



# Python for Data Analysts

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# My Background

- Originally from Sanford, Florida
- Went to The University of South Florida for Geography on an Army ROTC scholarship – studies focused on GIS
- Served 6 years in the Army Reserves as a Transportation Officer and deployed to Kuwait, Iraq, and Syria in 2018. This is where I found my love of Excel.
- Worked as a Transportation Manager for US Xpress for about 5 years while taking courses on SQL and Python. Founded manager project team that automated about a dozen processes saving hours of office time per week.
- Hired as the first Data Analyst for Albemarle County Fire Rescue in 2023!



## Agenda

- 1.The Basics
2. Data Exploration
3. Data Transformation
4. Date Time
5. Matplotlib
6. Seaborn
7. Plotly
8. AI Coding Demo

# The Basics

## Foundational Terms

Programming Languages

Integrated Development Environment (IDE)

Virtual Environment

Library/ Module



# Languages



Feature	Python	R
<b>General Purpose</b>	Full-featured programming language, ideal for data pipelines, dashboards, automation, APIs	Primarily built for statistical computing and visualization
<b>Ease of Learning</b>	Syntax is intuitive and readable—great for beginners from any field	More specialized; steeper learning curve for non-statisticians
<b>Libraries &amp; Tools</b>	Powerful libraries like pandas, geopandas, numpy, matplotlib, plotly, scikit-learn, and folium for fire service analytics, GIS, modeling, and reporting	Excellent for statistical models and custom data visualizations using ggplot2, dplyr, tidyr, caret
<b>GIS &amp; Spatial Analysis</b>	Strong integration with GeoPandas, Shapely, Folium, and web-based mapping like Leaflet and Kepler.gl	R also has packages like sf, sp, and tmap, but less support in web/GIS application development
<b>Automation &amp; Integration</b>	Easy to build scripts that talk to databases, APIs, Excel, ArcGIS Pro, CAD/NFIRS exports, and automate reporting	Possible in R, but not as well-supported or versatile
<b>Web &amp; App Development</b>	Seamless tools like Flask, Dash, and Streamlit for building interactive dashboards	Limited to Shiny (powerful but more complex setup)
<b>Community &amp; Support</b>	Massive global user base with endless tutorials, especially for beginners and applied data scientists	Strong in academic/statistical circles, but smaller user base in emergency services context

# IDEs



Feature	Jupyter Lab	VS Code
<b>Workflow Style</b>	Notebook-based: code, notes, tables, and plots side-by-side. Doesn't freeze up like MS Excel with thousands of rows!	Script-based: code runs top-to-bottom, outputs go to the terminal
<b>Best For</b>	Exploratory analysis, data cleaning, visual storytelling	Larger scripts, apps, and software development
<b>Ease of Use</b>	Great for beginners: run one cell at a time, tweak on the fly	Requires more structure and familiarity with files and environments
<b>Output Display</b>	Inline charts, tables, and maps	Plots pop out in separate windows or terminals
<b>Documentation</b>	Mix Markdown + Code for report-style analysis	Notes live in separate files or as comments
<b>File Management</b>	GUI for browsing folders and previewing datasets like Excel	Full file system view with more customization
<b>Reproducibility</b>	Each notebook becomes a live, explainable report	Requires extra effort to build that level of documentation

# Essential Python Libraries

```
graph TD; Center((Essential Python Libraries)); Center --- TDA[Tabular Data Analysis]; Center --- DV[Data Visualization]; Center --- AWD[Apps and Web Development]; Center --- GL[Geospatial Libraries]; TDA --- Pandas; TDA --- Datetime; TDA --- Numpy; DV --- Plotly; DV --- Seaborn; DV --- Matplotlib; AWD --- Django; AWD --- Flask; AWD --- Dash; AWD --- Streamlit; GL --- ArcPy; GL --- Rasterio; GL --- Geopandas; GL --- Folium; GL --- Shapely;
```

## Tabular Data Analysis

Pandas

Datetime

Numpy

## Data Visualization

Plotly

Seaborn

Matplotlib

## Geospatial Libraries

ArcPy

Rasterio

Geopandas

Folium

Shapely

## Apps and Web Development

Django

Flask

Dash

Streamlit

# Data types

Category	Type	Example	Common Fire Service Use	Notes / Tips
Numeric	int	42	Count of calls, stations, personnel	Whole numbers
	float	3.75	Turnout time, response time, percentages	Use .round(2) for cleaner reporting
	bool	True, False	Flag calls on weekends, identify delays	Used in filtering (df[df['IsWeekend'] == True])
Text	str	"Engine 5"	Unit IDs, station names, incident types	.str.upper(), .str.contains() for filters
Date & Time	datetime	2024-01-01 08:00	Dispatch, arrival, clear time	Use pd.to_datetime() to convert
	timedelta	0 days 00:07:15	Time between dispatch and arrival	Subtract datetimes directly to get this
Collections	list	[1, 2, 3]	List of units on scene, response times per shift	Can grow/shrink; order matters
	tuple	("E5", "ST01")	Station-unit pairs, lat/lon points	Fixed-length and immutable
	dict	{"Station": "E5", "Calls": 22}	Lookups by key (e.g., staffing, zone config)	Access via keys (mydict["Station"])
Pandas Types	object	"Albemarle County"	Text column (fallback for mixed types)	Convert to category for faster operations
	int64, float64	12, 5.8	Numeric columns in DataFrames	Result of importing CSVs with numbers
	datetime64[ns]	2024-01-01 08:00:00	Time-based indexing, resampling	Required for .resample() and .rolling()
	category	"Fire", "EMS", "MVC"	Call types, districts, stations	Saves memory, improves groupby/filter performance





Let's Get into it!

Data Exploration

```
[3]: import pandas as pd
data = pd.read_csv(r"C:\Users\bakard\Python\Scripts\presentation_dataset.csv")
```

```
•[5]: data = data[['PSAPDateTime', ## the Public Safety Answering Point
                  'CallID', ## The ID Of the Call
                  'FireRescueDistrict', ## The First Due Area/ Planning Zone
                  'CADType', ## The CAD Type - how the call went out
                  'CADCategory', ## The Category of the Call Type
                  'hexID', ## An arbitrary Geographical grid for analysis purposes
                  'Longitude', ## The X Axis Coordinate
                  'Latitude', ## The Y Axis Coordinate
                  'AppOwner', ## The Apparatus Owner
                  'UnitNumber', ## The Unit Number
                  'DispatchDateTime', ## The Time the Unit Received Dispatch
                  'EnrouteDateTime', ## The Time the Unit Marked En Route
                  'ArriveDateTime', ## The Time the Unit Arrived on Scene
                  'ClearDateTime', ## The Time the Unit Cleared the Incident
                  'TransportDateTime', ## The Time the Unit marked en route to the hospital
                  'AtHospitalDateTime' ## The Time the Unit arrived at the hospital
                ]]

# Convert PSAPDateTime to actual datetime format
data['PSAPDateTime'] = pd.to_datetime(data['PSAPDateTime']).copy()
```

- Load the data
- Select Columns
- Set PSAP to a datetime

# Explore the Data

```
data.dtypes
```

```
PSAPDateTime      datetime64[ns]  
CallID            int64  
FireRescueDistrict object  
CADType           object  
CADCategory       object  
hexID            int64  
Longitude         float64  
Latitude          float64  
AppOwner          object  
UnitNumber        object  
DispatchDateTime  object  
EnrouteDateTime   object  
ArriveDateTime    object  
ClearDateTime     object  
TransportDateTime object  
AtHospitalDateTime object  
dtype: object
```

```
•[19]: ## explore the shape of the dataframe
```

```
data.shape
```

```
[19]: (33189, 16)
```

# Explore the Data

```
## explore the descriptive statistics of the quantatative data in the dataframe
```

```
data.describe()
```

	PSAPDateTime	CallID	hexID	Longitude	Latitude	DispatchDateTime	EnrouteDateTime	ArriveDateTime
<b>count</b>	33189	3.318900e+04	33189.000000	33189.000000	33189.000000	33189	29524	24444
<b>mean</b>	2023-07-06 18:39:20.823597312	4.257255e+06	7015.192714	-78.524458	38.043766	2023-07-06 18:44:29.746476288	2023-07-07 01:50:33.577664	2023-07-07 00:46:37.057028352
<b>min</b>	2023-01-01 00:31:42.523000	4.141915e+06	7.000000	-78.831409	37.734385	2023-01-01 00:33:35.380000	2023-01-01 00:34:33.697000	2023-01-01 00:42:21.053000
<b>25%</b>	2023-04-05 12:53:27.852999936	4.200975e+06	5580.000000	-78.581706	38.013389	2023-04-05 13:21:11.660000	2023-04-05 20:43:49.751500032	2023-04-06 12:32:33.802249984
<b>50%</b>	2023-07-09 05:06:10.863000064	4.260135e+06	8114.000000	-78.494559	38.059419	2023-07-09 05:08:33.516999936	2023-07-09 09:36:12.797000192	2023-07-08 22:35:48.576499968
<b>75%</b>	2023-10-07 01:05:11.416999936	4.314118e+06	8949.000000	-78.456382	38.079205	2023-10-07 01:11:46.5699999872	2023-10-07 07:21:42.974249984	2023-10-07 02:30:32.389750016
<b>max</b>	2023-12-31 23:30:08.223000	4.361690e+06	11909.000000	-78.210995	38.247679	2023-12-31 23:31:58.860000	2023-12-31 23:33:36.513000	2023-12-31 23:43:49.380000
<b>std</b>	NaN	6.434231e+04	2884.559715	0.107547	0.074406	NaN	NaN	NaN

# Explore the Data

•[23]: *# explore the distribution of the categorical and other qualitative data*

```
data.CADType.value_counts()
```

```
[23]: CADType
      Motor Vehicle Crash - Injuries      3819
      General Illness                    3393
      Fall                              2602
      Cardiac Related                    2411
      Respiratory                       2360
      Unconscious                       1602
      Fire Alarm                        1548
      Neurological                      1348
      Outdoor Fire                      1178
      .....
```



Let's Move On!

Data Transformation

```
[29]: ## Sorting

data.sort_values(by='PSAPDateTime',ascending=False)
```

	PSAPDateTime	CallID	FireRescueDistrict	CADType	CADCategory	hexID	Longitude
<b>29756</b>	2023-12-31 23:30:08.223	4361690	Earlsville	Unconscious	EMS	9297	-78.441633
<b>29763</b>	2023-12-31 23:22:43.997	4361685	Crozet	Fall	EMS	1746	-78.708843
<b>29831</b>	2023-12-31 23:22:43.997	4361685	Crozet	Fall	EMS	1746	-78.708843
<b>29524</b>	2023-12-31 22:23:33.750	4361654	Ivy	Fire Alarm	Fires	4531	-78.615538
<b>29499</b>	2023-12-31 22:12:47.240	4361647	Pantops	Unconscious	EMS	9436	-78.430798

```
Incidents = data.drop_duplicates(subset='CallID')
```

```
Incidents.shape
```

```
(17297, 16)
```

# Handling Duplicates

A large yellow triangle is positioned in the bottom right corner of the slide, pointing towards the top right.



```
Incidents = data.drop_duplicates(subset='CallID')
```

```
Incidents.shape
```

```
(17297, 16)
```

```
Cancelled_enroute = data.sort_values(by=['PSAPDateTime', 'ArriveDateTime'], ascending=True)
```

```
Cancelled_enroute = Cancelled_enroute.drop_duplicates(subset='CallID', keep='first')
```

```
Cancelled_enroute = Cancelled_enroute[Cancelled_enroute.ArriveDateTime.isna()]
```

```
Cancelled_enroute.shape
```

```
(1211, 16)
```

```
arrived = data.sort_values(by=['PSAPDateTime', 'ArriveDateTime'], ascending=True)
```

```
arrived = data.dropna(subset='ArriveDateTime')
```

```
arrived = arrived.drop_duplicates(subset='CallID')
```

```
print(f"Total: {len(arrived) + len(Cancelled_enroute)}")
```

```
Total: 17297
```

# Mask Filtering

```
## filtering

WaterRescues = Incidents[Incidents['CADType'] == 'Water Rescue']

Scottsville_WaterRescues = Incidents[
    (Incidents['FireRescueDistrict'] == 'Scottsville') &
    (Incidents['CADType'] == 'Water Rescue')
]

## Print Statements and F Strings
print(
    f"""
    There were {len(WaterRescues)} Water Rescues in 2023
    {len(Scottsville_WaterRescues)} of {len(WaterRescues)} were in Scottsville's First Due
    """
)
```

```
There were 6 Water Rescues in 2023
1 of 6 were in Scottsville's First Due
```

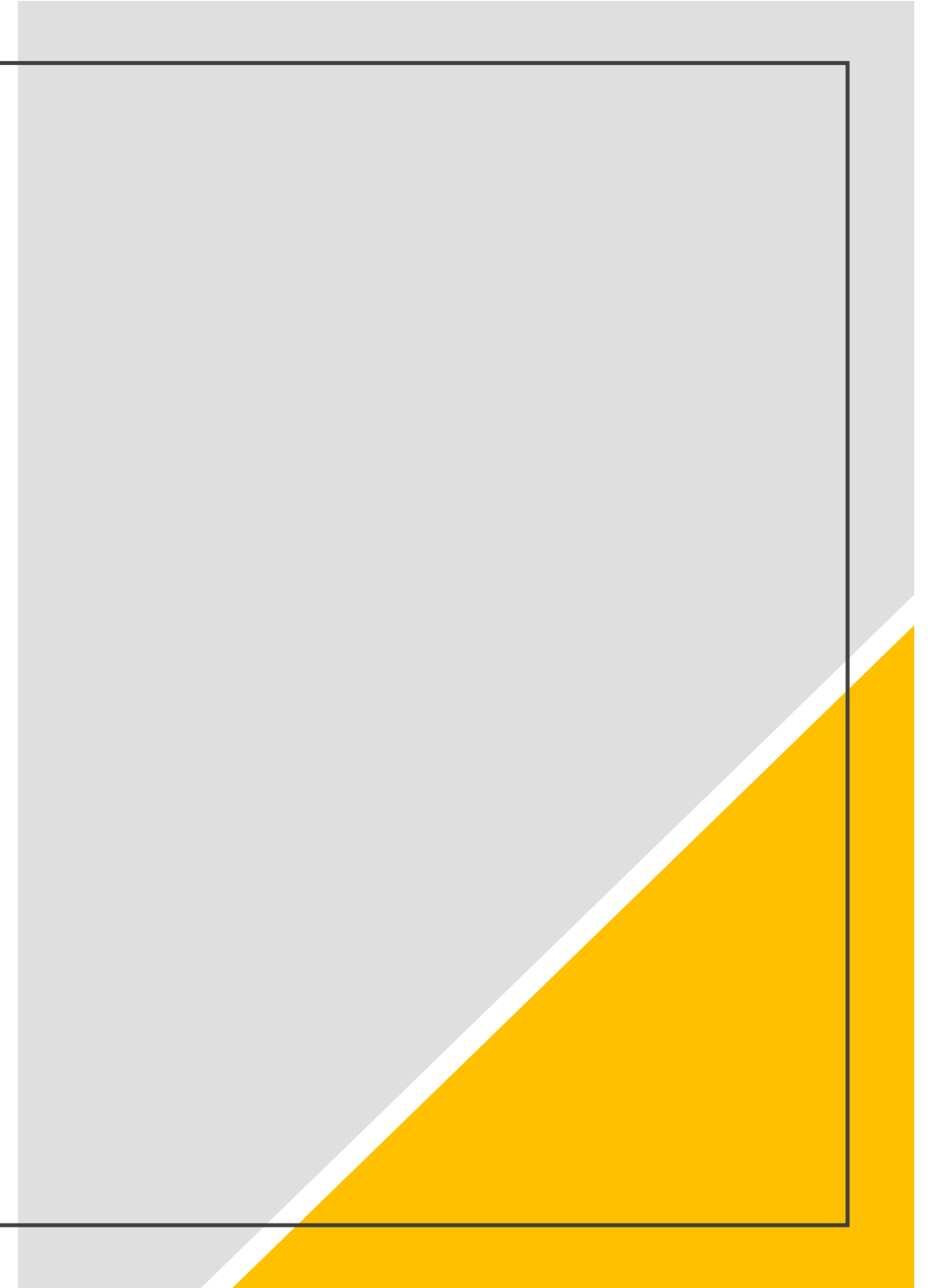
# Query Filtering

```
## Filtering Using .query
```

```
Incidents.query("CADType == 'Water Rescue' & FireRescueDistrict == 'Scottsville'")
```

	PSAPDateTime	CallID	FireRescueDistrict	CADType	CADCategory	hexID	Longitude	Latitude
<b>3248</b>	2023-07-04 16:33:31.947	4257204	Scottsville	Water Rescue	Rescue Incidents	5876.0	-78.570463	37.761031

Next:  
Handling  
Date Times



```
[ ]: # To convert multiple at once:
datetime_cols = [
    'DispatchDateTime',
    'EnrouteDateTime',
    'ArriveDateTime',
    'ClearDateTime',
    'TransportDateTime',
    'AtHospitalDateTime'
]
# 'For' loop example:
for col in datetime_cols:
    data[col] = pd.to_datetime(data[col], errors='coerce') # errors='coerce' handles bad/missing values safely

# Example: Nowe let's Filter for incidents on or after Jan 1, 2023
data = data[data['PSAPDateTime'].between('2023-01-01', '2024-01-01')]
```

- Convert multiple date columns
- 'For' Loops
- Filter by a datetime column

Data types have changed!

```
#explore the data types of the dataframe  
data.dtypes
```

```
PSAPDateTime      datetime64[ns]  
CallID            int64  
FireRescueDistrict  object  
CADType           object  
CADCategory       object  
hexID             int64  
Longitude          float64  
Latitude           float64  
AppOwner          object  
UnitNumber        object  
DispatchDateTime  datetime64[ns]  
EnrouteDateTime   datetime64[ns]  
ArriveDateTime    datetime64[ns]  
ClearDateTime     datetime64[ns]  
TransportDateTime  datetime64[ns]  
AtHospitalDateTime datetime64[ns]  
dtype: object
```

# Time Features Cheat Sheet

Feature	Code	Description
Date	<code>data['DispatchDateTime'].dt.date</code>	Removes the time portion
Time	<code>data['DispatchDateTime'].dt.time</code>	Removes the date portion
Hour	<code>data['DispatchHour'] = data['DispatchDateTime'].dt.hour</code>	Useful for hourly trends
Minute	<code>data['DispatchMinute'] = data['DispatchDateTime'].dt.minute</code>	Good for fine-grained time slices
Day of Week	<code>data['DispatchDOW'] = data['DispatchDateTime'].dt.dayofweek</code>	Monday = 0, Sunday = 6
Day Name	<code>data['DispatchDayName'] = data['DispatchDateTime'].dt.day_name()</code>	More readable version of DOW
Month	<code>data['DispatchMonth'] = data['DispatchDateTime'].dt.month</code>	1 to 12
Month Name	<code>data['DispatchMonthName'] = data['DispatchDateTime'].dt.month_name()</code>	Full name of month
Quarter	<code>data['DispatchQuarter'] = data['DispatchDateTime'].dt.quarter</code>	Q1 to Q4
Year	<code>data['DispatchYear'] = data['DispatchDateTime'].dt.year</code>	2023, 2024, etc.
Week Number	<code>data['DispatchWeek'] = data['DispatchDateTime'].dt.isocalendar().week</code>	ISO week of year
Is Weekend?	<code>data['IsWeekend'] = data['DispatchDateTime'].dt.dayofweek &gt;= 5</code>	True for Saturday/Sunday
AM/PM	<code>data['AM_PM'] = data['DispatchDateTime'].dt.strftime('%p')</code>	Shows 'AM' or 'PM'

```
## Time Series features
```

```
## Time of Day
```

```
data['HourOfDay'] = data['DispatchDateTime'].dt.hour
```

```
data['AM_PM'] = data['DispatchDateTime'].dt.strftime('%p')
```

```
data[['DispatchDateTime', 'HourOfDay', 'AM_PM']]
```

	DispatchDateTime	HourOfDay	AM_PM
0	2023-10-09 14:48:23.150	14	PM
1	2023-10-09 12:30:39.007	12	PM
2	2023-10-09 07:18:59.963	7	AM
3	2023-10-09 14:48:22.900	14	PM
4	2023-10-09 05:28:54.570	5	AM
...	...	...	...



```
## Day of Week
```

```
data['DayName'] = data['DispatchDateTime'].dt.day_name()  
data['IsWeekend'] = data['DispatchDateTime'].dt.dayofweek >= 5  
  
data[['DispatchDateTime', 'DayName', 'IsWeekend']]
```

	DispatchDateTime	DayName	IsWeekend
--	------------------	---------	-----------

0	2023-10-09 14:48:23.150	Monday	False
---	-------------------------	--------	-------

1	2023-10-09 12:30:39.007	Monday	False
---	-------------------------	--------	-------

```

## Months, Quarters, Years
data['MonthName'] = data['DispatchDateTime'].dt.month_name()
data['Quarter'] = data['DispatchDateTime'].dt.quarter
data['Year'] = data['DispatchDateTime'].dt.year

data[['DispatchDateTime', 'MonthName', 'Quarter', 'Year']]

```

	DispatchDateTime	MonthName	Quarter	Year
<b>0</b>	2023-10-09 14:48:23.150	October	4	2023
<b>1</b>	2023-10-09 12:30:39.007	October	4	2023
<b>2</b>	2023-10-09 07:18:59.963	October	4	2023
<b>3</b>	2023-10-09 14:48:22.900	October	4	2023
<b>4</b>	2023-10-09 05:28:54.570	October	4	2023
...	...	...	...	...
<b>34052</b>	2023-09-25 11:44:58.027	September	3	2023
<b>34053</b>	2023-09-25 21:59:01.303	September	3	2023

```
## Application: Create a column for Nights and Weekends/ or Daytime

# Extract hour and day of week
data['HourOfDay'] = data['DispatchDateTime'].dt.hour
data['DayOfWeek'] = data['DispatchDateTime'].dt.dayofweek # Monday = 0, Sunday = 6

# Create the column with default value
data['TimeCategory'] = 'Nights & Weekends'

# Overwrite with 'Daytime Weekday' where condition matches
weekday_daytime_mask = (
    (data['DayOfWeek'] < 5) & # Monday to Friday
    (data['HourOfDay'] >= 6) &
    (data['HourOfDay'] < 18)
)

data.loc[weekday_daytime_mask, 'TimeCategory'] = 'Daytime Weekday'

data[['DispatchDateTime', 'HourOfDay', 'DayOfWeek', 'DayName', 'TimeCategory']]
```

- Custom time features
- .loc

	HourOfDay	DayOfWeek	DayName	TimeCategory
2023-10-09 07:18:59.963	7	0	Monday	Daytime Weekday
2023-10-09 14:48:22.900	14	0	Monday	Daytime Weekday
2023-10-09 05:28:54.570	5	0	Monday	Nights & Weekends
...	...	...	...	...
2023-09-25 11:44:58.027	11	0	Monday	Daytime Weekday
2023-09-25 21:59:01.303	21	0	Monday	Nights & Weekends

```
## The All-Important Time Deltas
```

```
data['ResponseTime'] = data['ArriveDateTime'] - data['DispatchDateTime']
```

```
data.dtypes
```

```
ArriveDateTime      datetime64[ns]  
HourOfDay            int32  
AM_PM               object  
DayName              object  
IsWeekend            bool  
MonthName            object  
Quarter             int32  
Year                int32  
Hour                int32  
DayOfWeek            int32  
TimeCategory         object  
ResponseTime         timedelta64[ns]
```

```
dtype: object
```

# RESPONSE TIME & Other Time Deltas

```
data['ResponseTimeSeconds'] = (data['ResponseTime'].dt.total_seconds()).round(1)
data['ResponseTimeMinutes'] = (data['ResponseTime'].dt.total_seconds() / 60).round(1)

response_times = data[['DispatchDateTime', 'ArriveDateTime', 'ResponseTime', 'ResponseTimeSeconds', 'ResponseTimeMinutes']]
response_times
```

DispatchDateTime	ArriveDateTime	ResponseTime	ResponseTimeSeconds	ResponseTimeMinutes
2023-10-09 14:48:23.150	2023-10-09 14:56:05.310	0 days 00:07:42.160000	462.2	7.7
2023-10-09 12:30:39.007	2023-10-09 12:33:03.623	0 days 00:02:24.616000	144.6	2.4
2023-10-09 07:18:59.963	2023-10-09 07:27:45.213	0 days 00:08:45.250000	525.2	8.8
2023-10-09 14:48:22.900	2023-10-09 14:57:31.887	0 days 00:09:08.987000	549.0	9.1
2023-10-09 05:28:54.570	2023-10-09 05:34:33.683	0 days 00:05:39.113000	339.1	5.7
...	...	...	...	...
2023-09-25 11:44:58.027	2023-09-25 11:49:57.860	0 days 00:04:59.833000	299.8	5.0
2023-09-25 21:59:01.303	2023-09-25 22:05:29.437	0 days 00:06:28.134000	388.1	6.5
2023-09-25 19:44:40.390	2023-09-25 19:50:45.613	0 days 00:06:05.223000	365.2	6.1
2023-09-25 12:20:49.767	2023-09-25 12:24:23.970	0 days 00:03:34.203000	214.2	3.6
2023-09-25 14:58:03.410	NaT	NaT	NaN	NaN

```
development_area_response = data[['CallID', 'UnitNumber', 'DispatchDateTime', 'ArriveDateTime', 'ResponseTimeMinutes', 'DevRA', 'FireRescueDistrict']]

development_area_response = development_area_response[development_area_response['DevRA'] == 'development area']

development_area_response = development_area_response.dropna(subset='ResponseTimeMinutes')

development_area_response = development_area_response[development_area_response['ResponseTimeMinutes'] >= 0]

development_area_response = development_area_response.sort_values(by=['CallID', 'ResponseTimeMinutes'], ascending=True)

development_area_response = development_area_response.drop_duplicates(subset='CallID')
```

```
development_area_response.ResponseTimeMinutes.describe(percentiles=[.25,.5,.75,.9,.99])
```

```
count    10584.000000
mean         6.184769
std         4.055309
min         0.000000
25%         4.000000
50%         5.600000
75%         7.800000
90%        10.400000
99%        18.400000
max        152.400000
Name: ResponseTimeMinutes, dtype: float64
```

```
def response_time_90th(vals: pd.Series) -> float:
    """
    Compute the 90th percentile response time (NFPA-style).
    Uses 'higher' interpolation to reflect real-world performance thresholds.
    """
    return vals.quantile(0.90, interpolation='higher')
```

```
development_area_response_table = development_area_response.pivot_table(
    index='FireRescueDistrict',
    values='ResponseTimeMinutes',
    aggfunc=response_time_90th
)
```

PIVOT TABLES!

ResponseTimeMinutes	
FireRescueDistrict	
City	9.6
Crozet	7.3
East Rivanna	12.5
Hollymead	9.3
Ivy	9.7
Monticello	11.9
Pantops	9.5
Scottsville	9.4
Seminole	10.7
UVA	13.8

```
development_area_response_table = development_area_response.pivot_table(
    index='FireRescueDistrict',
    values='ResponseTimeMinutes',
    columns='MonthNumber',
    aggfunc=response_time_90th
)
```

MonthNumber	1	2	3	4	5	6	7	8	9	10	11	12
FireRescueDistrict												
City	11.0	10.2	10.4	9.9	9.5	8.2	10.5	12.2	11.1	8.6	9.5	7.3
Crozet	7.3	7.1	6.8	6.8	7.2	8.2	7.1	6.8	8.1	8.2	7.4	7.7
East Rivanna	10.3	12.0	9.1	14.7	14.8	12.5	14.6	11.1	13.5	14.2	9.3	11.5
Hollymead	8.5	9.5	9.2	9.4	9.8	10.4	8.7	9.3	9.1	7.9	9.7	8.6
Ivy	9.6	10.4	8.1	7.9	8.7	9.4	9.8	9.4	9.4	9.6	11.2	11.8
Monticello	10.7	11.3	11.5	11.3	12.3	13.0	13.1	12.8	11.1	11.5	11.4	12.2
Pantops	8.5	10.3	8.3	8.5	11.0	10.5	11.7	9.1	9.8	10.1	9.6	10.3
Scottsville	8.8	9.4	6.6	8.2	8.9	25.7	10.0	11.7	8.7	9.3	7.7	15.2
Seminole	10.3	9.7	11.0	9.9	10.8	11.5	10.9	10.5	11.3	10.8	11.1	11.1
UVA	7.3	8.8	6.8	8.4	9.7	7.3	14.8	5.2	7.5	13.8	11.2	NaN

PIVOT TABLES!



```

data_time_index = development_area_response.set_index('DispatchDateTime')

# Total calls per day
weekly_calls = data_time_index.resample('W').size().rename('WeeklyCallCount')

# Average response time per week
dev_weekly_90th = data_time_index['ResponseTimeMinutes'].resample('W').quantile(.9).rename('ResponseTime90th')

weekly_summary = pd.concat([weekly_calls, dev_weekly_90th], axis=1, names=['Weekly_Count', 'Weekly_90thPercentile_Response'])

```

	WeeklyCallCount	DevelopmentArea_ResponseTime90th
DispatchDateTime		
2023-01-01	32	10.16
2023-01-08	238	10.33
2023-01-15	185	9.46
2023-01-22	212	9.59
2023-01-29	223	10.46
2023-02-05	193	9.98
2023-02-12	187	9.76
2023-02-19	180	11.00

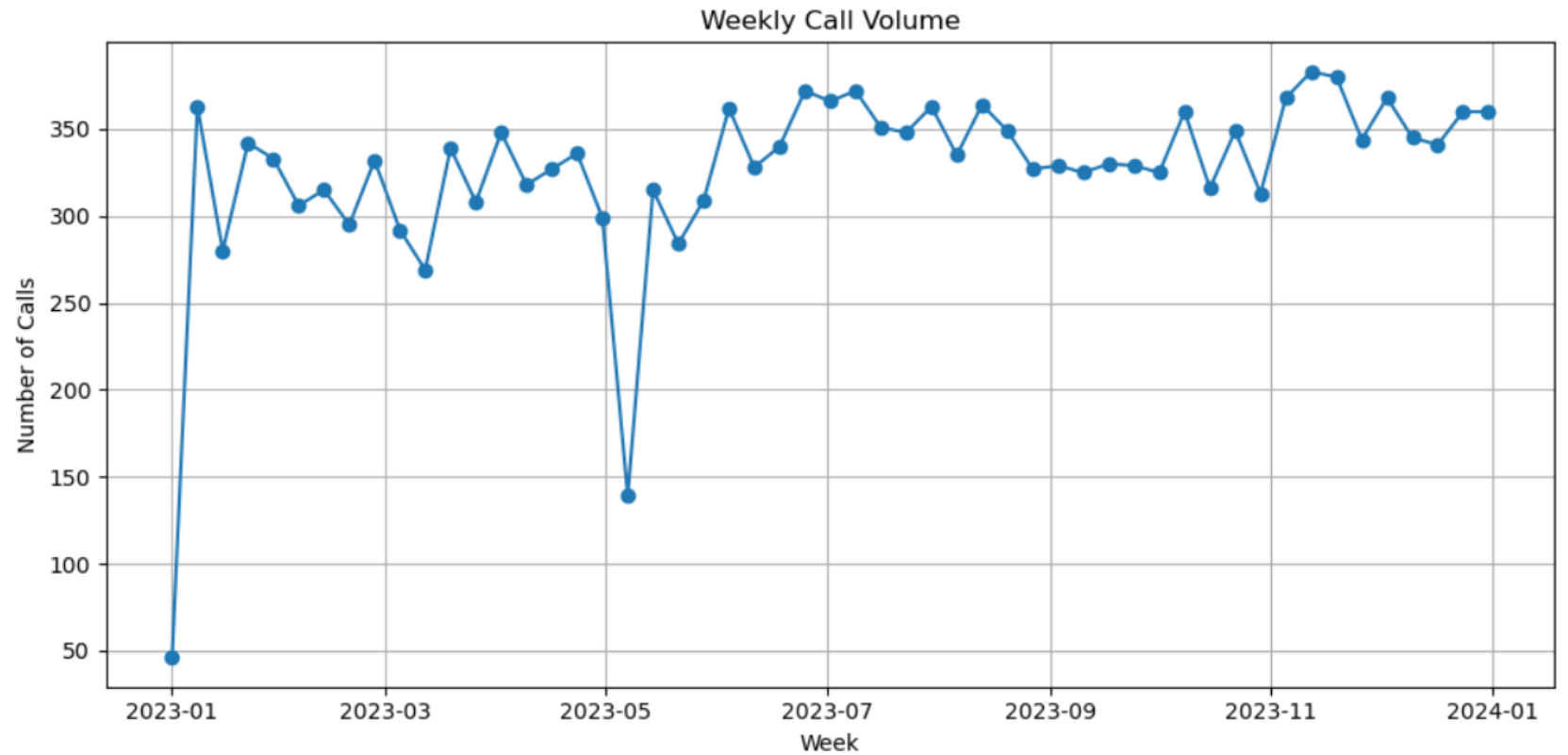


Let's talk about  
visuals!

```
import matplotlib.pyplot as plt
weekly_calls = Incidents.set_index('PSAPDateTime').resample('W').size()

plt.figure(figsize=(10, 5))
plt.plot(weekly_calls.index, weekly_calls.values, marker='o')
plt.title("Weekly Call Volume")
plt.xlabel("Week")
plt.ylabel("Number of Calls")
plt.grid(True)
plt.tight_layout()
plt.show()
```

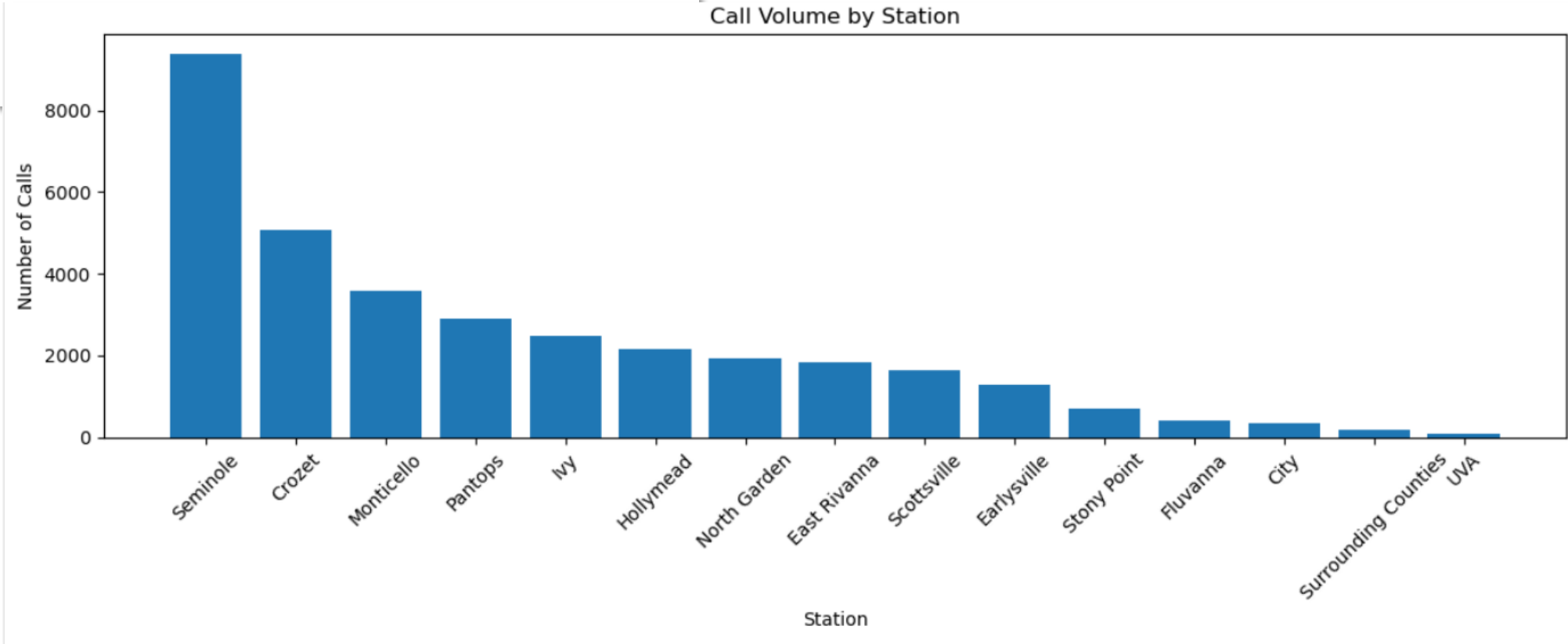
# MATPLOTLIB



```
calls_by_station = data['FireRescueDistrict'].value_counts()
```

```
plt.figure(figsize=(12, 5))  
plt.bar(calls_by_station.index, calls_by_station.values)  
plt.title("Call Volume by Station")  
plt.xlabel("Station")  
plt.ylabel("Number of Calls")  
plt.xticks(rotation=45)  
plt.tight_layout()  
plt.show()
```

MATPLOTLIB





# SEABORN

```
import seaborn as sns
```



```
# Create pivot table: counts of calls by Day of Week and Hour
```

```
heatmap_data = data.pivot_table(  
    index='DayName',  
    columns='Hour',  
    values='CallID', # or any column that exists  
    aggfunc='count'  
)
```

```
# Reorder days for readability
```

```
ordered_days = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
```

```
heatmap_data = heatmap_data.reindex(ordered_days)
```

```
heatmap_data
```

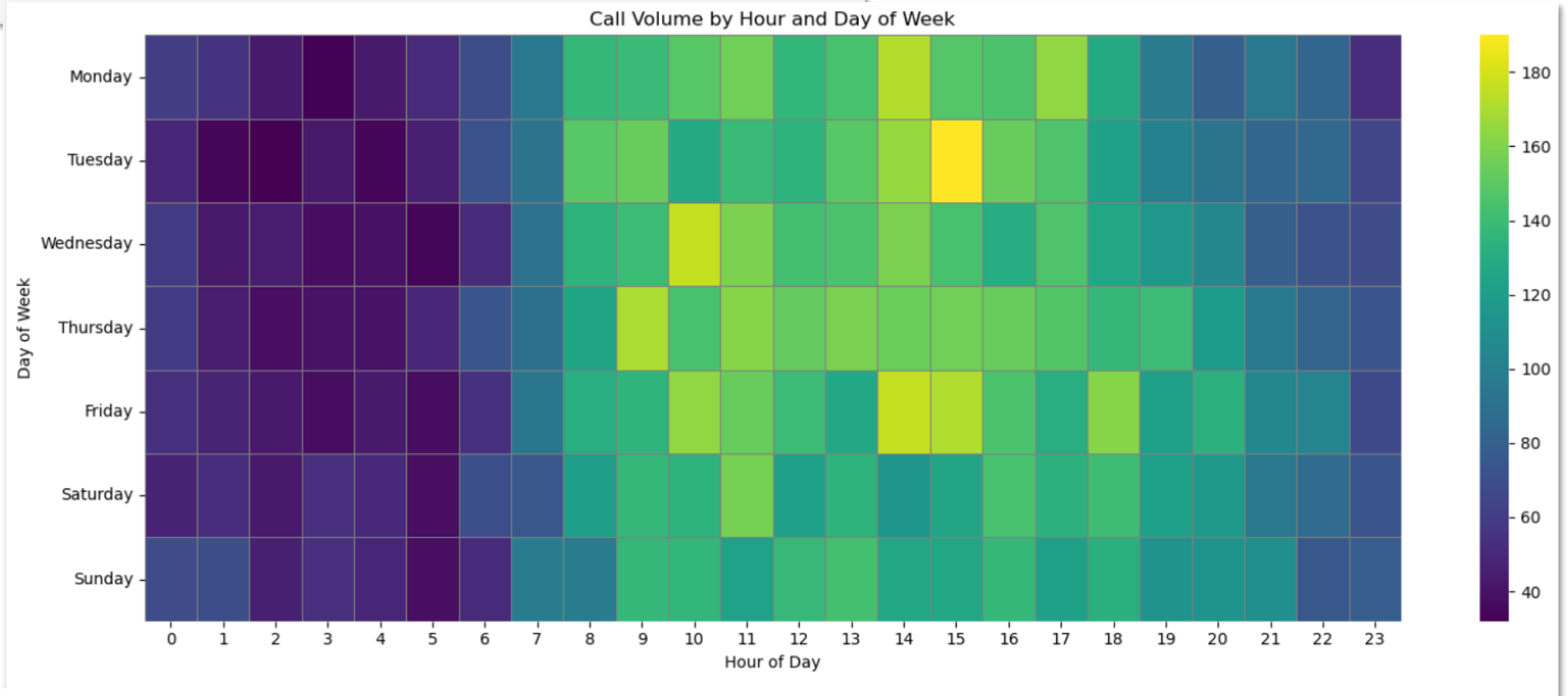


Hour	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	19	20	21	22	23	
DayName																						
Monday	60	55	43	33	43	51	69	95	137	139	...	172	148	145	164	128	97	79	95	83	52	
Tuesday	49	34	32	42	34	46	71	92	149	153	...	165	190	153	146	122	101	93	84	85	65	
Wednesday	59	42	44	37	39	34	51	91	134	140	...	158	144	130	146	126	116	105	79	72	68	
Thursday	59	44	38	40	40	49	73	90	124	170	...	154	156	153	147	137	140	118	96	82	73	
Friday	54	48	42	37	43	37	54	94	131	135	...	176	171	145	131	161	121	133	105	103	67	
Saturday	47	52	42	53	50	38	70	75	120	137	...	115	125	144	133	141	121	117	95	87	73	
Sunday	68	69	46	53	49	38	51	98	97	137	...	126	126	137	122	132	113	114	110	75	78	

7 rows × 24 columns

```
plt.figure(figsize=(15, 6))
sns.heatmap(heatmap_data, cmap='viridis', linewidths=0.5, linecolor='gray')
```

```
plt.title("Call Volume by Hour and Day of Week")
plt.xlabel("Hour of Day")
plt.ylabel("Day of Week")
plt.tight_layout()
plt.show()
```



```
import seaborn as sns
```

```
# Create pivot table: counts of calls by Day of Week and Hour
```

```
heatmap_data = development_area_response.pivot_table(  
    index='DayName',  
    columns='Hour',  
    values='ResponseTimeMinutes', # or any column that exists  
    aggfunc= response_time_90th  
)
```

```
# Reorder days for readability
```

```
ordered_days = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
```

```
heatmap_data = heatmap_data.reindex(ordered_days)
```

```
heatmap_data
```

```
plt.figure(figsize=(15, 6))
```

```
sns.heatmap(heatmap_data, cmap='viridis', linewidths=0.5, linecolor='gray')
```

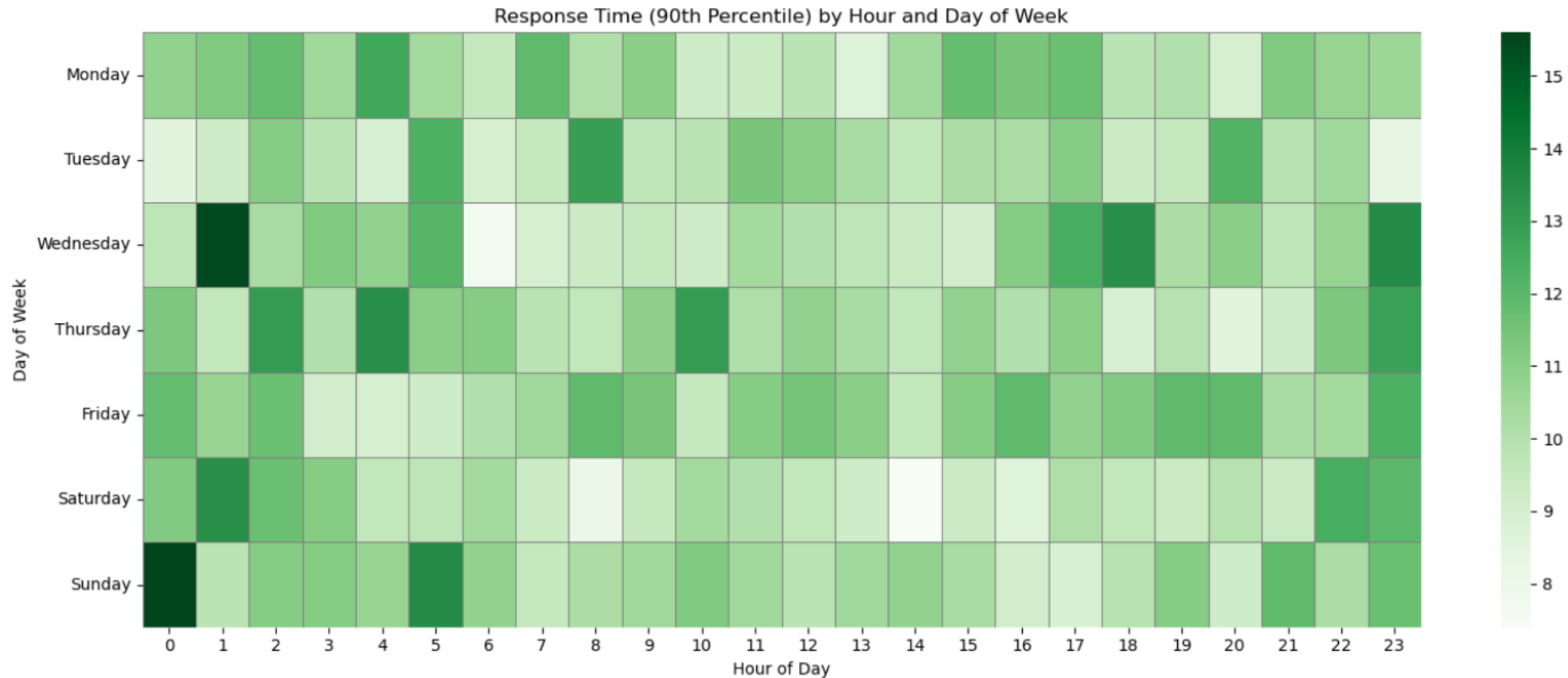
```
plt.title("Call Volume by Hour and Day of Week")
```

```
plt.xlabel("Hour of Day")
```

```
plt.ylabel("Day of Week")
```

```
plt.tight_layout()
```

```
plt.show()
```

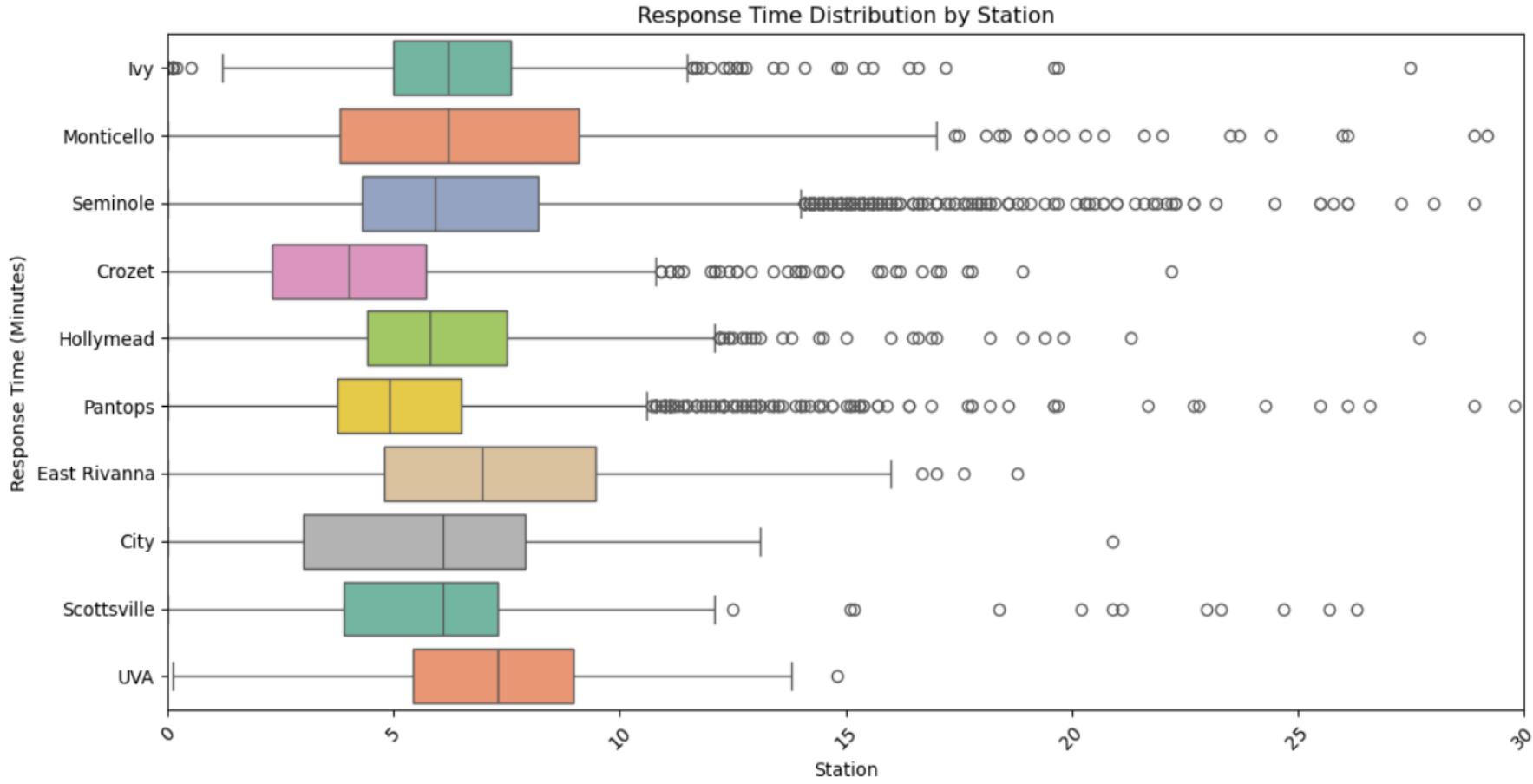




```
plt.figure(figsize=(12, 6))
```

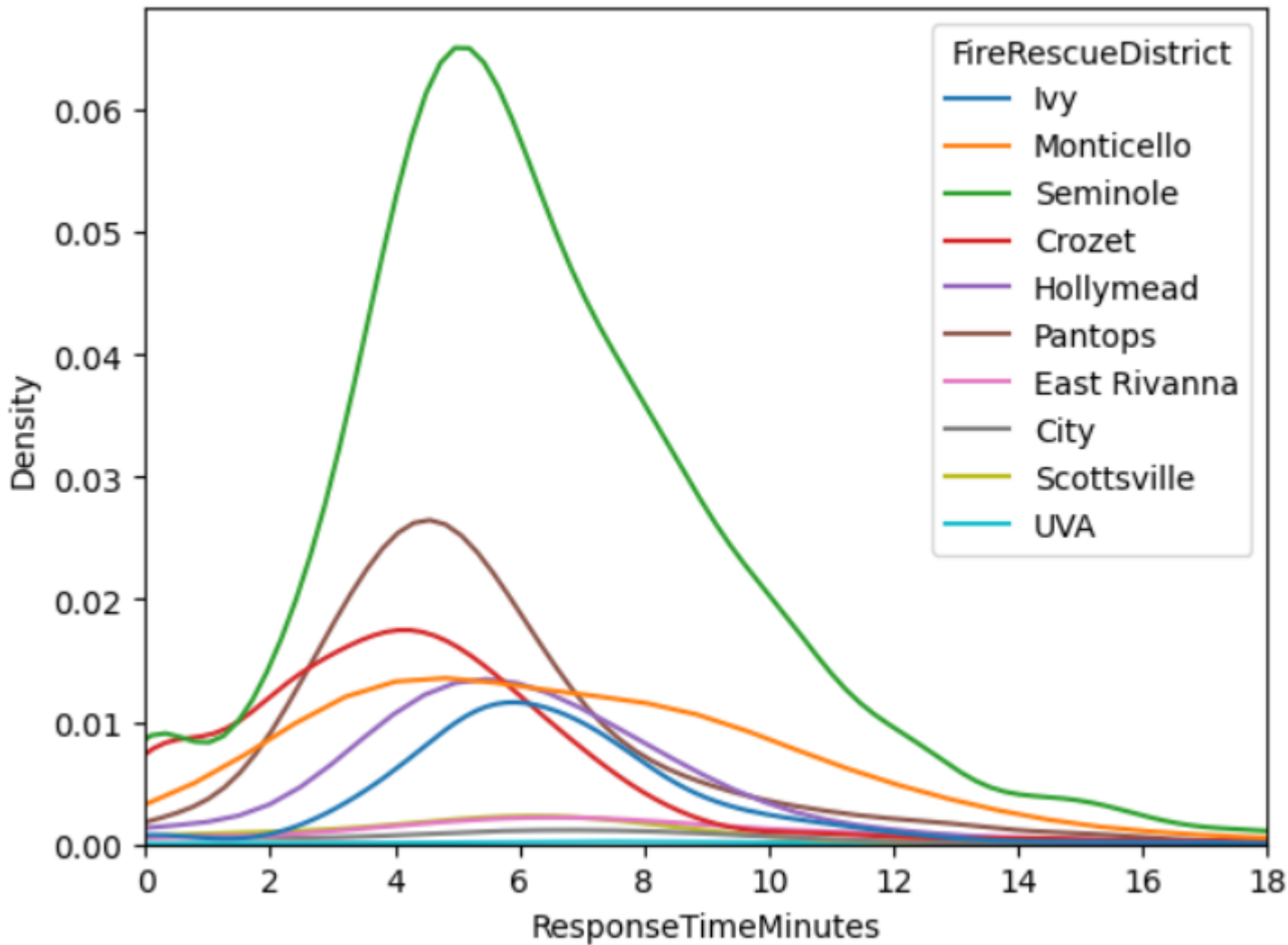
```
sns.boxplot(  
    data=development_area_response,  
    x='ResponseTimeMinutes', # or 'UnitID', 'Shift', etc.  
    y='FireRescueDistrict',  
    palette='Set2',  
    orient = 'h'  
)
```

```
plt.title("Response Time Distribution by Station")  
plt.xlabel("Station")  
plt.ylabel("Response Time (Minutes)")  
plt.xlim(0, 30) # Limit Y-axis to 30 minutes  
plt.xticks(rotation=45)  
plt.tight_layout()  
plt.show()
```



```
sns.kdeplot(data=development_area_response, x='ResponseTimeMinutes', hue='FireRescueDistrict')
plt.xlim(0,18)
```

(0.0, 18.0)



ResponseTimeMinutes	
FireRescueDistrict	
City	9.6
Crozet	7.3
East Rivanna	12.5
Hollymead	9.3
Ivy	9.7
Monticello	11.9
Pantops	9.5
Scottsville	9.4
Seminole	10.7
UVA	13.8



Plotly  
Interactive  
Charts!

```

# Ensure datetime column is parsed
Incidents['DispatchDateTime'] = pd.to_datetime(Incidents['DispatchDateTime'])
Incidents['Month'] = Incidents['DispatchDateTime'].dt.month

# Group by Month and CAD Category
monthly_group = Incidents.groupby(['Month', 'CADCategory']).size().unstack(fill_value=0)

# Sort by month (optional but clean)
monthly_group = monthly_group.sort_index()

# Create figure
fig = go.Figure()

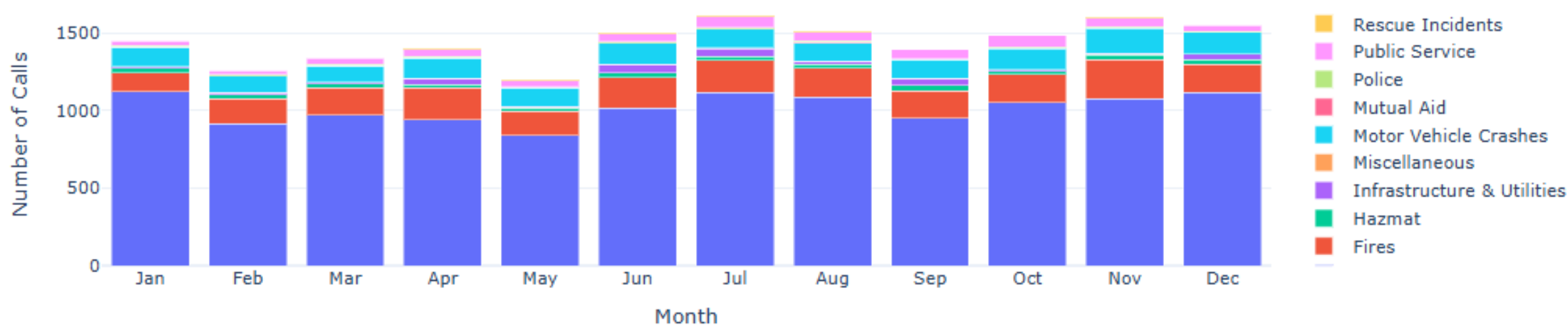
# Add a stacked bar trace for each CAD Category
for category in monthly_group.columns:
    fig.add_trace(
        go.Bar(
            x=monthly_group.index,
            y=monthly_group[category],
            name=category
        )
    )

# Update Layout
fig.update_layout(
    title="Call Volume by Month and CAD Category",
    xaxis_title="Month",
    yaxis_title="Number of Calls",
    barmode='stack',          # Stacked bar chart
    template="plotly_white",
    xaxis=dict(
        tickmode='array',
        tickvals=list(range(1, 13)),
        ticktext=['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
                  'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
    )
)

```



Call Volume by Month and CAD Category

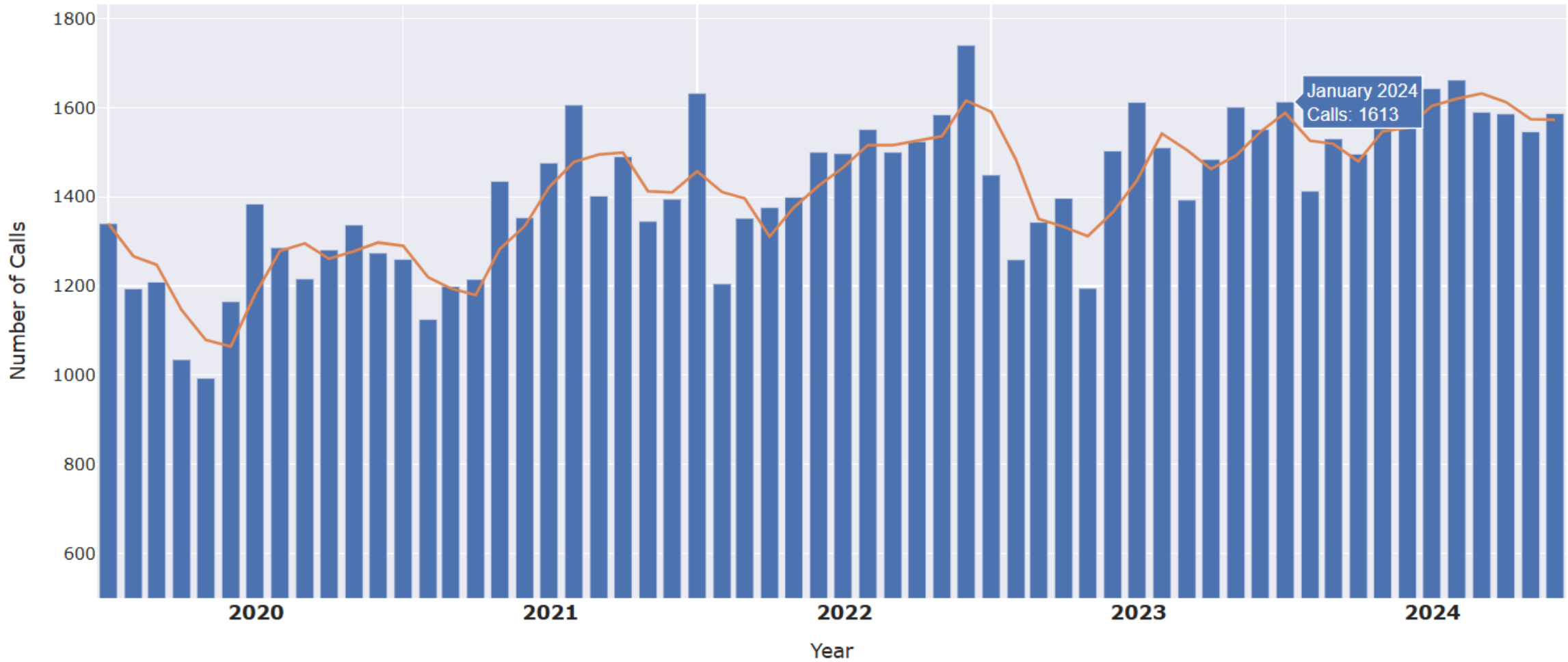


## Monthly Call Volume and 90-Day Rolling Average for All

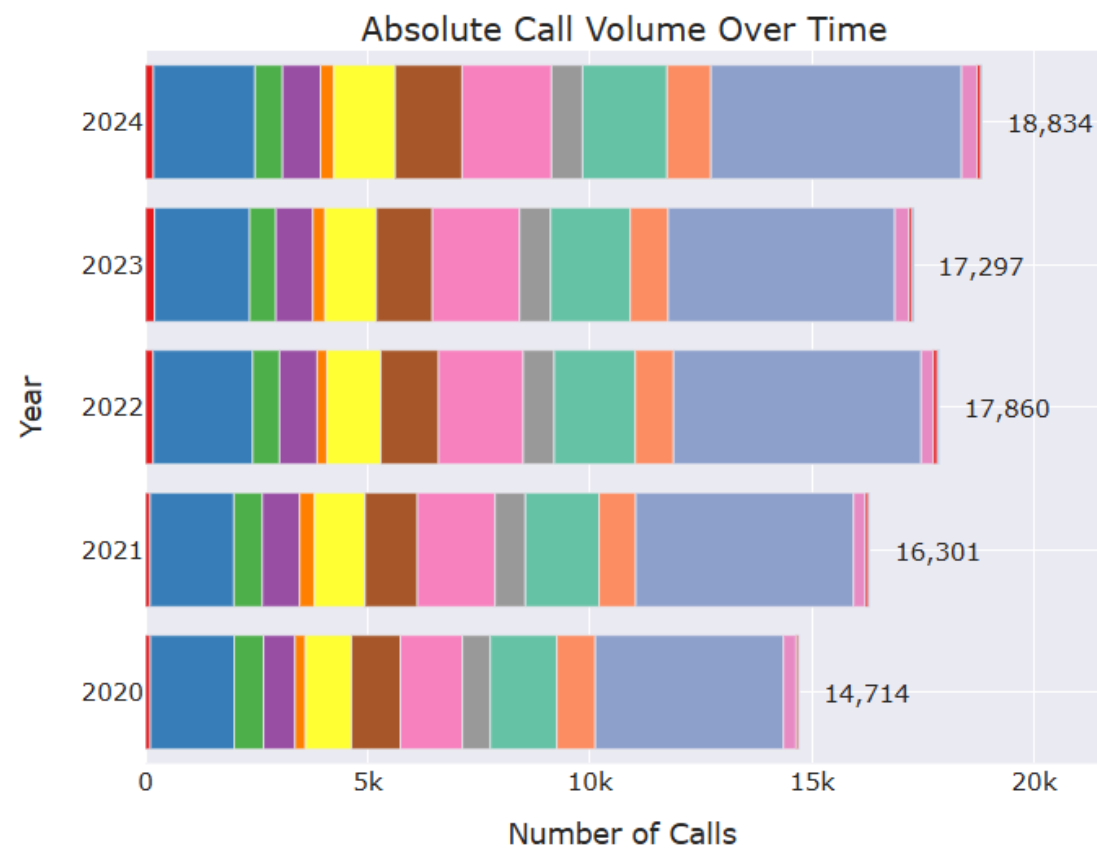
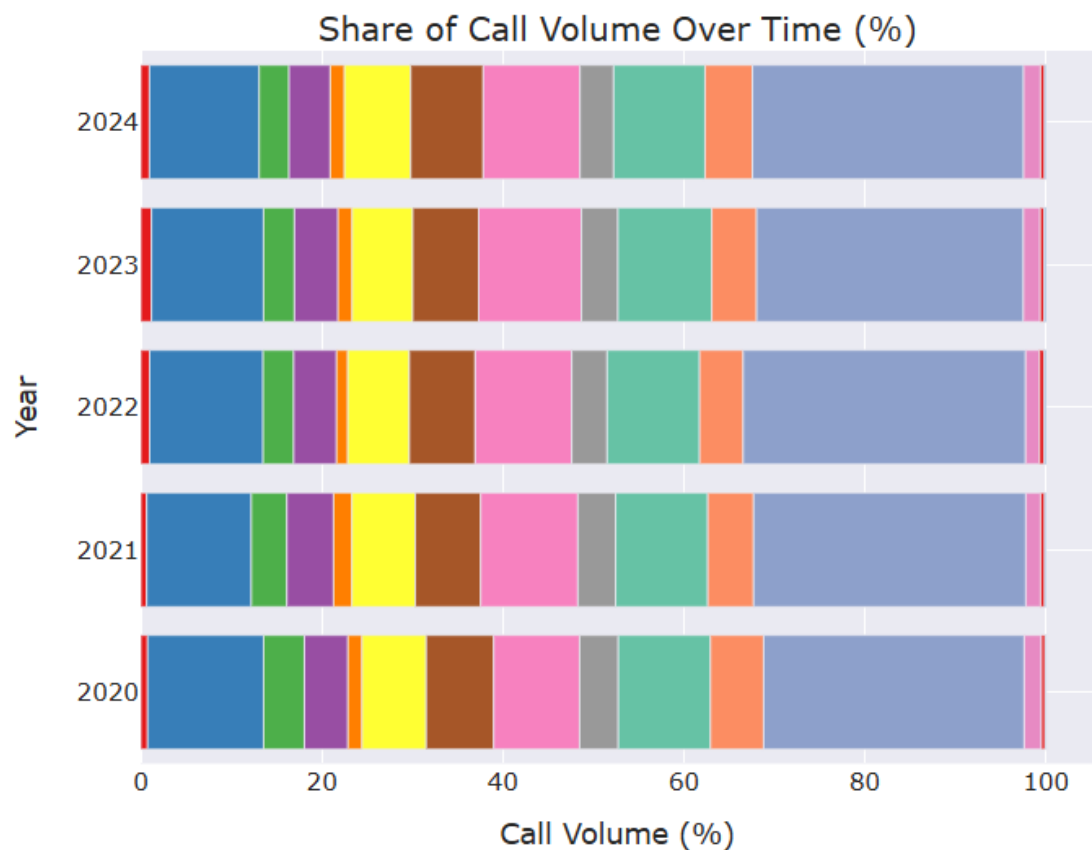


All ▼

■ Monthly Calls    — 90-Day Rolling Average

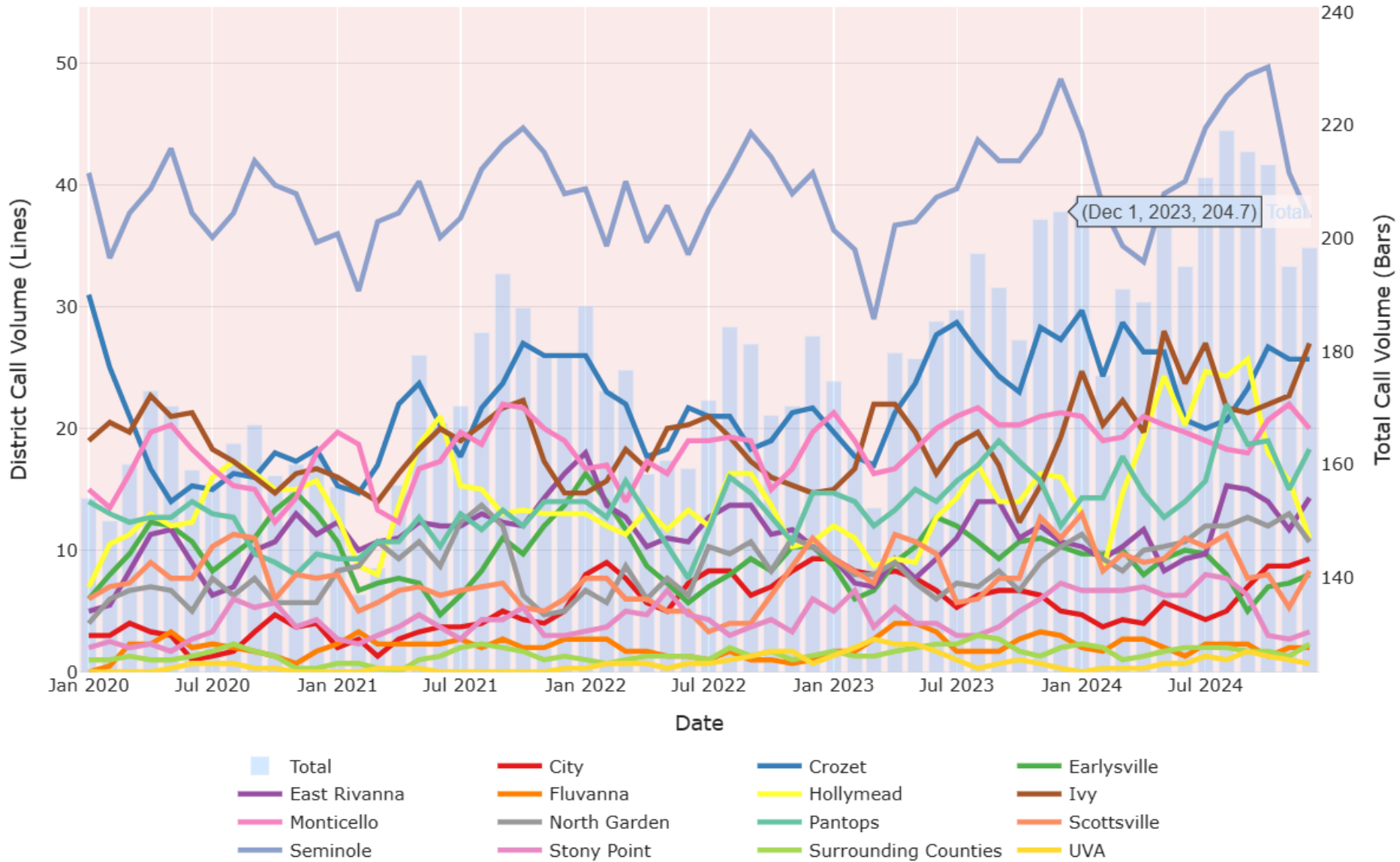


## Call Volume Distribution by FireRescueDistrict



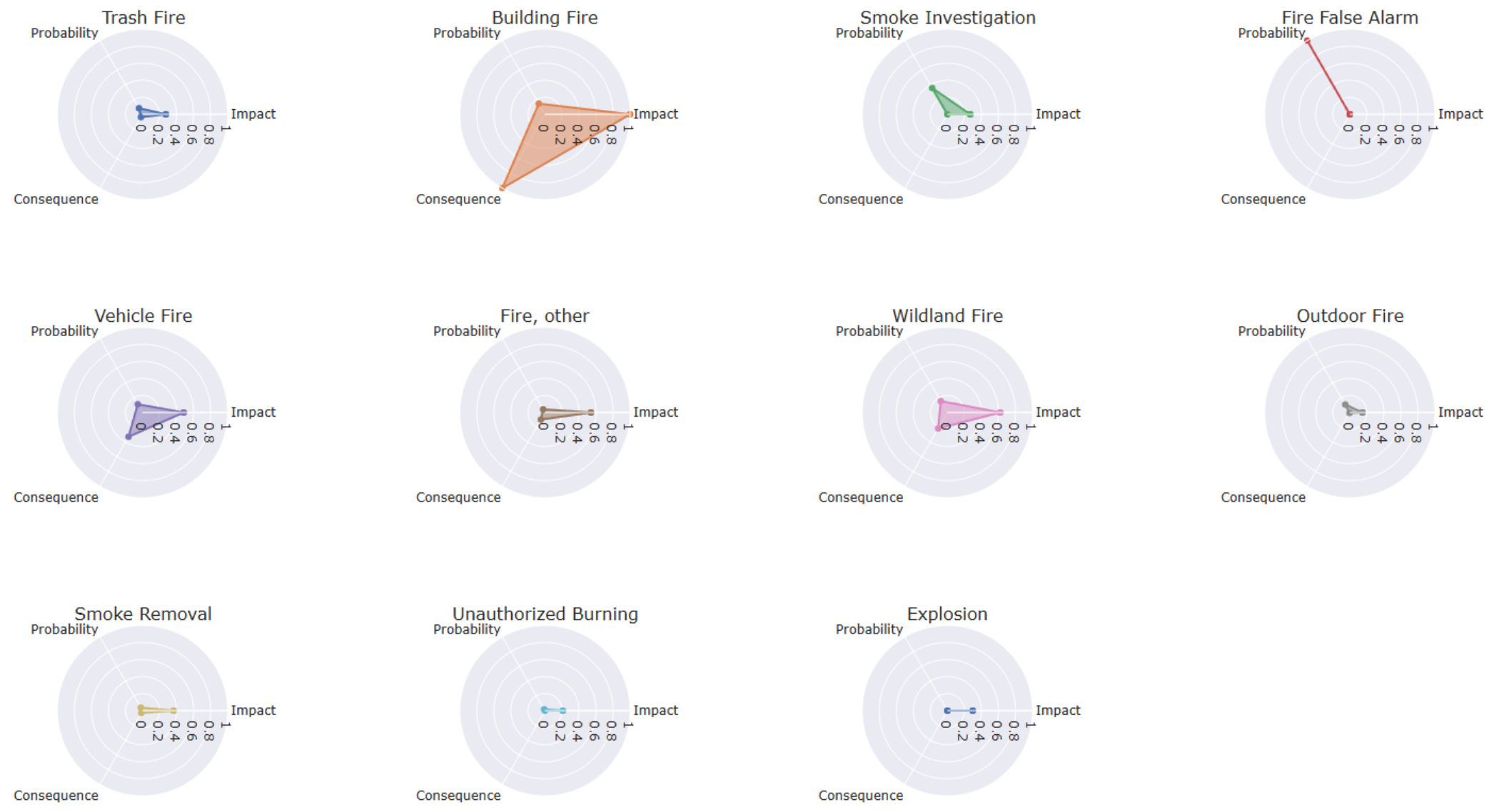
City Crozet Earlysville East Rivanna Fluvanna Hollymead Ivy Monticello North Garden Pantops  
Scottsville Seminole Stony Point Surrounding Counties UVA

# Fires 90-Day Rolling Monthly Average Call Volume by Fire/Rescue District



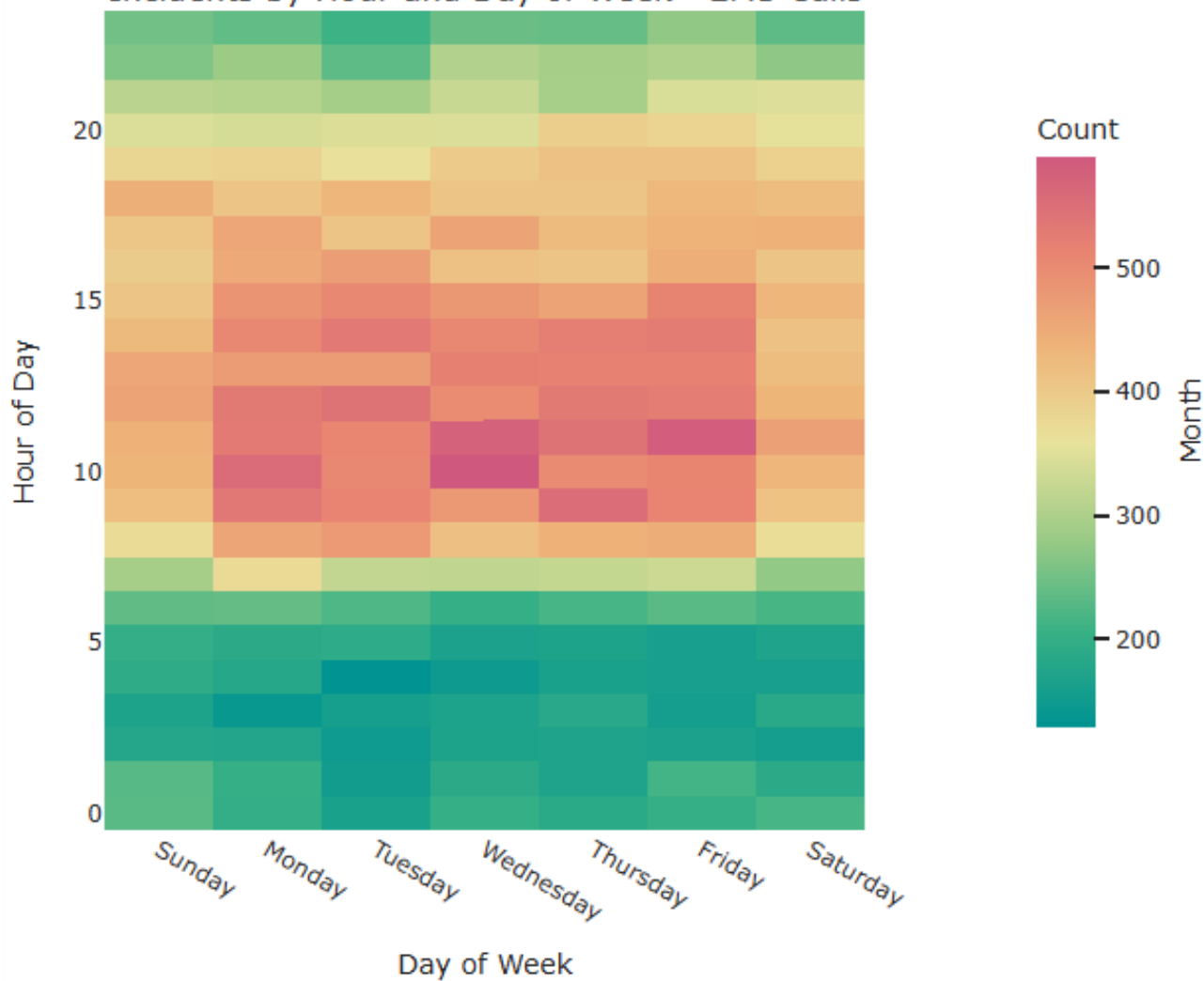


Fire Risk Components by CAD Type

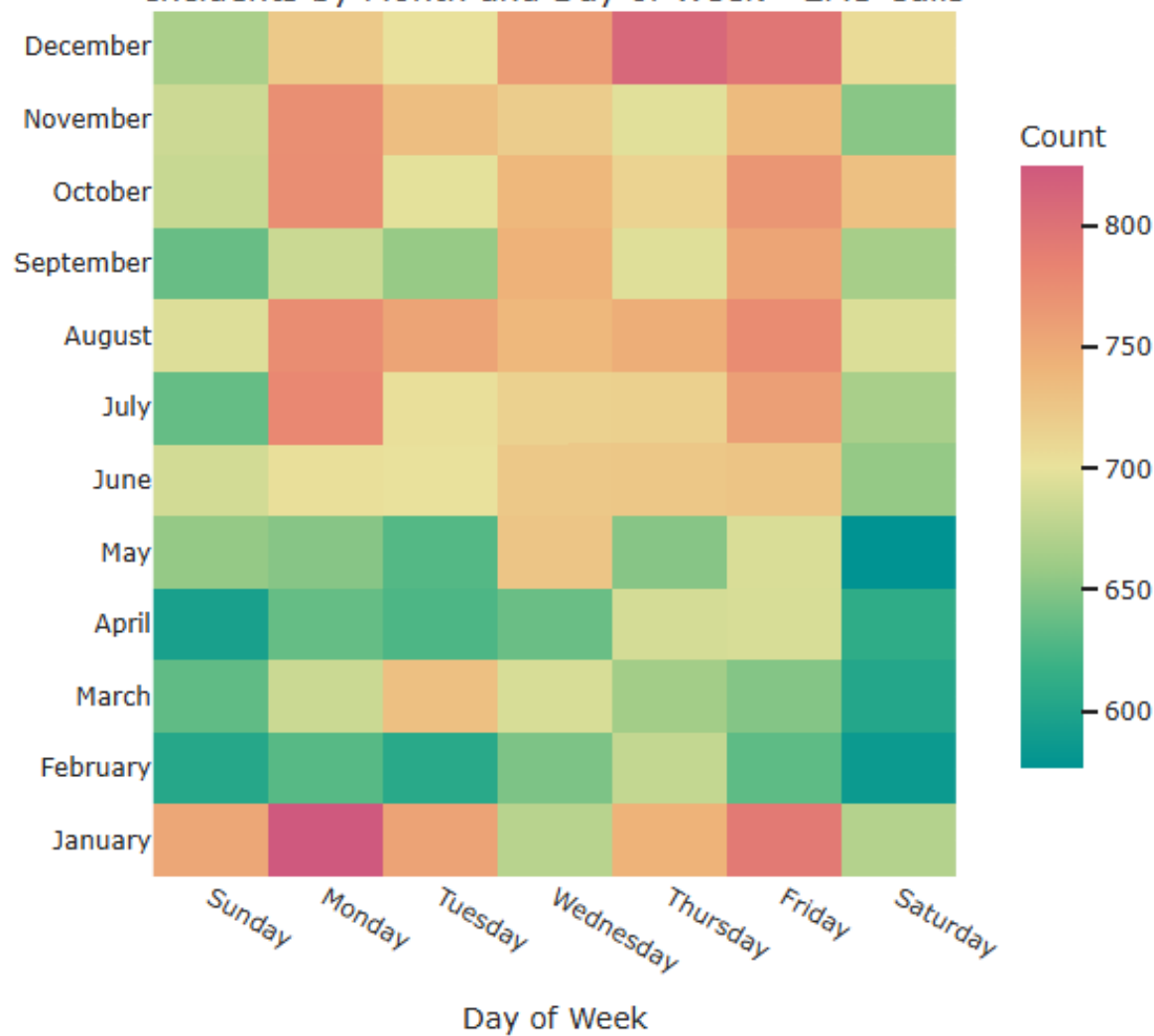


## Incident Pattern Analysis - EMS Calls

### Incidents by Hour and Day of Week - EMS Calls

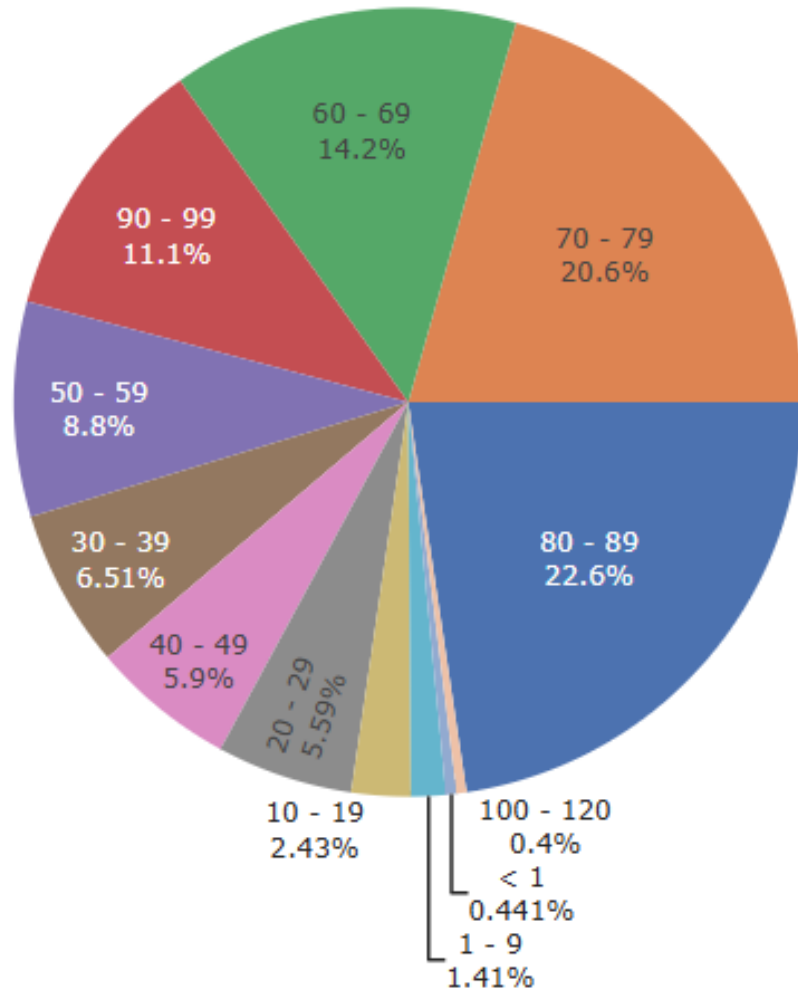


### Incidents by Month and Day of Week - EMS Calls

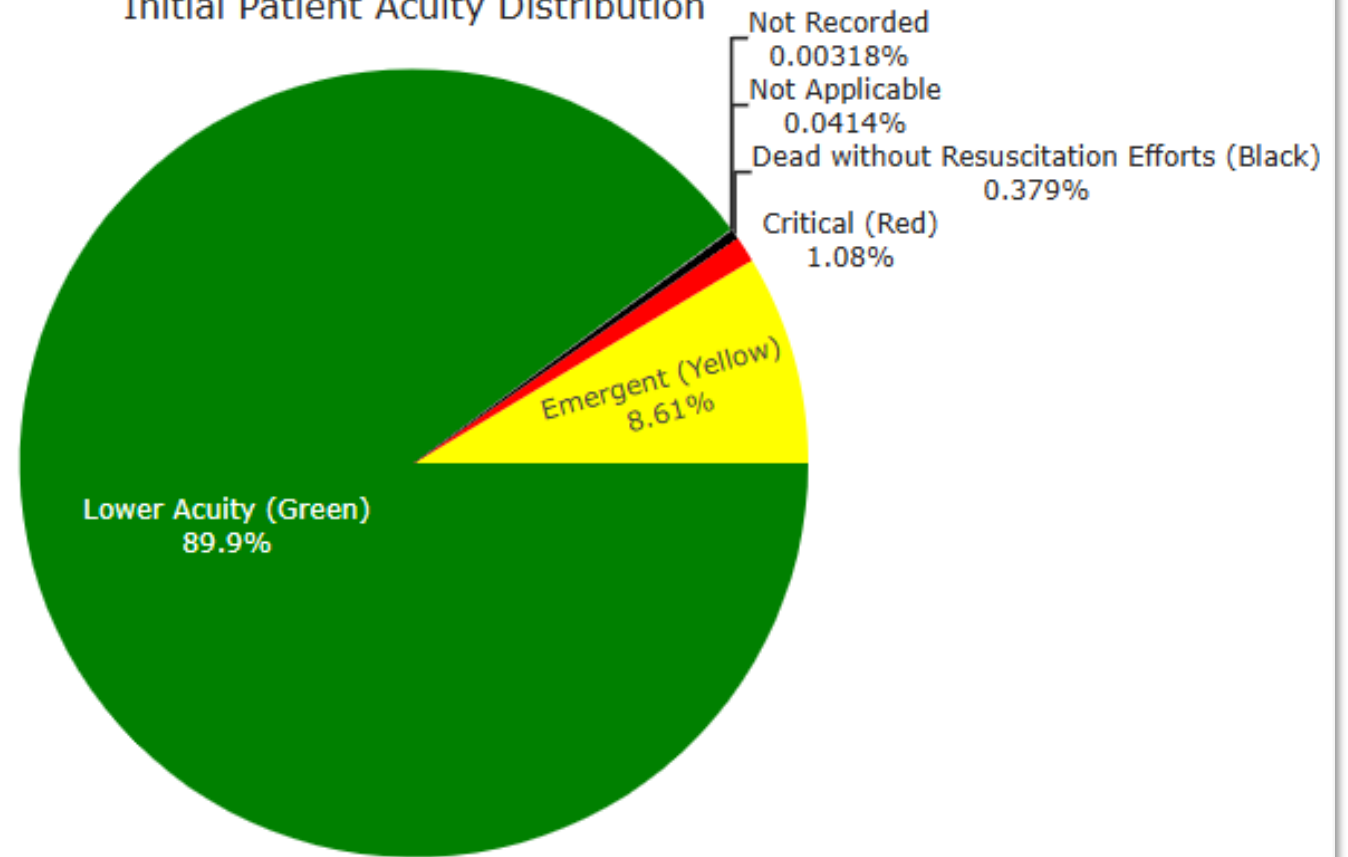


## Distribution of Patient Age Range and Initial Patient Acuity - EMS Calls

Patient Age Range Distribution



Initial Patient Acuity Distribution





# GENERATIVE AI DEMO



Questions