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 = "Junsheng"
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/collisions.zip'
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: Sat Dec  1 01:41:10 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 KEY',
                         parse_dates={'DATETIME':["DATE","TIME"]}, skiprows=skiprows)
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()
```

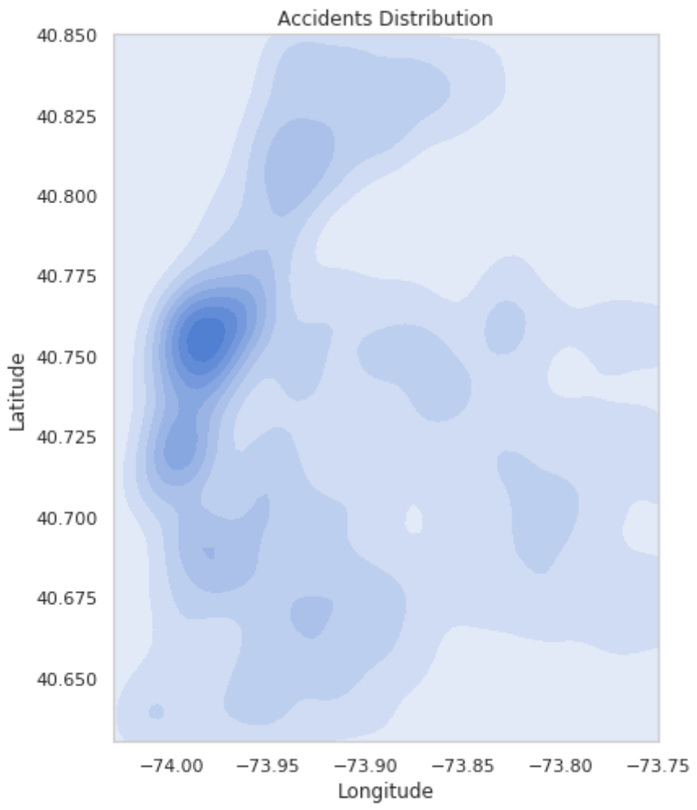
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 116691 entries, 3589202 to 3363795
Data columns (total 30 columns):
DATETIME                        116691 non-null datetime64[ns]
Unnamed: 0                      116691 non-null int64
BOROUGH                         100532 non-null object
ZIP CODE                        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
```

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/data=!3m1!4b1!4m5!3m4!1s0x89c2588f046ee661:0xa0b3281fcecc08c!8m2!3d40.7830603!4d-73.9712488) 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,-74.0394431,12z/data=!3m1!4b1!4m5!3m4!1s0x89c2588f046ee661:0xa0b3281fcecc08c!8m2!3d40.7830603!4d-73.9712488) that may be useful, and another page (https://www.6sqft.com/what-nycs-population-looks-like-day-vs-night/) that may be useful.

In [7]:
```
q1a_answer = r"""
Collisions happen most frequently in Midtown of Manhattan. And the closer the locations are to Midtown, the larger
the frequency of collissions there is likely to be.

Brooklyn and Queens have a much smaller frequency of collisions than Manhattan.
"""

# YOUR CODE HERE
#raise NotImplementedError()

print(q1a_answer)
```

```
Collisions happen most frequently in Midtown of Manhattan. And the closer the locations are to Midtown, the larger
the frequency of collissions there is likely to be.

Brooklyn and Queens have a much smaller frequency of collisions than Manhattan.
```

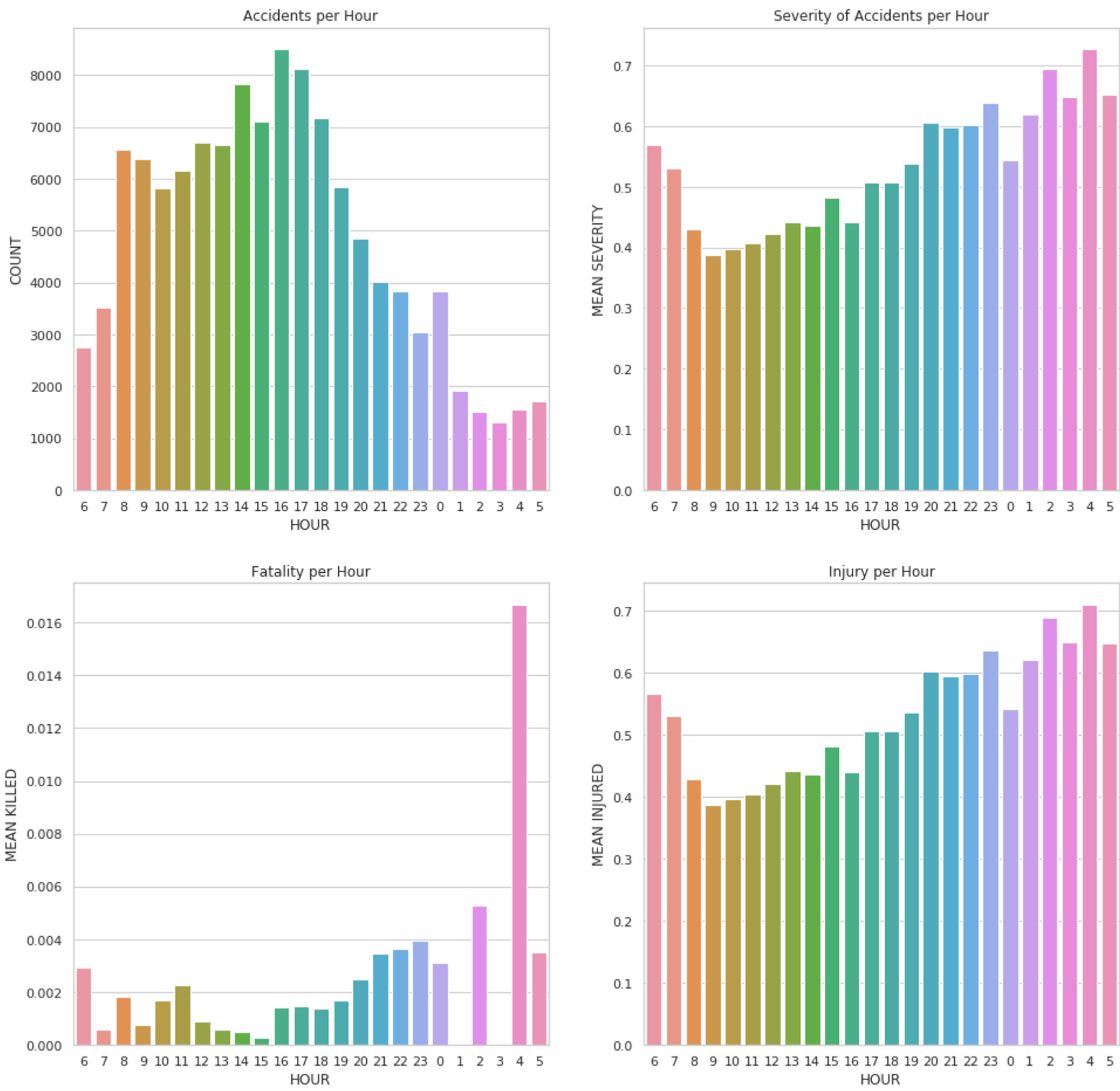
We see that an entry in accidents contains information on number of people injured/killed. Instead of using each of these columns separately, let's combine them into one column called `'SEVERITY'`. Let's also make columns `FATALITY` and `INJURY`, each aggregating the fatalities and injuries respectively.

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

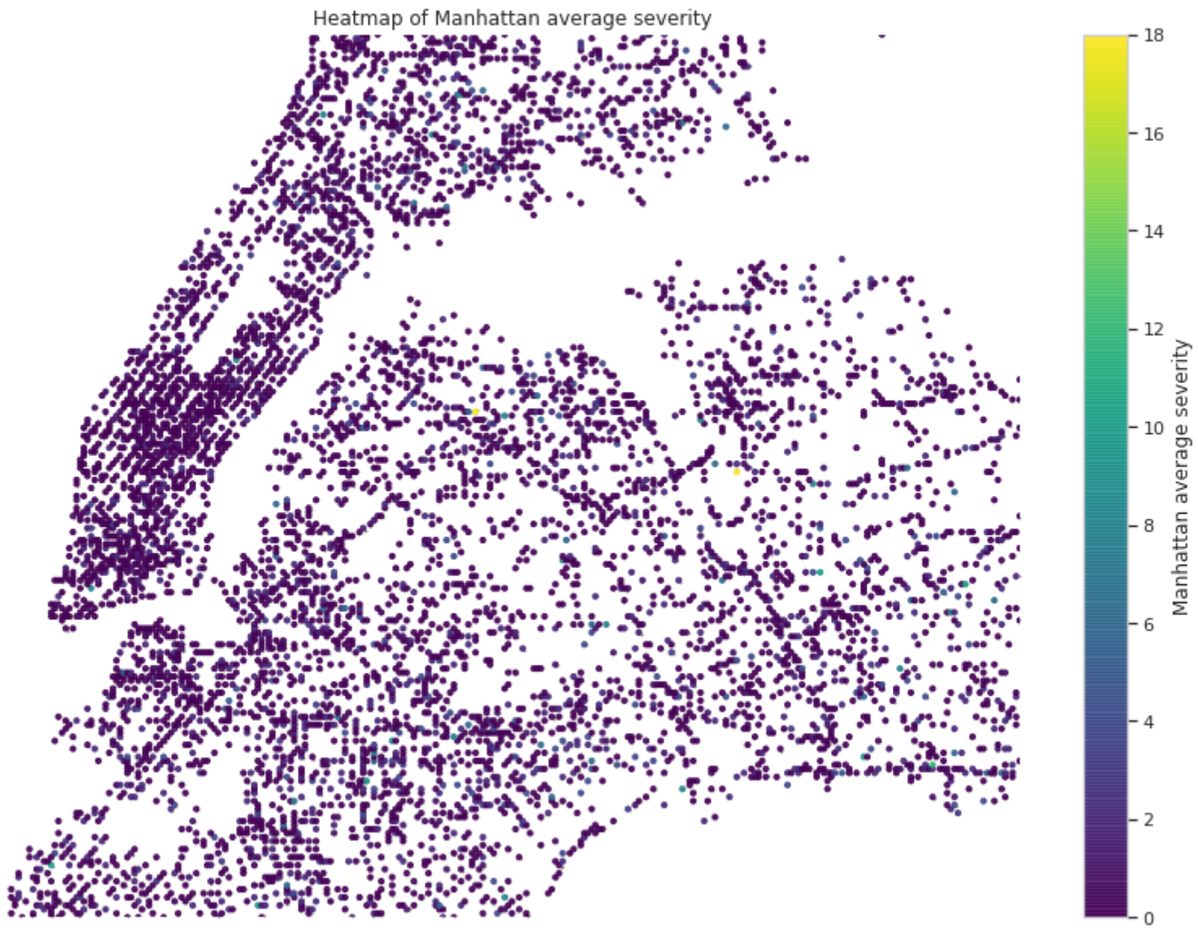
Based on the visualizations above, what can you say about each? Make a comparison between the accidents per hour vs the mean severity per hour. What about the number of fatalities per hour vs the number of injuries per hour? Why do we chose to have our hours start at 6 as opposed to 0?

In [10]:
```
q1b_answer = r"""
1.
(1).In the plot of accidents per hour, we can see that accidents happen more frequently in daytime than nighttime,
and accidents happen most frequently in rush hours, especially rush hours off work.
(2)In the plot of severity of accidents per hour, the accidents happen in the nighttime more severe those in the
daytime.
(3) In the plot of Fatality per hour, the mean killed numbers in nighttime are larger than that in daytime. And
meam killed number are extremy high at 4am
(4) In the plot of Injury per hour, the mean killed numbers in nighttime are larger than that in daytime.

2.When the number of the accidents per hour is large, the mean severity is small, and vice versa.

3.When the number of fatalities per hour is large, the number of injuries is also large, and vice versa.

4.

"""

# YOUR CODE HERE
#raise NotImplementedError()

print(q1b_answer)
```

```
1.
(1).In the plot of accidents per hour, we can see that accidents happen more frequently in daytime than nighttime,
and accidents happen most frequently in rush hours, especially rush hours off work.
(2)In the plot of severity of accidents per hour, the accidents happen in the nighttime more severe those in the
daytime.
(3) In the plot of Fatality per hour, the mean killed numbers in nighttime are larger than that in daytime. And
meam killed number are extremy high at 4am
(4) In the plot of Injury per hour, the mean killed numbers in nighttime are larger than that in daytime.

2.When the number of the accidents per hour is large, the mean severity is small, and vice versa.

3.When the number of fatalities per hour is large, the number of injuries is also large, and vice versa.

4.
```

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.

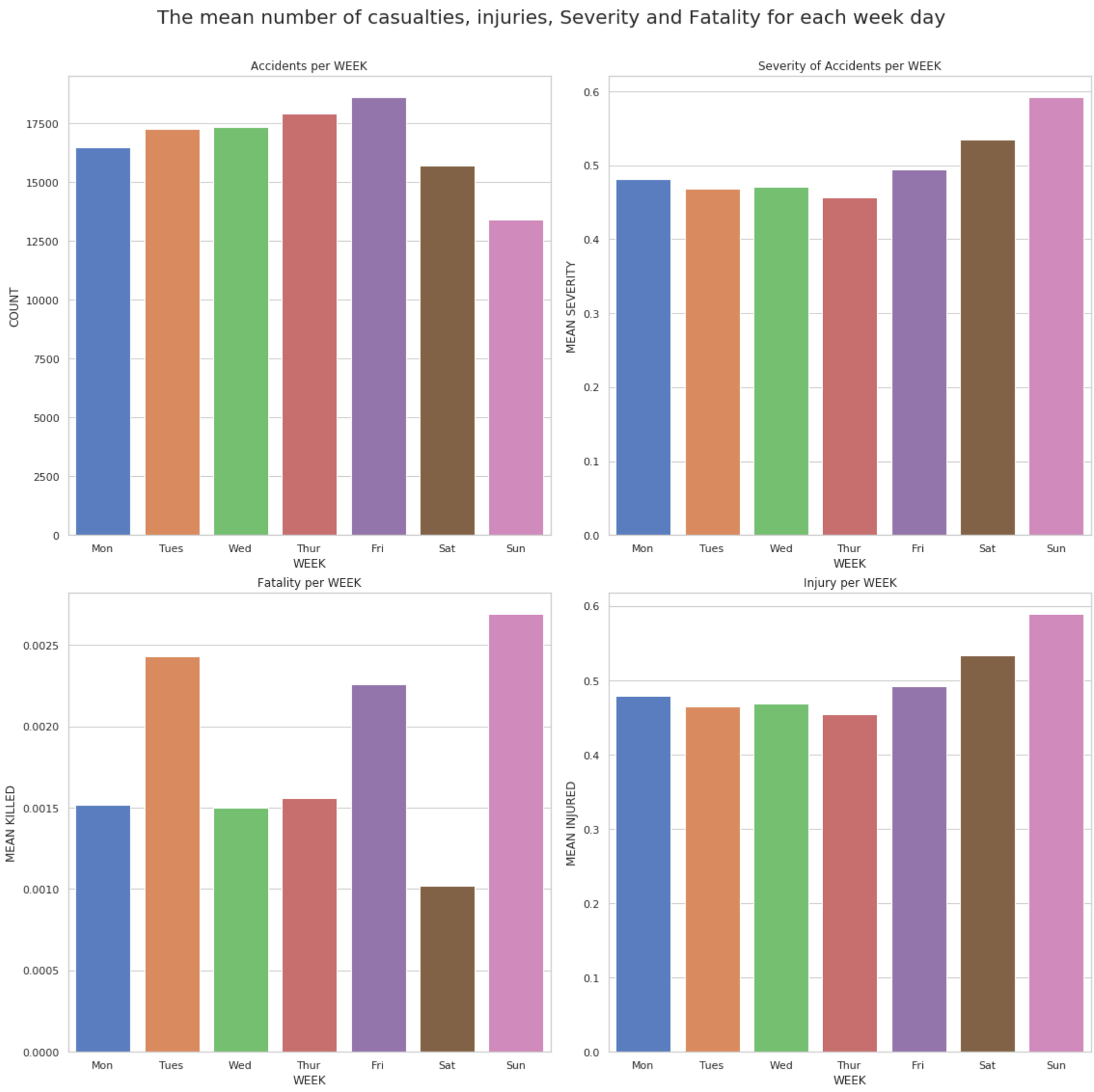
In [12]:
```
q1c_answer = r"""
I don't think the location of the accident has a significant impact on the severity.

We could drop some outliers and decrese the range of severity, so that we can make the color easier to
distinguish.
"""

# YOUR CODE HERE
#raise NotImplementedError()

print(q1c_answer)
```

```
I don't think the location of the accident has a significant impact on the severity.

We could drop some outliers and decrese the range of severity, so that we can make the color easier to
distinguish.
```

Question 1d

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

In [13]:
```
#the mean number of casualties, injuries, Severity and Fatality for each week day

fig, axes = plt.subplots(2, 2, figsize=(16,16))
weekday = ['Mon', 'Tues', 'Wed', 'Thur','Fri','Sat', 'Sun']
ax1 = axes[0,0]
ax2 = axes[0,1]
ax3 = axes[1,0]
ax4 = axes[1,1]

collisions['WEEK'] = collisions['DATETIME'].dt.weekday

plt.title('the mean number of casualties, injuries, Severity and Fatality for each week day')
collisions_count = collisions.groupby('WEEK').count()
collisions_count = collisions_count.reset_index()
sns.barplot(x='WEEK', y='SEVERITY', data=collisions_count,  ax=ax1)
plt.sca(ax1)
plt.xticks(range(7), weekday)
ax1.set_title("Accidents per WEEK")
ax1.set_xlabel("WEEK")
ax1.set_ylabel('COUNT')


collisions_mean = collisions.groupby('WEEK').mean()
collisions_mean = collisions_mean.reset_index()
sns.barplot(x='WEEK', y='SEVERITY', data=collisions_mean, ax=ax2)
plt.sca(ax2)
plt.xticks(range(7), weekday)
ax2.set_title("Severity of Accidents per WEEK")
ax2.set_xlabel("WEEK")
ax2.set_ylabel('MEAN SEVERITY')

fatality_count = collisions.groupby('WEEK').mean()
fatality_count = fatality_count.reset_index()
sns.barplot(x='WEEK', y='FATALITY', data=fatality_count, ax=ax3)
plt.sca(ax3)
plt.xticks(range(7), weekday)
ax3.set_title("Fatality per WEEK")
ax3.set_xlabel("WEEK")
ax3.set_ylabel('MEAN KILLED')

injury_count = collisions.groupby('WEEK').mean()
injury_count = injury_count.reset_index()
sns.barplot(x='WEEK', y='INJURY', data=injury_count, ax=ax4)
plt.sca(ax4)
plt.xticks(range(7), weekday)
ax4.set_title("Injury per WEEK")
ax4.set_xlabel("WEEK")
ax4.set_ylabel('MEAN INJURED')

fig.tight_layout()
plt.suptitle("The mean number of casualties, injuries, Severity and Fatality for each week day",size = 20)
fig.subplots_adjust(top = 0.92)
plt.show();
collisions = collisions.drop(columns=['WEEK'])
```



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 [14]:
```
q1e_answer = r"""
(1)I visualized the mean number of accidents, injuries, Severity and Fatality for each week day
(2)I want to show if the number of accidents, injuries, Severity and fatality behave differently in Weekdays and
weekends
(3)I chose barplot because there are only 7 days in a week, and I can list the data for each weekday. And it is
easier to make compasion with the barplot.
"""
# YOUR CODE HERE
#raise NotImplementedError()
print(q1e_answer)
```

```
(1)I visualized the mean number of accidents, injuries, Severity and Fatality for each week day
(2)I want to show if the number of accidents, injuries, Severity and fatality behave differently in Weekdays and
weekends
(3)I chose barplot because there are only 7 days in a week, and I can list the data for each weekday. And it is
easier to make compasion with the barplot.
```

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 [15]:
```
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 [16]:
```
remaining_col = ['DATETIME', 'TIME', 'START', 'END', 'DATE', 'LATITUDE', 'LONGITUDE', 'SEVERITY']
collisions_subset = collisions.drop(columns= [col for col in collisions.columns if col not in remaining_col])
# YOUR CODE HERE
#raise NotImplementedError()
collisions_subset.head(5)
```

Out[16]:

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

In [17]:
```
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 [18]:
```
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', 'pickup_latitude', 'duration']]
train_df['date'] = train_df['tpep_pickup_datetime'].dt.date
```

In [19]:
```
collisions_subset = collisions_subset[collisions_subset['DATETIME'].dt.weekofyear == 3]
train_df = train_df[train_df['tpep_pickup_datetime'].dt.weekofyear == 3]
```

In [20]:
```
# merge the dataframe here
merged = pd.merge(train_df,collisions_subset, how= 'left', left_on='date',right_on = 'DATE')

# YOUR CODE HERE
#raise NotImplementedError()

merged.head()
```

Out[20]:

	index	tpep_pickup_datetime	pickup_longitude	pickup_latitude	duration	date	DATETIME	LATITUDE	LONGITUDE	TIME	DATE	SEVERITY	START	END
0	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 10:35:00	40.701651	-73.991484	10	2016-01-21	0	2016-01-21 10:35:00	2016-01-21 11:35:00
1	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 13:20:00	40.704760	-74.014961	13	2016-01-21	0	2016-01-21 13:20:00	2016-01-21 14:20:00
2	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 16:00:00	40.732891	-73.920574	16	2016-01-21	4	2016-01-21 16:00:00	2016-01-21 17:00:00
3	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 18:30:00	40.714122	-73.831508	18	2016-01-21	0	2016-01-21 18:30:00	2016-01-21 19:30:00
4	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 00:05:00	40.700108	-73.953819	0	2016-01-21	0	2016-01-21 00:05:00	2016-01-21 01:05:00

In [21]:
```
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 [22]:
```
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) ** 2
    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 [23]:
```
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 = merged[(merged['tpep_pickup_datetime'] >= merged['START']) &
                           (merged['tpep_pickup_datetime'] <= merged['END']) &
                           (merged['start_to_accident'] <= 5)].index

# YOUR CODE HERE
#raise NotImplementedError()

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

```

In [24]:
```
assert merged['accident_close'].sum() > 16000
```

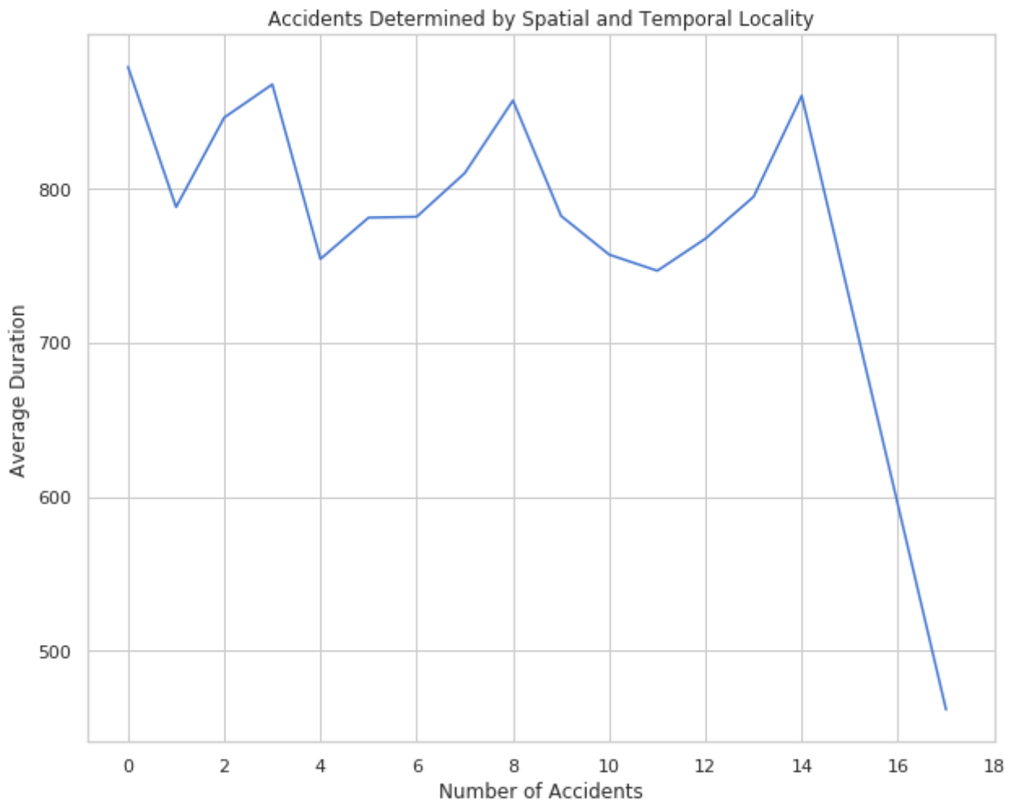
The last step is to aggregate the total number of proximal accidents. We want to count the total number of accidents that were close spatially and temporally and condition on that data.

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 [25]:
```
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
```

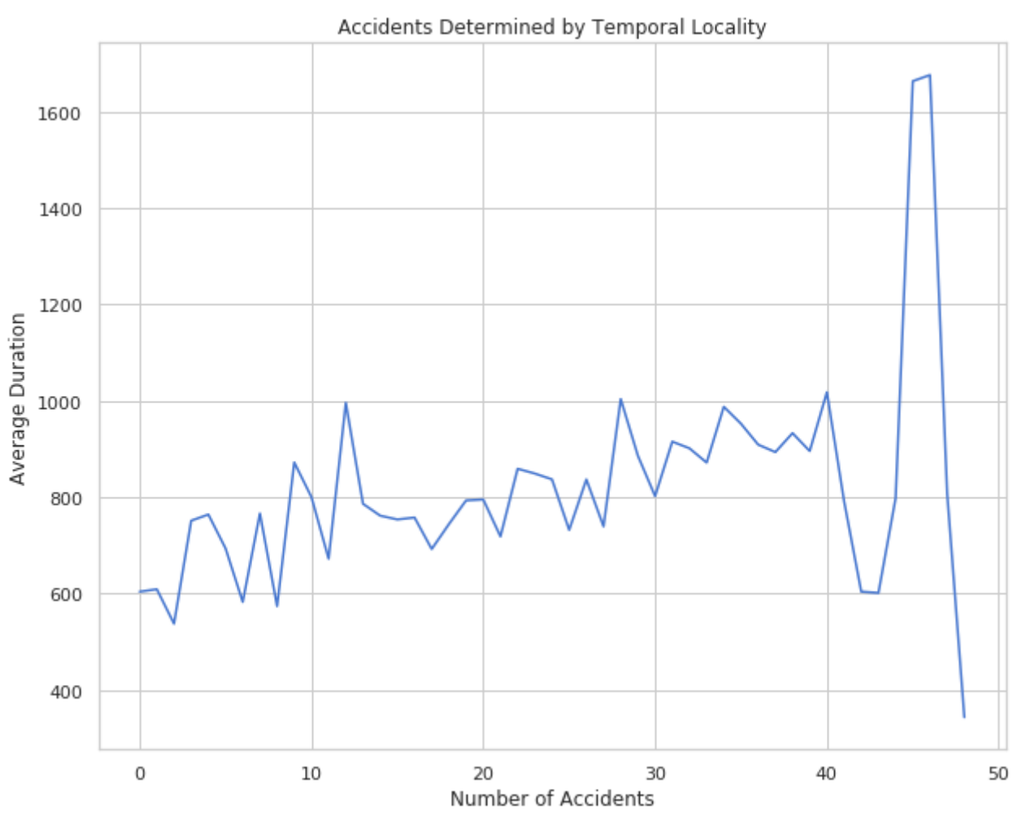
Next, for each value of `num_accidents`, we plot the average `duration` of rides with that number of accidents.

In [26]:
```
plt.figure(figsize=(10,8))
train_accidents.groupby('num_accidents')['duration'].mean().plot(xticks=np.arange(0, 20, 2))
plt.title("Accidents Determined by Spatial and Temporal Locality")
plt.xlabel("Number of Accidents")
plt.ylabel("Average Duration")
plt.show();
```

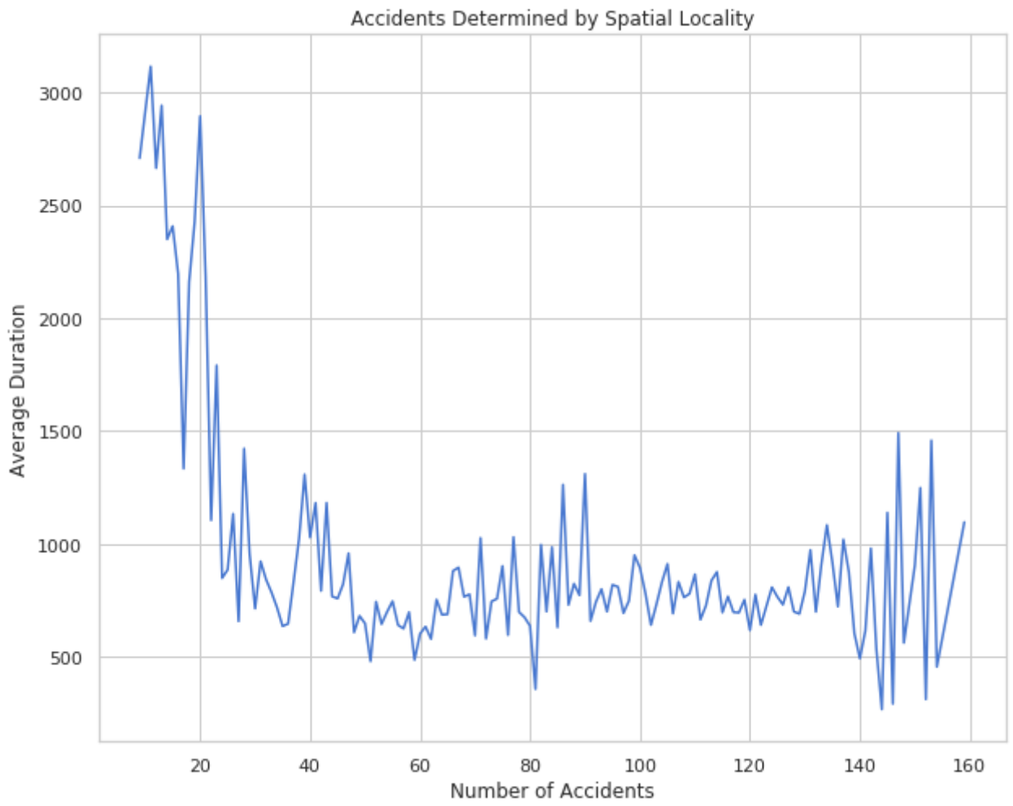


It seems that using both spatial and temporal proximity doesn't give us much insight on if collisions increase taxi ride durations. Let's try conditioning on spatial proximity and temporal proximity separately and see if there are more interesting results there.

In [27]:
```
# 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 [28]:
```
# 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 [29]:
```
merged
```

Out[29]:

	index	tpep_pickup_datetime	pickup_longitude	pickup_latitude	duration	date	DATETIME	LATITUDE	LONGITUDE	TIME	DATE	SEVERITY	START	END	start_to_accident	accident_close
0	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 10:35:00	40.701651	-73.991484	10	2016-01-21	0	2016-01-21 10:35:00	2016-01-21 11:35:00	4.433256	1
1	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 13:20:00	40.704760	-74.014961	13	2016-01-21	0	2016-01-21 13:20:00	2016-01-21 14:20:00	4.298554	1
2	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 16:00:00	40.732891	-73.920574	16	2016-01-21	4	2016-01-21 16:00:00	2016-01-21 17:00:00	6.587580	0
3	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 18:30:00	40.714122	-73.831508	18	2016-01-21	0	2016-01-21 18:30:00	2016-01-21 19:30:00	14.348166	0
4	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 00:05:00	40.700108	-73.953819	0	2016-01-21	0	2016-01-21 00:05:00	2016-01-21 01:05:00	5.894669	0
5	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 00:05:00	40.663972	-73.997766	0	2016-01-21	0	2016-01-21 00:05:00	2016-01-21 01:05:00	8.589078	0
6	16709	2016-01-21 22:28:17	-73.997986	40.741215	736.0	2016-01-21	2016-01-21 00:05:00	40.663972	-73.997766	0	2016-01-21	0	2016-01-21 00:05:00	2016-01-21 01:05:00	8.589078	0

In [30]:
```
q2d_answer = r"""
1.
(1)
For the accidents determined by temporal and spatial proximity, when number of such accidents increases, the
average duration decreases. And this conclusion doesn't comply with our experience, because accidents wiil result
in traffic jam, which will enlarge the mean durration for the rides that are temporal and spatial proximity.
(2)
My hypothsis: The mean severity of accidents determined by temporal and spatial proximity will affect the
duration. We can use the similiar visualization above to show the relationship between the mean severity of
accidents and the duration.

2.
(1)
For the accidents only determined by temporal proximity, the average duration increase as the number of such
accidents increases.
For the accidents only determined by spatial proximity, the average duration decreases as the number of such
accidents increases, and there is a obvious drop for the average duration when the number is around 30.
(2)
We should only consider temporal proximity, because the location will affect the avarage duration. In some
areas like Manhattan, the duration tends to be small. So spatial proximity will interference our test.
"""

# YOUR CODE HERE
#raise NotImplementedError()

print(q2d_answer)
```

```
1.
(1)
For the accidents determined by temporal and spatial proximity, when number of such accidents increases, the
average duration decreases. And this conclusion doesn't comply with our experience, because accidents wiil result
in traffic jam, which will enlarge the mean durration for the rides that are temporal and spatial proximity.
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For the accidents only determined by temporal proximity, the average duration increase as the number of such
accidents increases.
For the accidents only determined by spatial proximity, the average duration decreases as the number of such
accidents increases, and there is a obvious drop for the average duration when the number is around 30.
(2)
We should only consider temporal proximity, because the location will affect the avarage duration. In some
areas like Manhattan, the duration tends to be small. So spatial proximity will interference our test.
```

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**