIST INJURED       116691 non-null int64
NUMBER OF MOTORIST KILLED        116691 non-null int64
CONTRIBUTING FACTOR VEHICLE 1    115162 non-null object
CONTRIBUTING FACTOR VEHICLE 2    101016 non-null object
CONTRIBUTING FACTOR VEHICLE 3    7772 non-null object
CONTRIBUTING FACTOR VEHICLE 4    1829 non-null object
CONTRIBUTING FACTOR VEHICLE 5    434 non-null object
VEHICLE TYPE CODE 1              115181 non-null object
VEHICLE TYPE CODE 2              92815 non-null object
VEHICLE TYPE CODE 3              7260 non-null object
VEHICLE TYPE CODE 4              1692 non-null object
VEHICLE TYPE CODE 5              403 non-null object
TIME                             116691 non-null int64
DATE                             116691 non-null object
dtypes: datetime64[ns](1), float64(3), int64(10), object(16)
memory usage: 27.6+ MB
```

1: EDA of Accidents

Let's start by plotting the latitude and longitude where accidents occur. This may give us some insight on taxi ride durations. We sample N times (given) from the collisions dataset and create a 2D KDE plot of the longitude and latitude. We make sure to set the x and y limits according to the boundaries of New York, given below.

Here is a [map of Manhattan (https://www.google.com/maps/place/Manhattan,+New+York,+NY/@40.7590402,-74.0394431,12z/da 73.9712488)](https://www.google.com/maps/place/Manhattan,+New+York,+NY/@40.7590402,-74.0394431,12z/da73.9712488) for your convenience.

In [6]:
```
# Plot lat/lon of accidents, will take a few seconds
N = 20000
city_long_border = (-74.03, -73.75)
city_lat_border = (40.63, 40.85)

sample = collisions.sample(N)
plt.figure(figsize=(6,8))
sns.kdeplot(sample["LONGITUDE"], sample["LATITUDE"], shade=True)
plt.xlim(city_long_border)
plt.ylim(city_lat_border)
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.title("Accidents Distribution")
plt.show();
```



Question 1a

What can you say about the location density of NYC collisions based on the plot above?

Hint: Here is a [page (https://www.google.com/maps/place/Manhattan,+New+York,+NY/@40.7590402,-74.0394431,12 73.9712488)](https://www.google.com/maps/place/Manhattan,+New+York,+NY/@40.7590402,-74.0394431,12) that may be useful, and [another page (https://www.6sqft.com/what-nycs-population-looks-like-day-vs-night/)](https://www.6sqft.com/what-nycs-population-looks-like-day-vs-night/) that may be useful.

In [7]:
```
q1a_answer = r"""

Since most NYC people lives in the midtown of Manhattan, traffic collisions is de

"""

# YOUR CODE HERE
# raise NotImplementedError()

print(q1a_answer)
```

```
Since most NYC people lives in the midtown of Manhattan, traffic collisions is 
dense in that area. In general, it makes sense that the collosions density is h
igh in area where there are many people.
```

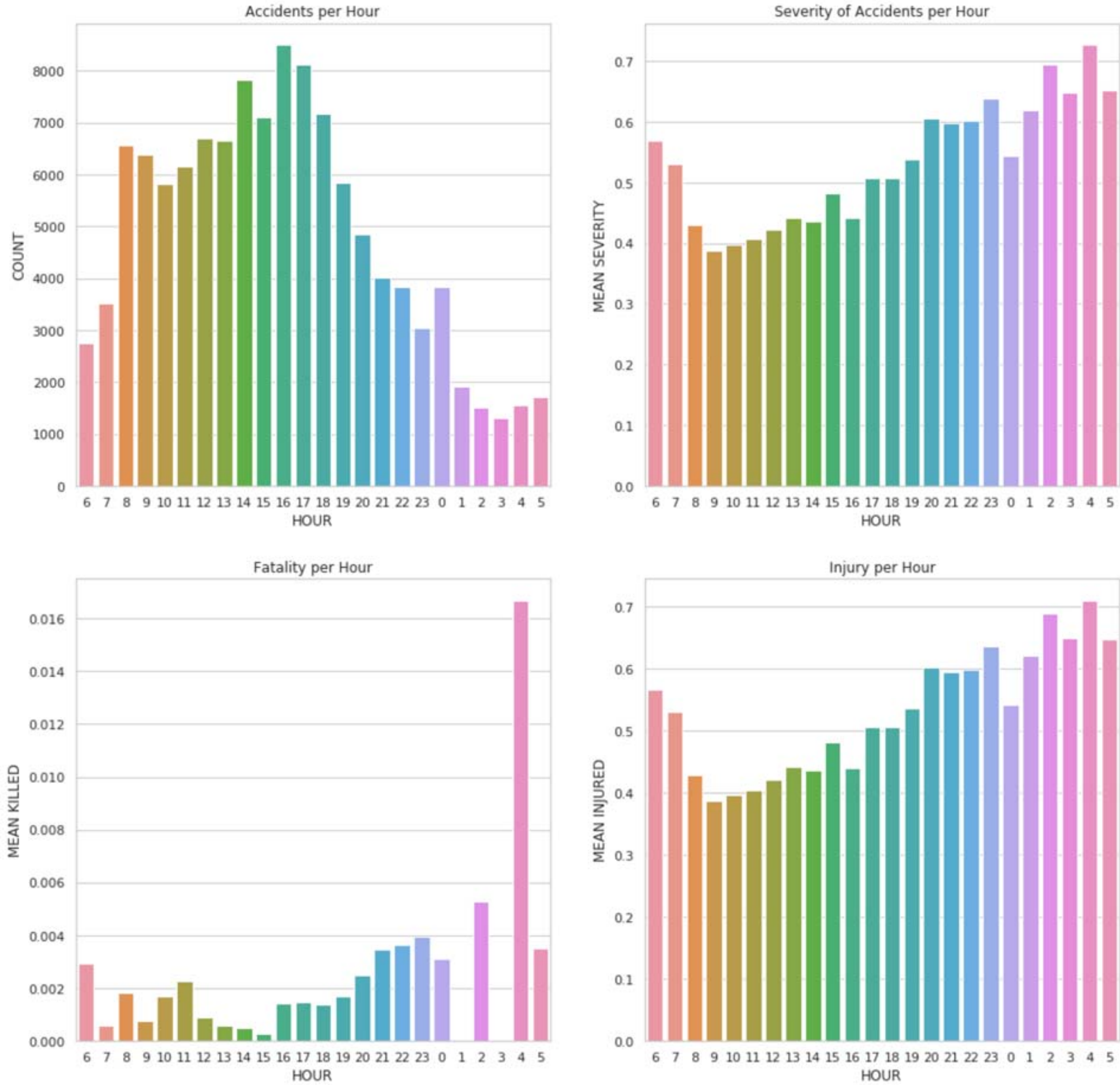
We see that an entry in accidents contains information on number of people injured/killed. Instead of using each of these columns separately, let's combine them into one column called `'SEVERITY'`. Let's also make columns `FATALITY` and `INJURY`, each aggregating the fatalities and injuries respectively.

In [8]:
```
collisions['SEVERITY'] = collisions.filter(regex=r'NUMBER OF *').sum(axis=1)
collisions['FATALITY'] = collisions.filter(regex=r'KILLED').sum(axis=1)
collisions['INJURY'] = collisions.filter(regex=r'INJURED').sum(axis=1)
```

Now let's group by time and compare two aggregations: count vs mean. Below we plot the number of collisions and the mean severity of collisions by the hour, i.e. the `TIME` column. We visualize them side by side and set the start of our day to be 6 a.m.

Let's also take a look at the mean number of casualties per hour and the mean number of injuries per hour, plotted below.

In [9]:
```
fig, axes = plt.subplots(2, 2, figsize=(16,16))
order = np.roll(np.arange(24), -6)
ax1 = axes[0,0]
ax2 = axes[0,1]
ax3 = axes[1,0]
ax4 = axes[1,1]

collisions_count = collisions.groupby('TIME').count()
collisions_count = collisions_count.reset_index()
sns.barplot(x='TIME', y='SEVERITY', data=collisions_count, order=order, ax=ax1)
ax1.set_title("Accidents per Hour")
ax1.set_xlabel("HOUR")
ax1.set_ylabel('COUNT')


collisions_mean = collisions.groupby('TIME').mean()
collisions_mean = collisions_mean.reset_index()
sns.barplot(x='TIME', y='SEVERITY', data=collisions_mean, order=order, ax=ax2)
ax2.set_title("Severity of Accidents per Hour")
ax2.set_xlabel("HOUR")
ax2.set_ylabel('MEAN SEVERITY')

fatality_count = collisions.groupby('TIME').mean()
fatality_count = fatality_count.reset_index()
sns.barplot(x='TIME', y='FATALITY', data=fatality_count, order=order, ax=ax3)
ax3.set_title("Fatality per Hour")
ax3.set_xlabel("HOUR")
ax3.set_ylabel('MEAN KILLED')

injury_count = collisions.groupby('TIME').mean()
injury_count = injury_count.reset_index()
sns.barplot(x='TIME', y='INJURY', data=injury_count, order=order, ax=ax4)
ax4.set_title("Injury per Hour")
ax4.set_xlabel("HOUR")
ax4.set_ylabel('MEAN INJURED')

plt.show();
```



Question 1b

Based on the visualizations above, what can you say about each? Make a comparison between the accidents per hour vs the mean severity per hour. What about the number of fatalities per hour vs the number of injuries per hour? Why do we chose to have our hours start at 6 as opposed to 0?

In [10]:
```
q1b_answer = r"""

Accidents per hour vs mean severity per hour: Between 8pm to 7am, there are relat

Number of fatalities per hour vs number of injuries per hour: Except for 4am, the

Besause naturally for human drivers, a "driving day" starts at 6am and ends with

"""

# YOUR CODE HERE
# raise NotImplementedError()

print(q1b_answer)
```

```
Accidents per hour vs mean severity per hour: Between 8pm to 7am, there are rel
atively fewer accidents but the mean severity is high.

Number of fatalities per hour vs number of injuries per hour: Except for 4am, t
he fatalities per hour is tiny. The number of injuries per hour is on average h
igh.

Besause naturally for human drivers, a "driving day" starts at 6am and ends wit
h 5am of next day.
```

Let's also check the relationship between location and severity. We provide code to visualize a heat map of collisions, where the x and y coordinate are the location of the collision and the heat color is the severity of the collision. Again, we sample N points to speed up visualization.

In [11]:
```
N = 10000
sample = collisions.sample(N)

# Round / bin the latitude and longitudes
sample['lat_bin'] = np.round(sample['LATITUDE'], 3)
sample['lng_bin'] = np.round(sample['LONGITUDE'], 3)

# Average severity for regions
gby_cols = ['lat_bin', 'lng_bin']

coord_stats = (sample.groupby(gby_cols)
               .agg({'SEVERITY': 'mean'})
               .reset_index())

# Visualize the average severity per region
city_long_border = (-74.03, -73.75)
city_lat_border = (40.63, 40.85)
fig, ax = plt.subplots(ncols=1, nrows=1, figsize=(14, 10))

scatter_trips = ax.scatter(sample['LONGITUDE'].values,
                           sample['LATITUDE'].values,
                           color='grey', s=1, alpha=0.5)

scatter_cmap = ax.scatter(coord_stats['lng_bin'].values,
                          coord_stats['lat_bin'].values,
                          c=coord_stats['SEVERITY'].values,
                          cmap='viridis', s=10, alpha=0.9)

cbar = fig.colorbar(scatter_cmap)
cbar.set_label("Manhattan average severity")
ax.set_xlim(city_long_border)
ax.set_ylim(city_lat_border)
ax.set_xlabel('Longitude')
ax.set_ylabel('Latitude')
plt.title('Heatmap of Manhattan average severity')
plt.axis('off');
```

Question 1c

Do you think the location of the accident has a significant impact on the severity based on the visualization above? Additionally, identify something that could be improved in the plot above and describe how we could improve it.

In [12]:
```
q1c_answer = r"""

Based on the scatter plot above, I think the location of accident doesn't have a

Many data points actually overlap each other. We can add some tiny random noise t

"""

# YOUR CODE HERE
# raise NotImplementedError()

print(q1c_answer)
```

```
Based on the scatter plot above, I think the location of accident doesn't have
a significant impact on the collisions severity.

Many data points actually overlap each other. We can add some tiny random noise
to the longitude and latitude of each data point.
```

Question 1d

Create a plot to visualize one or more features of the `collisions` table.

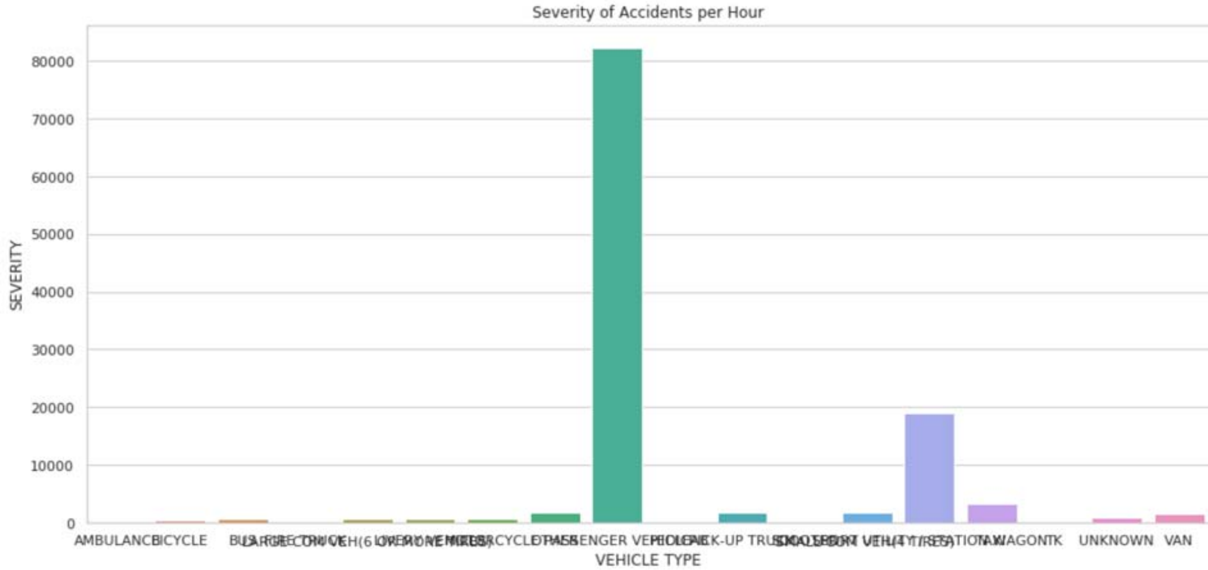
In [13]:
```
collisions.head()
```

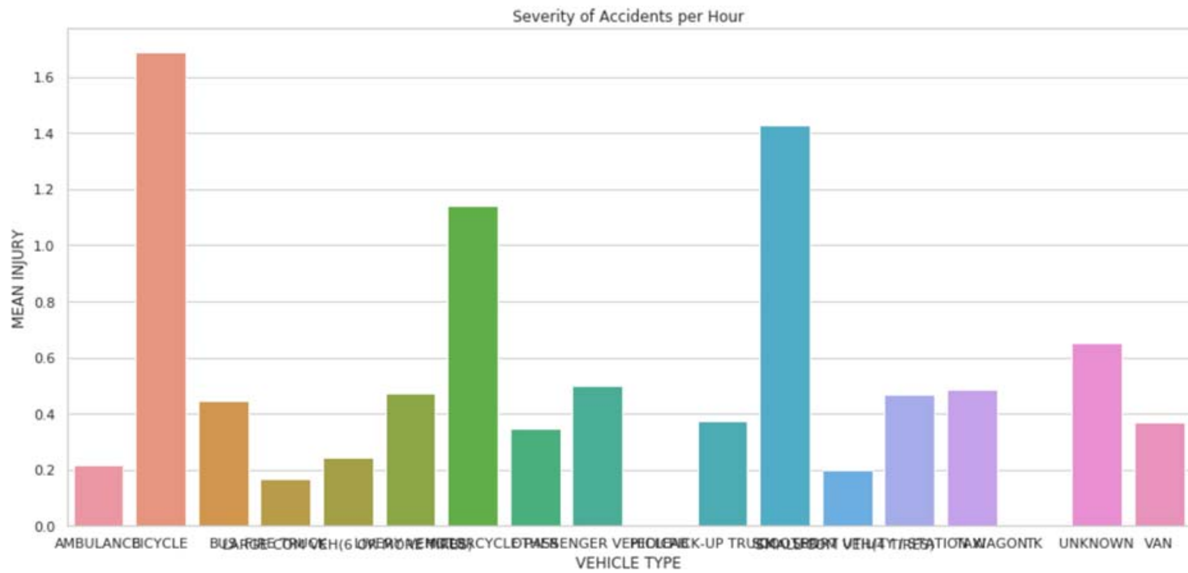
Out[13]:

	DATETIME	Unnamed: 0	BOROUGH	ZIP CODE	LATITUDE	LONGITUDE	LOCATION	ON STREET NAME
UNIQUE KEY								
3589202	2016-12-29 00:00:00	207836	NaN	NaN	40.844107	-73.897997	(40.8441075, -73.8979971)	NaN
3587413	2016-12-26 14:30:00	208475	NaN	NaN	40.692347	-73.881778	(40.6923473, -73.8817778)	NaN
3578151	2016-11-30 22:50:00	214339	NaN	NaN	40.755480	-73.741730	(40.75548, -73.74173)	NaN
3567096	2016-11-23 20:11:00	218291	NaN	NaN	40.771122	-73.869635	(40.7711224, -73.8696353)	NaN
3565211	2016-11-21 14:11:00	219698	NaN	NaN	40.828918	-73.838403	(40.8289179, -73.8384031)	NaN

5 rows × 33 columns

In [14]:
```
# YOUR CODE HERE
# raise NotImplementedError()
### BEGIN Solution
fig, axes = plt.subplots(2, 1, figsize=(16,16))
order = np.roll(np.arange(24), -6)
ax1 = axes[0]
ax2 = axes[1]

collisions_count = collisions.groupby('VEHICLE TYPE CODE 1').count()
collisions_count = collisions_count.reset_index()
sns.barplot(x='VEHICLE TYPE CODE 1', y='SEVERITY', data=collisions_count, ax=ax1
ax1.set_title("Severity of Accidents per Hour")
ax1.set_xlabel("VEHICLE TYPE")
ax1.set_ylabel('SEVERITY')


collisions_mean = collisions.groupby('VEHICLE TYPE CODE 1').mean()
collisions_mean = collisions_mean.reset_index()
sns.barplot(x='VEHICLE TYPE CODE 1', y='INJURY', data=collisions_mean, ax=ax2)
ax2.set_title("Severity of Accidents per Hour")
ax2.set_xlabel("VEHICLE TYPE")
ax2.set_ylabel('MEAN INJURY');

### END Solution
```





Question 1e

Answer the following questions regarding your plot in 1d.

1. What feature you're visualization
2. Why you chose this feature
3. Why you chose this visualization method

In [15]:
```
q1e_answer = r"""

I am visualizing the number of accidents catagorized by the involved vehicle type

I want to invistigate the relationship between vehicle type and accidents severit

Since the type of vehicles is catagorical data, it is good to use bar plot to vis

"""
# YOUR CODE HERE
# raise NotImplementedError()
print(q1e_answer)
```

```
I am visualizing the number of accidents catagorized by the involved vehicle ty
pe.

I want to invistigate the relationship between vehicle type and accidents sever
ity, injuries and hence I pick the vehicle type.

Since the type of vehicles is catagorical data, it is good to use bar plot to v
isualize multiple categorical data.
```

2: Combining External Datasets

It seems like accident timing and location may influence the duration of a taxi ride. Let's start to join our NYC Taxi data with our collisions data.

Let's assume that an accident will influence traffic in the surrounding area for around 1 hour. Below, we create two columns, `START` and `END` :

- `START` : contains the recorded time of the accident
- `END` : 1 hours after `START`

Note: We chose 1 hour somewhat arbitrarily, feel free to experiment with other time intervals outside this notebook.

In [16]:
```
collisions['START'] = collisions['DATETIME']
collisions['END'] = collisions['START'] + pd.Timedelta(hours=1)
```

Question 2a

Drop all of the columns besides the following: `DATETIME` , `TIME` , `START` , `END` , `DATE` , `LATITUDE` , `LONGITUDE` , `SEVERITY` . Feel free to experiment with other subsets outside of this notebook.

In [17]:
```
collisions_subset = collisions[["DATETIME", "TIME", "START", "END", "DATE", "LATI
# YOUR CODE HERE
# raise NotImplementedError()
collisions_subset.head(5)
```

Out[17]:

UNIQUE KEY	DATETIME	TIME	START	END	DATE	LATITUDE	LONGITUDE	SEVERITY
3589202	2016-12-29 00:00:00	0	2016-12-29 00:00:00	2016-12-29 01:00:00	2016-12-29	40.844107	-73.897997	0
3587413	2016-12-26 14:30:00	14	2016-12-26 14:30:00	2016-12-26 15:30:00	2016-12-26	40.692347	-73.881778	0
3578151	2016-11-30 22:50:00	22	2016-11-30 22:50:00	2016-11-30 23:50:00	2016-11-30	40.755480	-73.741730	2
3567096	2016-11-23 20:11:00	20	2016-11-23 20:11:00	2016-11-23 21:11:00	2016-11-23	40.771122	-73.869635	0
3565211	2016-11-21 14:11:00	14	2016-11-21 14:11:00	2016-11-21 15:11:00	2016-11-21	40.828918	-73.838403	0

In [18]:
```
assert collisions_subset.shape == (116691, 8)
```

Question 2b

Now, let's merge our `collisions_subset` table with `train_df`. Start by merging with only the date. We will filter by a time window in a later question.

We should be performing a left join, where our `train_df` is the left table. This is because we want to preserve all of the taxi rides in our end result. It happens that an inner join will also work, since both tables contain data on each date.

Note that the resulting `merged` table will have multiple rows for every taxi ride row in the original `train_df` table. For example, `merged` will have 483 rows with `index` equal to 16709, because there were 483 accidents that occurred on the same date as ride #16709.

Because of memory limitation, we will select the third week of 2016 to analyze. Feel free to change to it week 1 or 2 to see if the observation is general.

In [19]:
```
data_file = Path("./", "cleaned_data.hdf")
train_df = pd.read_hdf(data_file, "train")
train_df = train_df.reset_index()
train_df = train_df[['index', 'tpep_pickup_datetime', 'pickup_longitude', 'picku
train_df['date'] = train_df['tpep_pickup_datetime'].dt.date
```

In [20]:
```
collisions_subset = collisions_subset[collisions_subset['DATETIME'].dt.weekofyea
train_df = train_df[train_df['tpep_pickup_datetime'].dt.weekofyear == 3]
```

In [21]:
```
# merge the dataframe here
merged = pd.merge(train_df, collisions_subset, how="left", left_on="date", right_

# YOUR CODE HERE
# raise NotImplementedError()

merged.head()
```

Out[21]:

	index	tpep_pickup_datetime	pickup_longitude	pickup_latitude	duration	date	DATETIME	TIM
0	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 10:35:00	1
1	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 13:20:00	1
2	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 16:00:00	1
3	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 18:30:00	1
4	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 00:05:00	

In [22]:
```
assert merged.shape == (1528162, 14)
```

Question 2c

Now that our tables are merged, let's use temporal and spatial proximity to condition on the duration of the average length of a taxi ride. Let's operate under the following assumptions.

Accidents only influence the duration of a taxi ride if the following are satisfied:

1) The haversine distance between the the pickup location of the taxi ride and location of the recorded accident is within 5 (km). This is roughly 3.1 miles.

2) The start time of a taxi ride is within a 1 hour interval between the start and end of an accident.

Complete the code below to create an `'accident_close'` column in the `merged` table that indicates if an accident was close or not according to the assumptions above.

In [23]:
```
def haversine(lat1, lng1, lat2, lng2):
    """
    Compute haversine distance
    """
    lat1, lng1, lat2, lng2 = map(np.radians, (lat1, lng1, lat2, lng2))
    average_earth_radius = 6371
    lat = lat2 - lat1
    lng = lng2 - lng1
    d = np.sin(lat * 0.5) ** 2 + np.cos(lat1) * np.cos(lat2) * np.sin(lng * 0.5)
    h = 2 * average_earth_radius * np.arcsin(np.sqrt(d))
    return h

def manhattan_distance(lat1, lng1, lat2, lng2):
    """
    Compute Manhattan distance
    """
    a = haversine(lat1, lng1, lat1, lng2)
    b = haversine(lat1, lng1, lat2, lng1)
    return a + b
```

In [24]:
```
start_to_accident = haversine(merged['pickup_latitude'].values,
                              merged['pickup_longitude'].values,
                              merged['LATITUDE'].values,
                              merged['LONGITUDE'].values)
merged['start_to_accident'] = start_to_accident

# initialze accident_close column to all 0 first
merged['accident_close'] = 0

# Boolean pd.Series to select the indices for which accident_close should equal 1
# (1) record's start_to_accident <= 5
# (2) pick up time is between start and end
is_accident_close = np.array(merged['start_to_accident'] <= 5) & (np.array(merged
# YOUR CODE HERE
# raise NotImplementedError()

merged.loc[is_accident_close, 'accident_close'] = 1
```

In [25]:
```
assert merged['accident_close'].sum() > 16000
```

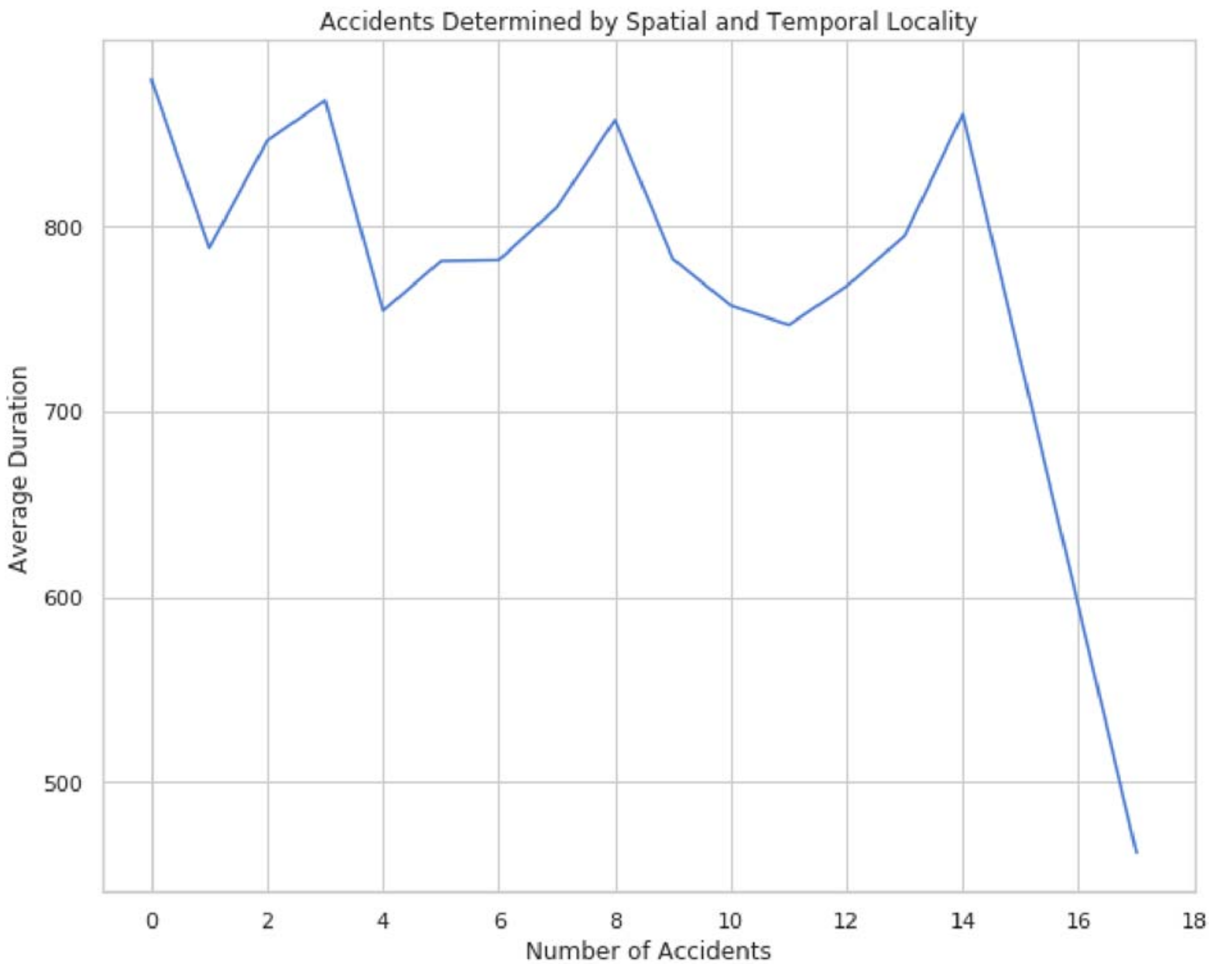
The last step is to aggregate the total number of proximal accidents. We want to count the total number of accidents that were close spatially and temporally and condition on that data.

The code below create a new data frame called `train_accidents` , which is a copy of `train_df` , but with a new column that counts the number of accidents that were close (spatially and temporally) to the pickup location/time.

In [26]:
```
train_df = train_df.set_index('index')
num_accidents = merged.groupby(['index'])['accident_close'].sum().to_frame()
train_accidents = train_df.copy()
train_accidents['num_accidents'] = num_accidents
```

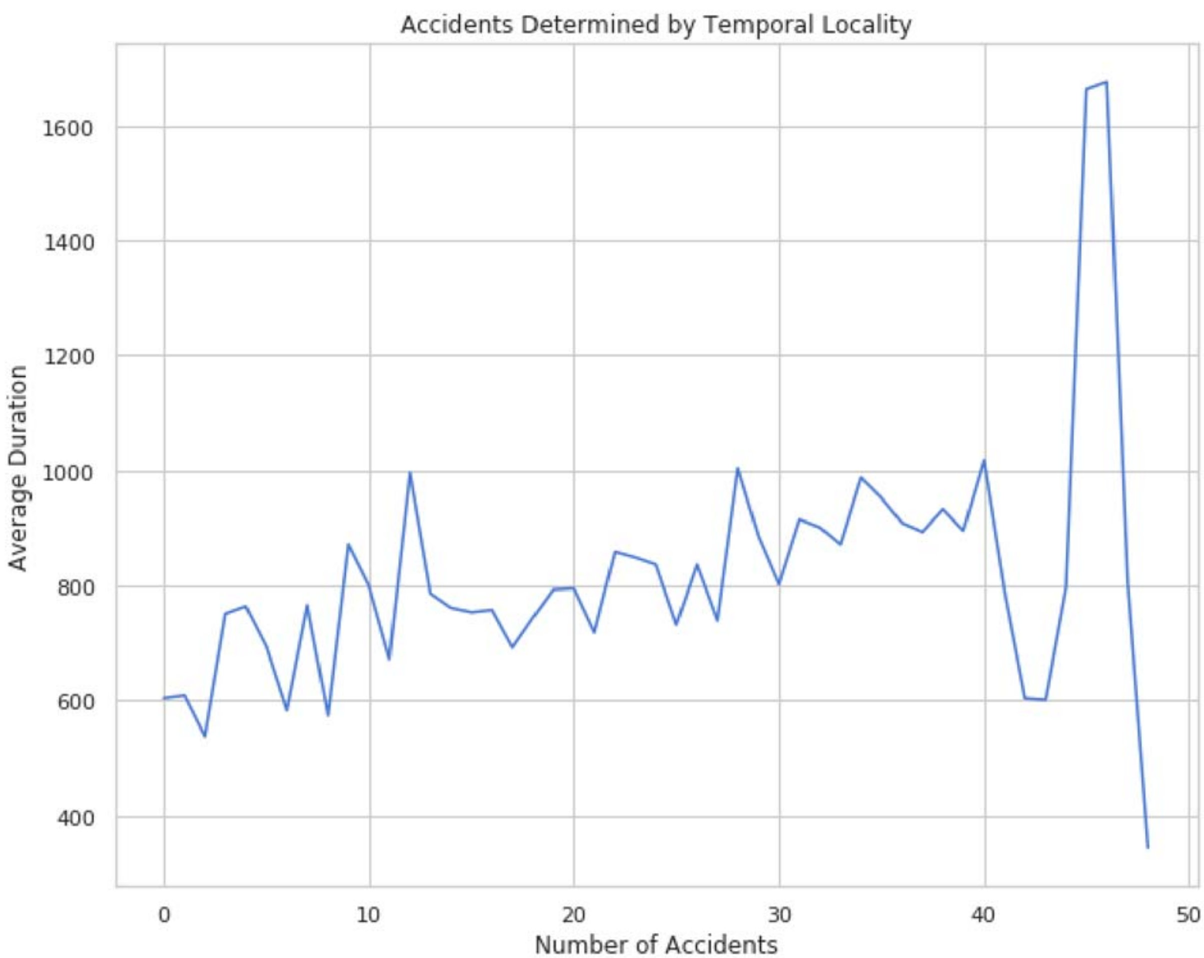
Next, for each value of `num_accidents` , we plot the average `duration` of rides with that number of accidents.

In [27]:
```
plt.figure(figsize=(10,8))
train_accidents.groupby('num_accidents')['duration'].mean().plot(xticks=np.arang
plt.title("Accidents Determined by Spatial and Temporal Locality")
plt.xlabel("Number of Accidents")
plt.ylabel("Average Duration")
plt.show();
```

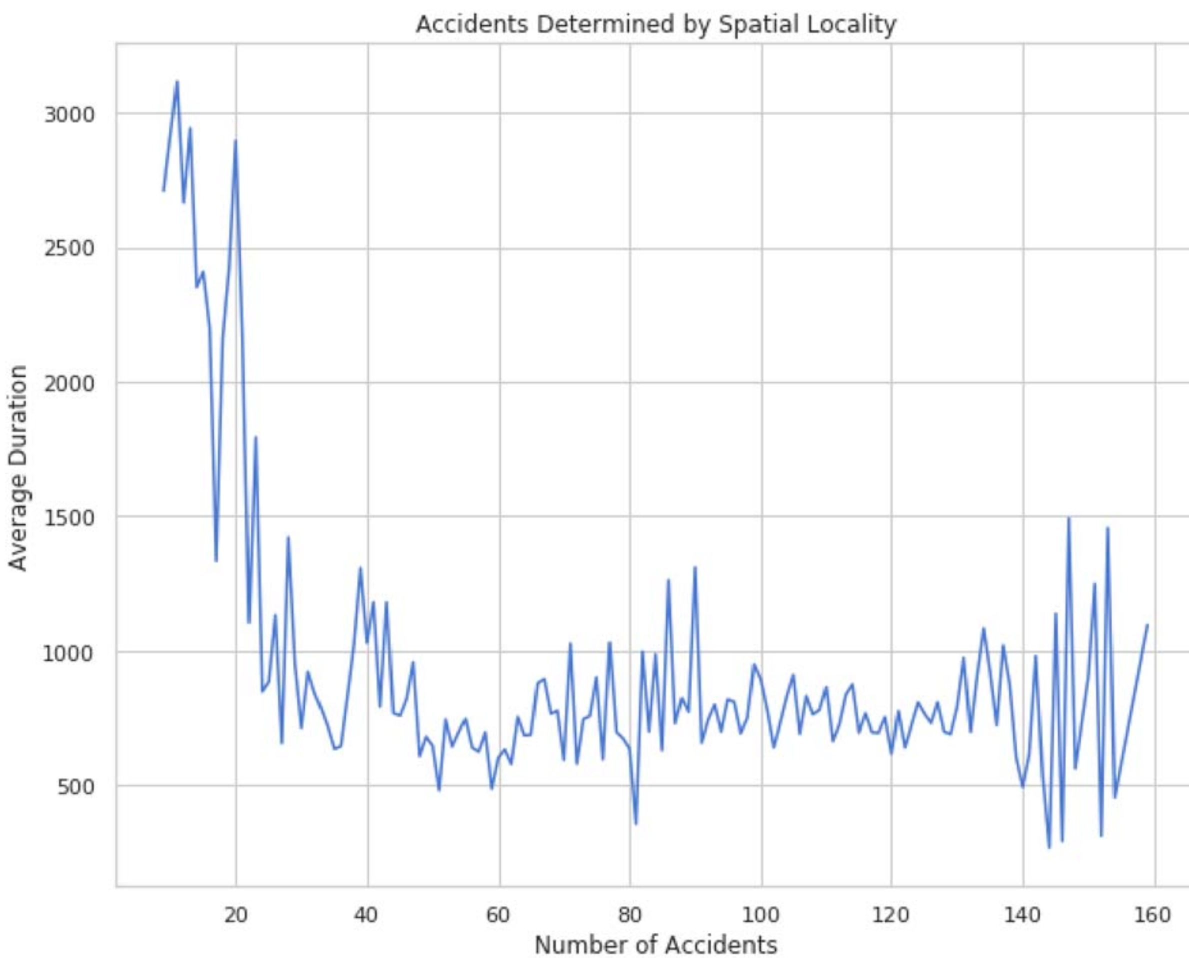


It seems that using both spatial and temporal proximity doesn't give us much insight on if collisions increase taxi ride durations. Let's try conditioning on spatial proximity and temporal proximity separately and see if there are more interesting results there.

In [28]:
```
# Temporal locality

# Condition on time
index = (((merged['tpep_pickup_datetime'] >= merged['START']) & \
         (merged['tpep_pickup_datetime'] <= merged['END'])))

# Count accidents
merged['accident_close'] = 0
merged.loc[index, 'accident_close'] = 1
num_accidents = merged.groupby(['index'])['accident_close'].sum().to_frame()
train_accidents_temporal = train_df.copy()
train_accidents_temporal['num_accidents'] = num_accidents

# Plot
plt.figure(figsize=(10,8))
train_accidents_temporal.groupby('num_accidents')['duration'].mean().plot()
plt.title("Accidents Determined by Temporal Locality")
plt.xlabel("Number of Accidents")
plt.ylabel("Average Duration")
plt.show();
```



In [29]:
```
# Spatial locality

# Condition on space
index = (merged['start_to_accident'] <= 5)

# Count accidents
merged['accident_close'] = 0
merged.loc[index, 'accident_close'] = 1
num_accidents = merged.groupby(['index'])['accident_close'].sum().to_frame()
train_accidents_spatial = train_df.copy()
train_accidents_spatial['num_accidents'] = num_accidents

# Plot
plt.figure(figsize=(10,8))
train_accidents_spatial.groupby('num_accidents')['duration'].mean().plot()
plt.title("Accidents Determined by Spatial Locality")
plt.xlabel("Number of Accidents")
plt.ylabel("Average Duration")
plt.show();
```



Question 2d

By conditioning on temporal and spatial proximity separately, we reveal different trends in average ride duration as a function of number of accidents nearby.

What can you say about the temporal and spatial proximity of accidents to taxi rides and the effect on ride duration? Think of a new hypothesis regarding accidents and taxi ride durations and explain how you would test it.

Additionally, comment on some of the assumptions being made when we condition on temporal and spatial proximity separately. What are the implications of only considering one and not the other?

In [30]:
```
q2d_answer = r"""

If the accidents are temporally closed, in a certain range, the more accidents, t
If the accidents are spatially closed, the more accidents, the shorter the ride d

Hypothesis:

When we conditioned on temporal proximity, we assume the other factors are the sa
When we conditioned on spatial proximity, we assume the other factors are the sam

"""

# YOUR CODE HERE
# raise NotImplementedError()

print(q2d_answer)
```

```
If the accidents are temporally closed, in a certain range, the more accidents,
the longger the mean ride duration.
If the accidents are spatially closed, the more accidents, the shorter the ride
duration on average.

Hypothesis:

When we conditioned on temporal proximity, we assume the other factors are the
same.
When we conditioned on spatial proximity, we assume the other factors are the s
ame. We are also assuming independency of the temporal and spatial proximity.
```

Part 3 Exports

We are not requiring you to export anything from this notebook, but you may find it useful to do so. There is a space below for you to export anything you wish.

In [31]:
```
Path("data/part3").mkdir(parents=True, exist_ok=True)
data_file = Path("data/part3", "data_part3.hdf") # Path of hdf file
...
```

Out[31]:
```
Ellipsis
```

Part 3 Conclusions

We merged the NYC Accidents dataset with our NYC Taxi dataset, conditioning on temporal and spatial locality. We explored potential features by visualizing the relationship between number of accidents and the average duration of a ride.

Please proceed to part 4 where we will be engineering more features and building our models using a processing pipeline.

Submission

You're almost done!

Before submitting this assignment, ensure that you have:

1. Restarted the Kernel (in the menubar, select Kernel→Restart & Run All)
2. Validated the notebook by clicking the "Validate" button.

Then,

1. **Submit** the assignment via the Assignments tab in **Datahub**
2. **Upload and tag** the manually reviewed portions of the assignment on **Gradescope**

In [ ]:

In [ ]: