Abstract

Crime analysis is a critical concern in urban management, particularly for cities like Kansas, where understanding crime dynamics directly impacts public safety and resource allocation. This project presents a detailed analysis of crime data spanning the years 2020 to 2024, focusing on identifying trends and patterns that influence crime rates and locations. By leveraging a robust preprocessing pipeline, which includes merging datasets, handling missing values, and standardizing critical features, we prepare the data for insightful analysis. We utilize Hive for efficient querying and exploration of crime distributions based on various factors such as time, type, and location, complemented by visualizations that elucidate key findings. The dataset encompasses a wide range of parameters, enabling the identification of crime hotspots and trends, thereby providing law enforcement and policymakers with actionable insights to enhance public safety measures. Through this analysis, we aim to equip stakeholders with data-driven strategies to effectively address crime and improve community safety in Kansas.

Abbreviations

HiveQL Hive Query Language

DVFlag Domestic Violence flag

IBRS Incident Based - (classification system used in criminal justice data to categorize

offenses)

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1. Introduction Problem Statement:

To analyze and visualize the Crime data of the Kansas City in Missouri, USA.

Crime analysis is a crucial component in developing effective strategies for urban safety and resource management, helping law enforcement and policymakers make data-driven decisions to improve public welfare. In Kansas, the need for an in-depth understanding of crime trends and patterns has grown as the city seeks to address criminal activity efficiently and proactively. This project focuses on analyzing crime data from Kansas over the span of five years, from 2020 to 2024, aiming to identify patterns, trends, and potential correlations within the data. By examining both the temporal and spatial aspects of crime, this analysis provides insights that are valuable for public safety stakeholders and community leaders in Kansas.

To ensure data integrity and reliability, the project began with rigorous preprocessing of yearly crime datasets. The data preparation phase involved merging files from each year, renaming columns for clarity, handling missing values in key demographic and time variables, and standardizing features. Specific techniques, such as filling missing demographic data and converting date and time fields, were used to optimize the dataset for analysis. This comprehensive approach to data cleaning was crucial for enabling accurate analysis and setting a strong foundation for drawing meaningful insights. The resulting dataset captures key attributes like crime type, location, and timing, facilitating multi-dimensional analysis across the city.

Once the dataset was prepared, Hive was used to perform various analytical queries, allowing for efficient exploration of crime by offense type, time of day, and location, as well as demographic factors like age, race, and sex. This step was essential for identifying crime hotspots, seasonal trends, and other relevant patterns that may influence resource allocation and policy decisions. The findings were further enhanced through visualization, revealing critical insights that could help Kansas City officials prioritize interventions and deploy resources effectively. By delivering a comprehensive overview of crime trends in Kansas, this analysis supports efforts to improve public safety through data-driven decision-making and targeted crime prevention strategies.

2. Methodology

We have taken data of each year from the website and combined them into a single file.

Data-Link: - https://data.kcmo.org/browse?category=Crime

2.1 Dataset Description

The Kansas crime dataset now comprises **488,023 entries** and **31 columns**, offering an expansive view of crime incidents in Kansas City. Each row represents a unique crime report with detailed attributes capturing temporal, geographic, and demographic information. The key features in this dataset include:-

- **Report_No**: Unique identifier for each reported crime.
- Reported_year, Reported_month, Reported_day, Reported_hour,
 Reported_minute: Detailed breakdown of the date and time each crime was reported.
- From_year, From_month, From_day, From_hour, From_minute: Date and time when the crime was initially committed.
- Offense: Type of crime committed.
- **IBRS**: Incident-Based Reporting System code for the offense.
- **Description**: A detailed description of the offense.
- **Beat**: Numeric code representing the patrol beat for the incident.
- Address: Specific address of the incident.
- City: Specifies the city, consistently "KANSAS CITY" across all entries.
- **Zip_Code**: Zip code of the crime location.
- **Rep_Dist**: Reporting district within Kansas City.
- **Area**: Geographic area categorization for resource planning.
- **DVFlag**: Indicator of whether the incident involved domestic violence.
- **Involvement**: Type of involvement for individuals associated with the crime.
- **Race**: Race of the individuals involved.
- **Sex**: Gender of the individuals involved.
- **Age**: Age of individuals, with missing values imputed as needed.
- **Firearm_Used_Flag**: Boolean flag indicating firearm involvement.
- **Age_Group**: Categorical grouping of age for demographic analysis.
- **Age Range**: Range category for age, with some missing values.
- **Age Group**: Additional categorization of age for analytical flexibility.

- **Reported_Hour**: Hour at which the crime was reported, as a float.
- Month_Year: Concatenated month and year, allowing monthly trend analysis.

This dataset provides a valuable foundation for analyzing crime patterns in Kansas City over multiple years. The diversity of temporal, demographic, and geographic features enables thorough exploration of crime dynamics, supporting visualizations and insights into seasonal, spatial, and demographic trends.

RangeIndex: 488023 entries, 0 to 488022								
Data columns (total 28 columns):								
#	Column	Non-Null Count	Dtype					
0	Report_No	488023 non-null	object					
1	Reported_Date	488023 non-null	object					
2	Reported Time	96220 non-null	object					
3	From_Date	488017 non-null	object					
4	From Time	96219 non-null	object					
5	To_Date	230928 non-null	object					
6	To Time	32101 non-null	object					
7	Offense	488023 non-null	object					
8	IBRS	442699 non-null	object					
9	Description	442699 non-null	object					
10	Beat	488006 non-null	object					
11	Address	488023 non-null	object					
12	City	488020 non-null	object					
13	Zip Code	455154 non-null	object					
14	Rep_Dist	403560 non-null	object					
15	Area	488010 non-null	object					
10	DV/F1	40000011	-1-2					

Α	В	C	D	E	F	G	Н	1	J	K	L	M	
Report_No	Reported_year	Reported_month	Reported_day	Reported_hour	Reported_minute	From_yea	From_mo	From_day	From_hcl	From_m	Offense	IBRS	Descriptio
KC21055624	2021	8	21	19	45	2021	8	21	19	45	Murder	09A	Murder
KC21012401	2021	2	24	11	35	2021	2	24	11	35	Stealing from Building/Residence	23D	Theft Fron
KC21010791	2021	2	17	11	41	2021	2	11	20	30	Stolen Auto	24	10 Motor Vel
KC21012025	2021	2	22	17	55	2021	2	22	17	55	Assault (Aggravated)	13A	Aggravate
KC21003742	2021	1	. 17	22	8	2021	1	17	21	30	Assault (Aggravated)	13A	Aggravate
KC21004380	2021	1	. 20	16	44	2021	1	20	16	44	Assault (Aggravated)	13A	Aggravate
KC21005430	2021	1	. 25	12	9	2020	4	13	12	0	Forgery	25	0 Counterfe
KC21008041	2021	2	. 5	11	14	2020	12	19	12	0	Identity Theft	26F	Identity Th
KC21011417	2021	2	20	1	41	2021	2	20	1	38	Robbery (Armed Street)	12	20 Robbery
KC21011702	2021	2	21	11	. 3	2021	2	20	17	0	Stolen Auto	24	10 Motor Veh
KC21012637	2021	2	25	11	45	2021	2	4	11	45	Identity Theft	26F	Identity Th
KC21010718	2021	2	17	C	6	2021	2	17	0	4	Murder	09A	Murder
KC21006497	2021	1	. 29	13	59	2021	1	29	15	45	Stealing â€" Shoplift	23C	Shoplifting
KC21015438	2021	3	9	13	9	2021	3	9	13	9	Soliciting Prostitution	40A	Prostitutio
KC21009523	2021	2	11	11	27	2021	2	7	18	0	Stolen Auto	24	10 Motor Veh
KC21013729	2021	3	2	8	43	2021	3	1	21	30	Stealing from Auto (Theft from Au	t 23F	Theft Fron
KC21009495	2021	2	11	8	45	2021	2	3	10	56	Embezzlement	27	70 Embezzler
KC21010861	2021	2	17	15	52	2021	2	17	15	52	Assault (Non-Aggravated)	13B	Simple Ass
KC21013274	2021	2	28	5	19	2021	2	28	5	19	Murder	09A	Murder
KC21009313	2021	2	10	14	1	2020	2	10	14	10	Stealing â€" Shoplift	23C	Shoplifting
KC21006619	2021	1	. 30	2	57	2021	1	30	2	57	Murder	13A	Aggravate
KC21012281	2021	2	23	18	34	2021	2	23	18	30	Stolen Auto	24	10 Motor Vel
KC21011079		2	18	16	41	2021	2	18	16	30	Patronizing Prostitution	40A	Prostitutio

Fig 1 Kansas Crime Data

In this project we used Hive and Pyspark to analyze and visualize the data.

2.2 Dataset loading

We loaded the data and had a quick overview of the data and checked for the null values. We got many Null value values, we modified the Null data points to some variable like any missing Sex is denoted as 'U' etc. We also renamed some columns for our easiness of use and merged all 5 data files.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 488023 entries, 0 to 488022
Data columns (total 28 columns):
    Column
                       Non-Null Count
                                        Dtype
    Report_No
                       488023 non-null object
    Reported_Date
                      488023 non-null object
    Reported Time
                       96220 non-null
                                        object
    From_Date
                       488017 non-null object
    From Time
                       96219 non-null
                                        object
    To_Date
                       230928 non-null
                                        object
    To Time
                       32101 non-null
                                        object
    Offense
                       488023 non-null
                                        object
    IBRS
                       442699 non-null
    Description
                       442699 non-null
10
                       488006 non-null
11 Address
                       488023 non-null
12 City
                       488020 non-null
13 Zip Code
                       455154 non-null
14
    Rep_Dist
                       403560 non-null
                       488010 non-null
15 Area
                                        object
16 DVFlag
                       488023 non-null
                                        object
17 Involvement
                      488023 non-null
                                        object
                       423268 non-null
18
    Race
                                        object
19 Sex
                       429353 non-null
                                        object
20 Age
                        360034 non-null
                                        float64
21 Firearm Used Flag 188347 non-null
                                        object
                       445903 non-null
22
    Location
                                        object
23 Reported Time
                       391803 non-null
                                        object
24 From Time
                        391798 non-null
                                        object
25 To_Time
                       131281 non-null
                                        object
26 Age_Range
                        286877 non-null
                                        object
27 Fire Arm Used Flag 299676 non-null object
dtvpes: float64(1). object(27)
            Fig 2 Data_info_before_processing
```

2.3 Preprocessing

Checked for null values

Missing values are addressed by filling in categorical variables like Sex and Race with 'U' for unknown, while the Age column is filled with the rounded mean age. Essential columns are filtered to exclude rows with null values, and a summary of remaining nulls is generated for transparency.

<class 'pandas.core.frame.dataframe'=""></class>						
Index	c: 349353 entries,	0 to 349566				
Data	columns (total 31	columns):				
#	Column	Non-Null Count	Dtype			
0.00			50 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5			
0	Report_No	349353 non-null	object			
1	Reported_year	349353 non-null	int64			
2	Reported_month	349353 non-null	int64			
3	Reported_day	349353 non-null	int64			
4	Reported hour	349353 non-null	int64			
5	Reported_minute	349353 non-null	int64			
6	From year	349353 non-null	int64			
7	From_month	349353 non-null	int64			
8	From_day	349353 non-null	int64			
9	From hour	349353 non-null	int64			
10	From_minute	349353 non-null	int64			
11	Offense	349353 non-null	object			
12	IBRS	349353 non-null	object			
13	Description	349353 non-null	object			
14	Beat	349353 non-null	float64			
15	Address	349353 non-null	object			
16	City	349353 non-null	object			
17	Zip_Code	349353 non-null	object			
18	Rep_Dist	349353 non-null	object			
19	Area	349353 non-null	object			
20	DVFlag	349353 non-null	object			
21	Involvement	349353 non-null	object			
22	Race	349353 non-null	object			
23	Sex	349353 non-null	object			
24	Age	349353 non-null	float64			
25	Firearm_Used_Flag	349353 non-null	bool			
26	Age_Group	349353 non-null	category			
27	Age Range	347544 non-null	category			
28	Age Group	349353 non-null	category			
29	Reported_Hour	349353 non-null	float64			
30	Month Year	349353 non-null	object			

Fig 3 Data_info_after_pre-processing

Date and time information is extracted into separate year, month, day, hour, and minute components, and unnecessary original columns are dropped. We made a column representing if the fire arms were used in the crime or not and another column representing if the crime was a domestic violence crime or not both were represented in true or false. We divided the ages into age groups giving a range of 10 for each age group.

3. Data analysis

We have used hive for data analysis. After preprocessing the complete data, we exported them into a csv file named 'filtered_data.csv' consisting of 31 columns and 349,353 rows in total.

3.1 Load data into Hadoop Ifs

Create a new folder and then uploaded the file to the HDFS.

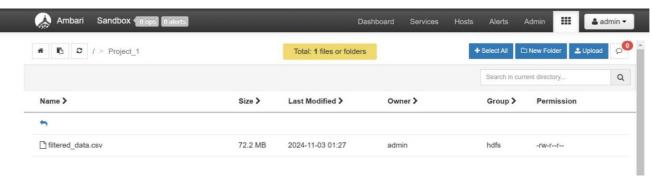


Fig 4 Hdfs File Loc

Get the function to the local file system in Hadoop.

```
]# hdfs dfs -get /Project_1/filtered_data.csv
root@sandbox ~]# ls -l
otal 134728
                                      2016 anaconda-ks.cfg
                           20 Oct 25
                                      2016 build.out
                     75719611 Nov
                                   2 20:21 filtered_data.csv
                         4096 Oct 25
                                      2016 hdp
           root root
                                      2016 install.log
           root root
                          1680 Jun
                                       2016 install.log.syslog
           root root
           root root 61829279 Nov
                                   2 16:04 KCDP_Final_Crime_Data_Original_1.csv
                                      2016 sandbox.info
                           48 Oct 25
                                      2016 start_ambari.sh -> /usr/lib/hue/tools/start_scripts/start_ambari.sh
rwxrwxrwx 1 root
                                      2016 start_hbase.sh -> /usr/lib/hue/tools/start_scripts/start_hbase.sh
  ot@sandbox ~]#
```

Fig 5 Loading file into LFS

3.2 Hive initiation

Creating a database and using that data base in hive.

```
hive> create database Crime_Database;

OK

Time taken: 0.157 seconds

hive> use Crime_Database;

OK

Time taken: 0.27 seconds

hive>
```

Creating the table

```
hive> create table crime_data(Report_No string,Reported_year int,Reported_month int,Reported_day int,Reported_hour int,Reported_minute int,F rom_year int,From_month int,From_day int,From_hour int,From_minute int,offense string,IBRS string,Description string,Beat float,Address string,City string,Zip_code float,Rep_Dist string,Area string,DVFlag boolean,Involvement string,Race string,Sex string,Age float,Firearm_Used_Fl ag boolean,Age_Group string,Age_Range string,Age_Group2 string,Reported_Hour_f float,Month_Year string)

> row format delimited fields terminated by ',';

OK
Time taken: 0.631 seconds
hive>
```

Loading the data to the table

```
hive> load data local inpath 'filtered_data.csv' into table crime_data;
Loading data to table crime_database.crime_data
Table crime_database.crime_data stats: [numFiles=1, numRows=0, totalSize=75719611, rawDataSize=0]
OK
Time taken: 1.298 seconds
hive>
```

Verifying data from the table

Fig 6 Table in hive

select count(*) from crime data;

select distinct offense from crime data;

```
Stolen Auto
Suicide
Suicide - Attempted
 Tampering
 Tampering with Physical Evidence
 Tavern/Nightclub Response Report
 Terroristic Threats
 Tobacco Law Violation
 Tow-In Report/Authorization Not to Tow
 Trafficking in Identifications
Trespass of Real Property
 Unlawful Endangerment of Another
 Jnregistered Sex Offender
Vehicular - Fatality
Vehicular - Injury
Vehicular - Injury Hit and Run
Vehicular - Non-Injury
 /ehicular - Non-Injury Hit and Run
/ehicular - Fatality
Vehicular – Injury
Vehicular – Injury Hit and Run
Vehicular - Injury hit and Run

Vehicular - Non-Injury

Vehicular - Non-Injury Hit and Run

Violation of Ex-Parte Order of Protection

Violation of Full Order of Protection
 Time taken: 12.344 seconds, Fetched: 156 row(s)
```

3.3 Data Analysis

1. Yearly Trends over the years 2020 to 2024.

select Reported_year,count(*) as total_crimes
from crime_data group by Reported_year
order by Reported year;

```
> from crime_data
    > group by Reported_year
Query ID = root_20241102205829_608ea929-3e09-4d9a-b2d7-f96187a499a7
Total jobs = 1
 aunching Job 1 out of 1
 ez session was closed. Reopening...
 Session re-established.
Status: Running (Executing on YARN cluster with App id application 1730562569604 0011)
        VERTICES
                     STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED

        Map 1 ......
        SUCCEEDED
        5
        5

        Reducer 2 .....
        SUCCEEDED
        1
        1

        Reducer 3 .....
        SUCCEEDED
        1
        1

OK
NULL
2020
                  53703
2021
                  67425
2022
                 75414
2023
                  82141
2024
                  70670
 Time taken: 18.13 seconds, Fetched: 6 row(s)
```

Fig 7 Query 1

We got 53703 crimes for 2020, 67425 crimes in the year 2021, 75414 for the year 2022, 82141 crimes for the year 2023 and 70670 crimes for the year 2024.

We can observe that there is highest no of crimes int 2023.

The ranking of the no of crimes in the year goes like: -

- 1. 2023
- 2. 2022
- 3. 2024
- 4. 2021
- 5. 2020

2. Analysis over the months

```
select Reported_month,count(*) as total_crimes
from crime_data
group by Reported_month
order by Reported month;
```

```
ive> select Reported_month,count(*) as total_crimes
   > from crime_data
   > group by Reported_month
   > order by Reported_month;
Query ID = root_20241102210108_64869534-5c3e-40de-9ce1-5af062d9a192
otal jobs = 1
aunching Job 1 out of 1
Status: Running (Executing on YARN cluster with App id application_1730562569604_0011)
       VERTICES STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
Map 1 ..... SUCCEEDED
Reducer 2 .... SUCCEEDED
Reducer 3 .... SUCCEEDED
                                                                                 0
             NULL
                      28181
                       25768
                       28173
                       28681
                       31411
                       32557
                       34625
                       34885
                       33141
                       29380
             11
                       22644
             12
                       19907
             Time taken: 13.119 seconds, Fetched: 13 row(s)
             nive>
```

Fig 8 Query 2

Over the Period of 12 months across the year 2020 to 2025, we have a ranking of : -

1.	August:	34885
2.	July:	34625
3.	September:	33141
4.	June:	32557
5.	May:	31411
6.	October:	29380
7.	April:	28681
8.	January:	28181
9.	March:	28173
10.	February:	25768
11.	November:	22644
12.	December:	19907

3. Top 5 offenses in the data: -

```
select offense,count(*) as offense_count
from crime_data
group by offense
order by offense_count desc
limit 5;
```

```
from crime_data group by offense
    order by offense_count desc
uery ID = root_20241102210321_3a9a52a3-bd5e-459b-9c25-48bc97f49c40
Total jobs = 1
aunching Job 1 out of 1
Status: Running (Executing on YARN cluster with App id application_1730562569604_0011)
       VERTICES
                    STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
                  SUCCEEDED
                  SUCCEEDED
                                                                                0
Stolen Auto
                                                29800
Oomestic Violence Assault (Non-Aggravated)
roperty Damage 26083
stealing from Auto (Theft from Auto)
ssault (Aggravated) 23430
ime taken: 12.079 seconds, Fetched: 5 row(s)
```

Fig 9 Query 3

We examined the frequency of various offenses recorded in the crime dataset. By aggregating the data, we identified the top five most prevalent offenses, highlighting the most common types of criminal activity reported. This insight not only sheds light on the current crime landscape but also aids in understanding trends and patterns within the community.

4. Top 5 Offenses by ZIP Code

```
select Zip_code,count(*) as offenses_by_zip_code
from crime_data
group by Zip_code
order by offenses_by_zip_code desc
limit 5;
```

Fig 10 Query 4

This query retrieves the top five ZIP codes with the highest number of reported offenses, providing insights into geographic crime distribution. It counts the total offenses for each ZIP code and sorts the results in descending order.

5. Average Age of Offenders by Offense Type

```
select offense, avg (Age) as Avg age offenders
from crime data
group by offense
order by Avg age offenders desc;
```

```
>> select offense,avg(Age) as Avg_age_offenders
> from crime_data
> order by Avg_age_offenders desc;
uery ID = root_20241102211805_6e1e6675-673e-48a9-9107-c1bfd0dc0bba
aunching Job 1 out of 1
Status: Running (Executing on YARN cluster with App id application 1730562569604 0011)
      VERTICES STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
Nossession of Gambling Device or Records 71.0
Financial Exploitation of the Elderly 64.11428571428571
Elder Abuse 54.734939759036145
Curfew Violation 48.4
Animal Bite 47.0
Identity Theft 44.062875309078066
Comestic Violence Lethality Screen for First Responders (LAP) 44.0
Abandonment of a Child 34.529411764705884
Rape - Statutory 34.493506493506494
Kidnapping 34.46712802768166
Invasion of Privacy 34.16564417177914
Murder 34.14713656387665
Eluding / Resisting a Lawful Stop
                                                 34.01764057331863
Adult Entertainment Violation 34.0
Domestic Violence Burglary (Residential)
                                                           33.857290589451914
                           33.6
False Imprisonment
Domestic Violence Robbery (Strong-Armed)
                                                           33.536986301369865
Liquor Law Violation 33.526315789473685
Cold Case Sex Offense 33.25
                           33.11904761904762
Rape - Statutory
Suicide – Attempted
                             32.75
Police Vehicle Damage (Form 154 P.D.)
Human Trafficking/Commercial Sex Acts 32.25581395348837
Outside Correspondence 32.0
Escape from Custody/Confinement 32.0
Officer Involved Shooting - Fatal
                                                 31.695652173913043
Tobacco Law Violation 31.6666666666668
Tavern/Nightclub Response Report
                                                 31.16666666666668
Interdiction 30.75
Possession of Illegal Firearm 30.37074829931973
/ehicular - Fatality
Suicide 27.0
Offense NULL
Time taken: 13.993 seconds, Fetched: 156 row(s)
hive>
```

Fig 11 Query 5

This query calculates the average age of offenders for each type of offense. By grouping the data by offense and ordering the results in descending order, it highlights which offenses are associated with older or younger offenders, aiding in demographic analysis.

6. Firearm count

```
select count(case when Firearm Used Flag = True then 1 end) as
Firemarm Used,
count(case when Firearm Used Flag = False then 1 end) as
Firearm not used
from crime data;
                > count(case when Firearm_Used_Flag = False then 1 end) as Firearm_not_used
                 > from crime data:
              Query ID = root_20241102214929_77dfeb0d-0694-405a-91fc-6391facede2b
               otal jobs = 1
               aunching Job 1 out of 1
               ez session was closed. Reopening...
               Session re-established.
               Status: Running (Executing on YARN cluster with App id application_1730562569604_0012)
                    VERTICES STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
               lap 1 ..... SUCCEEDED 5
seducer 2 ..... SUCCEEDED 1
               31599 315841
               ime taken: 15.535 seconds, Fetched: 1 row(s)
```

Fig 12 Query 6

This query counts the number of offenses involving firearms versus those that do not. By separating the counts based on the `Firearm_Used_Flag`, it provides insights into the prevalence of firearm use in crimes, which is essential for understanding safety and policy implications.

7. DvFlag Count

```
select count(case when DVFlag = True then 1 end) as
Domestic_violence,
count(case when DVFlag = False then 1 end) as
Non_Domestic_violence
from crime_data;
```

Fig 13 Query 7

This query distinguishes between domestic violence and non-domestic violence incidents within the dataset. By counting occurrences based on the `DVFlag`, it offers valuable insights into the prevalence of domestic violence, aiding in resource allocation and community safety strategies.

8. Firearm Usage by Offense Type

```
select offense,count(*) as Firearm_Usage
from crime_data
where Firearm_Used_Flag = True
group by offense
order by Firearm Usage desc;
```

```
tealing - Shoplift
Violation of Ex-Parte Order of Protection
Sexual Misconduct - Juvenile
Discharge of Firearm (LEO Only) 4
Stealing - Other
Unfounded 4
Vehicular - Non-Injury 4
Suicide - Attempted 3
ampering
State Warrant Arrest
alse Imprisonment
/ehicular - Injury
Patronizing Prostitution
Stealing from Building/Residence 2
Mental Health/Crisis Intervention Team (CIT) Report
Attempt to Locate Motor Vehicle 2
Vehicular - Non-Injury Hit and Run
Interdiction
alse Report
Service of an Ex-Parte Order of Protection
Confiscated Firearm
/ehicular - Injury Hit and Run 1
Possession of Drug Paraphernalia
Unlawful Endangerment of Another 1
Time taken: 11.355 seconds, Fetched: 85 row(s)
```

Fig 14 Query 8

This query analyzes firearm usage across different offenses by counting incidents where firearms were used. By grouping the data by offense type, it highlights the most prevalent crimes involving firearms, providing essential insights for law enforcement and community safety initiatives.

9. Top 5 Domestic Violence Flag by offense

```
select offense,count(*) as DV_offenses
from crime_data
where DVFlag = True
group by offense
order by DV_offenses desc
limit 5;
```

Fig 15 Query 9

This query identifies the top five offenses classified as domestic violence by counting incidents marked with the Domestic Violence flag. It provides a focused view of the most common domestic violence offenses, aiding in targeted intervention and prevention efforts within the community.

10. Offenses by Reported Year and Month (Year-Month Breakdown)

```
select Reported_year,Reported_month,count(*) as
offenses_by_year_month
from crime_data
group by Reported_year,Reported_month
order by Reported year,Reported month;
```

2022	8	6806				
2022	9	6697				
2022	10	6875				
2022	11	5527				
2022	12	5484				
2023	1	6388				
2023	2	5385				
2023	3	6318				
2023	4	6601				
2023	5	7060				
2023	6	7479				
2023	7	7881				
2023	8	7949				
2023	9	7408				
2023	10	7055				
2023	11	6707				
2023	12	5910				
2024	1	6552				
2024	2	6609				
2024	3	6764				
2024	4	7051				
2024	5	7595				
2024	6	7782				
2024	7	8565				
2024	8	8219				
2024	9	7341				
2024	10	4192				
Time	taken:	10.978 seconds,	Fetched:	59	row(s)	

Fig 16 Query 10

This query aggregates the total number of offenses reported each month across different years. By providing a year-month breakdown, it enables the analysis of crime trends over time, helping to identify seasonal patterns and shifts in criminal activity.

11. Race and Gender Distribution for Domestic Violence Cases

```
select Race,Sex,count(*) as DV_by_race_gender
from crime data
```

```
where DVFlag = True
group by Race,Sex
order by DV_by_race_gender desc;
```

```
ive> select Race,Sex,count(*) as DV_by_race_gender
    > from crime_data
    > where DVFlag = True
> group by Race, Sex
> order by DV_by_race_gender desc;
Query ID = root_20241102220801_d4f44ae1-b374-4159-980c-ffd26032ed3a
Total jobs = 1
Launching Job 1 out of 1
Status: Running (Executing on YARN cluster with App id application_1730562569604_0012)
         VERTICES STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED

      Map 1 ......
      SUCCEEDED
      5
      0

      Reducer 2 .....
      SUCCEEDED
      1
      1
      0

      Reducer 3 .....
      SUCCEEDED
      1
      1
      0

                                                                                                   0
      OK
                    M
                                  10000
                                   9008
                    F
                                   5997
                    Μ
                                   5367
                    U
                                   415
                                   363
                                   362
                    Μ
                    Μ
                                   37
                                   28
                    U
                                    2
                    U
                                    1
      Time taken: 9.818 seconds, Fetched: 11 row(s)
      hive>
```

Fig 17 Query 11

This query counts domestic violence incidents categorized by race and gender. By grouping the data in this manner, it reveals patterns of domestic violence across different demographic groups, facilitating targeted interventions and informed policy-making to address these issues.

12. Count of Unique Offense Descriptions

```
select count(distinct Description) as unique_desc
from crime data;
```

Fig 18 Query 12

This query calculates the number of unique offense descriptions in the crime dataset. By identifying distinct offenses, it provides insights into the variety and complexity of crime types recorded, which can help in understanding crime trends and law enforcement strategies.

13. Top 5 Most Common Offense Description

```
select Description,count(*) as desc_count
from crime data
group by Description
order by desc count desc
limit 5;
                > from crime_data
                > group by Description
                > order by desc_count desc
                 ID = root_20241102221314_c8cbb279-14fb-4370-91c5-9310c7519667
             aunching Job 1 out of 1
            Status: Running (Executing on YARN cluster with App id application_1730562569604_0012)
                    VERTICES STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
             Map 1 ..... SUCCEEDED SUCCEEDED
             Reducer 3 ..... SUCCEEDED
             Simple Assault 48457
             Notor Vehicle Theft 36256
Aggravated Assault 34955
             Aggravated Assault
             /andalism/Destruction of Property
             heft From Motor Vehicle 23169
Time taken: 10.026 seconds, Fetched: 5 row(s)
```

Fig 19 Query 13

This query identifies the top five most common offense descriptions in the crime dataset by counting occurrences of each description. It helps highlight prevalent crime types, which can inform public safety initiatives and resource allocation for law enforcement.

14. Top 5 Most Frequent Reporting District

```
select Rep_Dist,count(*) as offenses_by_Repdist
from crime_data
group by Rep_Dist
order by offenses_by_Repdist desc
limit 5;
```

Fig 20 Query 14

This query retrieves the five representative districts with the highest number of reported offenses. By analyzing offenses by district, it provides insights into crime concentration areas, aiding law enforcement in targeting resources and strategies effectively.

15. Top 5 Streets with Most Reported Offenses

```
select Address,count(*) as offense_by_address
from crime_data
group by Address
order by offense_by_address desc
limit 5;
```

Fig 21 Query 15

This query identifies the top five addresses with the highest frequency of reported offenses. By pinpointing high-crime locations, it assists in understanding crime hotspots and enables law enforcement to allocate resources and implement preventive measures more effectively.

16. Offenses by Reported Day of the Week

```
OK
Monday 53007
Friday 50580
Tuesday 50367
Wednesday 49985
Thursday 48491
Saturday 48482
Sunday 48441
NULL 1
Time taken: 12.441 seconds, Fetched: 8 row(s)
hive>
```

Fig 22 Query 16

This query analyzes the distribution of offenses by day of the week, counting the total offenses for each day. By identifying trends related to specific days, it aids in understanding crime patterns and optimizing policing strategies for higher crime days.

17. Percentage of Offenses Involving Firearms

```
SELECT (COUNT(IF(Firearm_Used_Flag = TRUE, 1, NULL)) * 100.0) /
COUNT(*) AS Firearm_Usage per FROM crime_data;
```

Fig 23 Query 17

This query calculates the percentage of offenses where firearms were used by comparing the count of firearm-related offenses to the total number of offenses. It provides insight into the prevalence of firearm use in crimes, which is crucial for assessing public safety and policy implications.

18. Age Distribution for Top 3 Offenses

```
SELECT Offense, Age, COUNT(*) AS Age_Distribution
from crime_data
where offense in ('Stolen Auto','Domestic Violence Assault (Non-Aggravated)','Property Damage')
group by offense,Age
order by offense,Age;
```

```
New SELECT Offense, Age, COUNT(*) AS Age_Distribution

> rhom crume data

> where offense in ('Stolen Auto', 'Domestic Violence Assault (Non-Aggravated)', 'Property Damage')

> group by offense, Age;

Query ID = root_2004;102225951_6f597b5c-a886-46e6-82ec-6503593c1d91

Total jobs = 1

Launching Job 1 out of 1

Status: Running (Executing on YARN cluster with App id application_1730562569604_0013)

**VERTICES** STATUS** TOTAL COMPLETED RUNNING PENDING FAILED KILLED

**Map 1 ... SUCCEDED 5 5 0 0 0 0

Reducer 3 ... SUCCEDED 1 1 0 0 0 0

Reducer 3 ... SUCCEDED 1 1 0 0 0 0

Reducer 3 ... SUCCEDED 1 1 0 0 0 0

**PRATICES: 03/03 [**Instrumental Security | 100X ELAPSED TIME: 10.96 3

**Demestic Violence Assault (Non-Aggravated) NULL 94

Demestic Violence Assault (Non-Aggravated) 18.0 486

Demestic Violence Assault (Non-Aggravated) 19.0 596

Demestic Violence Assault (Non-Aggravated) 21.0 777

Demestic Violence Assault (Non-Aggravated) 22.0 888

Domestic Violence Assault (Non-Aggravated) 85.0 7

Domestic Violence Assault (Non-Aggravated) 86.0 5

Domestic Violence Assault (Non-Aggravated) 87.0 5

Domestic Violence Assault (Non-Aggravated) 99.0 1

Property Damage 20.0 315

Property Damage 21.0 406

Property Damage 22.0 437

Property Damage 23.0 555

Property Damage 23.0 565

Property Damage 23.0 669

Property Damage 23.0 643

Property Damage 23.0 487

Property Damage
```

Fig 24 Query 18

```
roperty Damage 77.0
                           38
roperty Damage 78.0
                           37
roperty Damage 79.0
roperty Damage 80.0
                           38
roperty Damage 81.0
                           27
roperty Damage 82.0
                           16
roperty Damage 83.0
                           15
roperty Damage 84.0
                           23
roperty Damage 85.0
roperty Damage 86.0
                           14
roperty Damage 87.0
roperty Damage 88.0
                           8
roperty Damage 89.0
Property Damage 90.0
                          4
roperty Damage 91.0
roperty Damage 93.0
roperty Damage 94.0
roperty Damage 95.0
roperty Damage 96.0
roperty Damage 98.0
roperty Damage 99.0
Stolen Auto
tolen Auto
                 18.0
                           303
tolen Auto
                 19.0
                           385
tolen Auto
                 20.0
                           508
tolen Auto
                 21.0
                          623
tolen Auto
                 22.0
                           710
                 23.0
tolen Auto
                          810
                  24.0
                   105
90
             73.0
74.0
tolen Auto
             76.0
77.0
tolen Auto
tolen Auto
                   68
61
tolen Auto
             79.0
                   50
28
tolen Auto
             81.0
tolen Auto
             84.0
tolen Auto
tolen Auto
tolen Auto
             91.0
tolen Auto
tolen Auto
tolen Auto
             97.0
             98.0
ime taken: 11.44 seconds, Fetched: 240 row(s)
```

This query analyses the age distribution of offenders for specific offenses: 'Stolen Auto,' 'Domestic Violence Assault (Non-Aggravated),' and 'Property Damage.' It groups the data by offense and age, providing a detailed view of how age correlates with these particular crimes, which can aid in targeted prevention strategies.

19. Get the Top 5 Areas with the Most Offenses Per Month

```
SELECT Reported_month, Area, offenses_bymonth_area from (
SELECT Reported_month, Area, COUNT(*) AS offenses_bymonth_area,ROW_NUMBER() OVER (PARTITION BY Reported_month ORDER BY COUNT(*) DESC)
AS rank
```

```
from crime data
GROUP BY Reported month, Area
   ranked data
where rank <=5
ORDER BY Reported_month, offenses_bymonth_area DESC;
                ve> SELECT Reported_month, Area, offenses_bymonth_area
>> from (
>> SELECT Reported_month, Area, COUNT(*) AS offenses_bymonth_area,ROW_NUMBER() OVER (PARTITION BY Reported_month ORDER BY COUNT(*) DESC)
               S rank

> from crime_data

> GROUP BY Reported_month, Area

>) ranked_data

> where rank <=5

> ORDER BY Reported_month, offenses_bymonth_area DESC;
uery ID = root_2024102230025_d1e5721a-665c-4b76-9cc1-d5f2827aee20

tal_jobs = 1

aunching Job 1 out of 1
               tatus: Running (Executing on YARN cluster with App id application_1730562569604_0013)
                            STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
                                        CPD
                                                       7836
                                        EPD
                                                       7073
                                        MPD
                                                       5300
                                        SPD
                                                       3013
                                        NPD
                                                       2415
                                        CPD
                                                       7271
                                        EPD
                                                       6542
                                        MPD
                                                       4891
                          2
                                        SPD
                                                       2706
                                        NPD
                                                       2113
                                        CPD
                                                       7803
                                        EPD
                                                       6886
                                        MPD
                                                       5511
                                        SPD
                                                       3135
                                        NPD
                                                       2371
                          4
                                        CPD
                                                       7592
                                        EPD
                                                       7511
                                        MPD
                                                       5681
                                        SPD
                                                       3121
                                        NPD
                                                       2340
                                        CPD
                                                       8817
                                        EPD
                                                       7851
                                        MPD
                                                       6120
                                        SPD
                                                       3271
                                        NPD
                                                       2676
                                        CPD
                                                       9061
                                        EPD
                                                       8432
                                        MPD
                                                       6678
                                        SPD
                                                       2956
```

Fig 25 Query 19

```
SPD
                  3686
         NPD
                  3028
         CPD
                  9805
         EPD
                  8563
         MPD
                  7005
         SPD
                  3495
         NPD
                  3022
         CPD
         EPD
                  8238
         MPD
                  6457
         SPD
                  3420
         NPD
                  2943
10
         CPD
                  8258
10
10
         EPD
                  7261
         MPD
                  5758
         SPD
                  3101
         NPD
                  2508
         CPD
                  6245
         EPD
                  5800
         MPD
                  4461
11
11
12
12
12
         SPD
                  2370
         NPD
                  1885
         CPD
                  5519
         EPD
                  4739
         MPD
                  3909
         SPD
                  2244
12
         NPD
                  1773
Time taken: 11.275 seconds, Fetched: 61 row(s)
```

This query extracts the top five areas with the highest offense counts for each month. By ranking the areas based on their offense totals, it provides insights into monthly crime patterns, allowing law enforcement and policymakers to allocate resources effectively and address community concerns regarding safety.

20. Top 5 Most Common Involvement Type

```
select Involvement,count(*) as involvement_count
from crime_data
group by Involvement
order by involvement_count desc
limit 5;
```

Fig 26 Query 20

This query identifies the five most common types of involvement in crimes by counting occurrences in the dataset. By grouping and sorting the data based on involvement, it highlights prevalent roles—such as victim, suspect, or witness—within criminal incidents, aiding in understanding crime dynamics and community impact.

```
21. Top 5 Areas with Highest Average Offender Age select Area, avg (Age) as Avg_Age_offenders from crime_data group by Area order by Avg_Age_offenders desc limit 5;
```

```
nive> select Area,avg(Age) as Avg_Age_offenders
  > from crime_data
   > group by Area
   > order by Avg_Age_offenders desc
puery ID = root_20241102233447_ccbc3eb2-8ce6-480d-b9ab-76b6c602f4de
[otal iobs = 1
aunching Job 1 out of 1
Status: Running (Executing on YARN cluster with App id application_1730562569604_0014)
      VERTICES
                  STATUS TOTAL COMPLETED RUNNING PENDING FAILED KILLED
dap 1 ...... SUCCEEDED SUCCEEDED
         .... SUCCEEDED 1 1
SCP
      39.220682036845666
      38.93589787545285
      38.82174466404319
       38.76328372280962
       38.621529108932585
      ken: 11.668 seconds,
```

Fig 27 Query 21

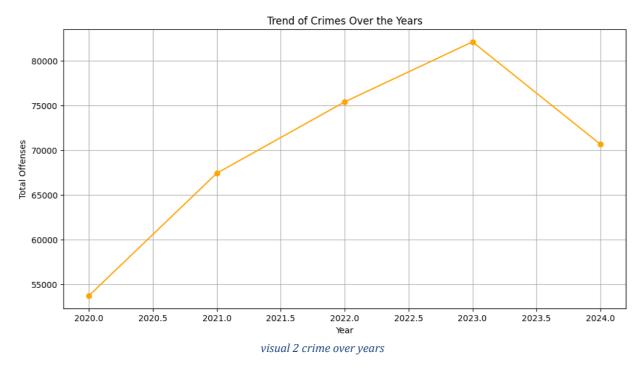
This query calculates the average age of offenders in different areas, providing insight into demographic trends related to crime. By grouping the data by area and sorting by average age, it identifies the top five areas with the oldest offenders, which can inform targeted interventions and resource allocation in law enforcement and community programs.

3.4 Visualization of the Data: -

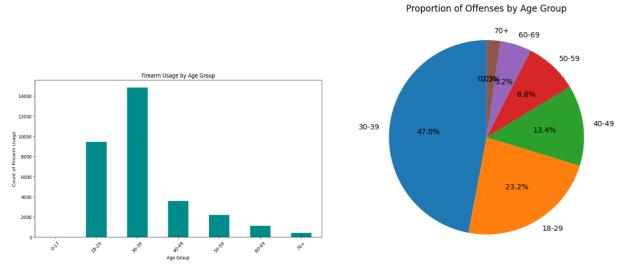
```
13s [1] 1 from pyspark.sql import SparkSession
2 # Create a Spark session
3 spark = SparkSession.builder.appName("KCCrime").getOrCreate()
```

visual 1 pyspark initialization

Initiating the pyspark session to do the visualization of the Crime data.

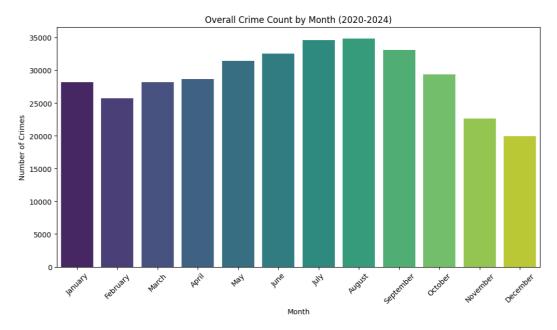


The Line plot above represents the Year wise crimes and we can observe that during the year 2023 the crime rate was very high. Over the years of 2020 to 2023 there has been a continuous increase in the crimes and the total year data of 2024 is not collected but till October 2024 we can observe that the number of offenses is less



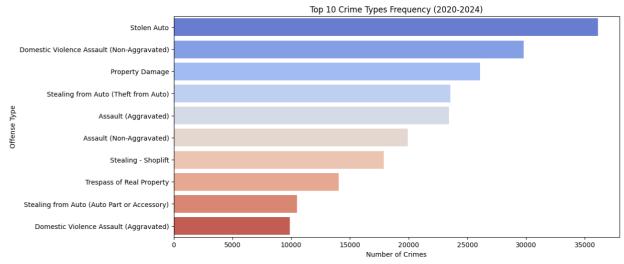
visual 3 Crimes over the age groups

We observe that the age group of 30-39 has access to a Firearms and they do crimes with them. So we need to make sure to check all the people in that age group so that the crimes related to the firearm's reduces.



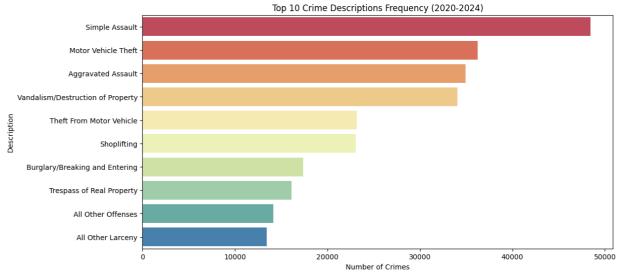
visual 4 Crimes over the month

The above image represents that there is a high crime in august and during the period of June – September the crime rate has been high, least during the year December. We can draw a conclusion that the police should be on high alert during these months.



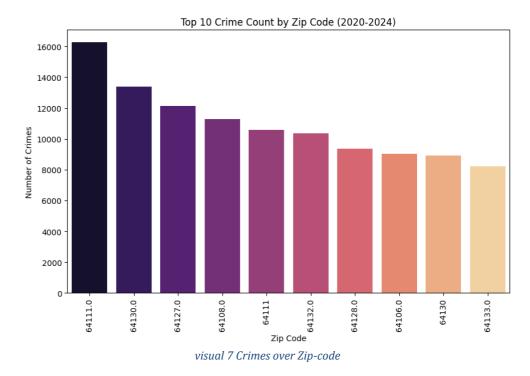
visual 5 Crimes over the type of offenses

Stolen Auto's Crime is the highest type of offense that's occurred over the years.

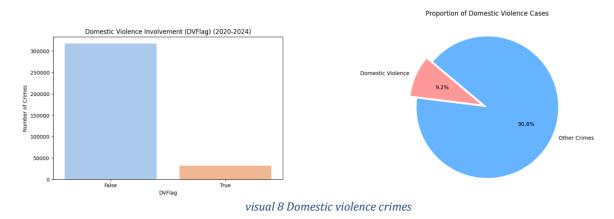


visual 6 Crimes over the descriptions

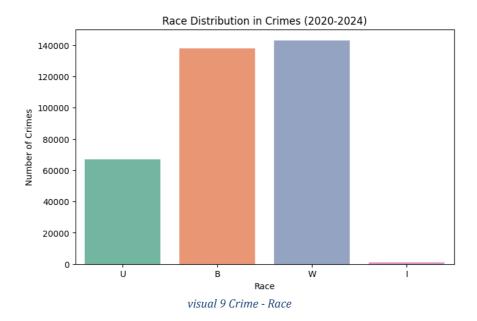
Here we can see that the word simple Assault is the most common and the highest number of crime that has been occurring.



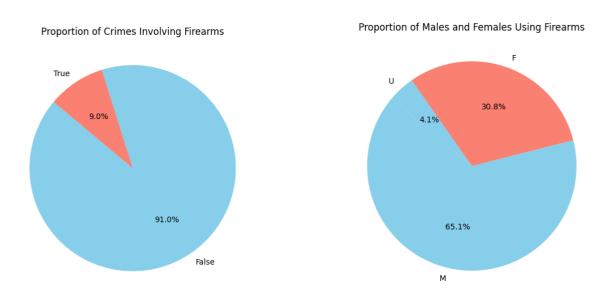
In the above graph we observe that the number of crimes is high in the zip-codes 64111 and 64130 so there is a need to increase the patrols, the number of cops in that area and surveillance should also increase to reduce the number of crimes.



We can clearly observe the difference in the crimes that represents that there are very few domestic crimes that are happening but stull over 40k crimes relating to the domestic violence have happened over the period of time. Its 9.2% is the no of domestic crimes that are happening.

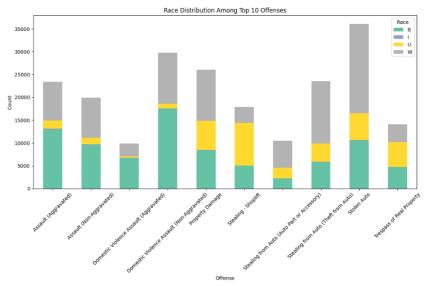


So we observe that we have mainly two races and there are 70k crimes where the race of the person who's done the crime is not mentioned. This represents that we lack in data.



visual 10 Percentage of crime involving Firearms

There is 9% of crimes that are happening while using the firearms. And the no of females and males in that 9% is represented to the right.



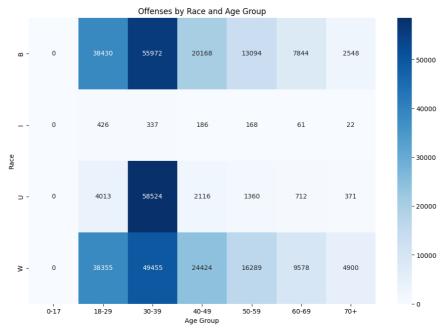
visual 11 Race Distribution among Top 10 crimes.

The graph represents the Crimes and their respective ratio of races that have caused that respective crime. We see that the main race that's causing the stolen auto crime is the White race.



visual 12 Gender Distribution over area

The heat-map represents that there is high number of crime-offenses in the area 'CPD', which implicates that the cops should try to do better at reducing the crimes and increase the surveillance. The Area OSPD is very friendly environment having the lease no of crimes.



visual 13 Offenses by race and age-group

As we have already seen that the crimes in the age group was already high in the age group 30-39 we can observe that there are all the races that have done the crimes but the crimes done by the boys is a bit higher than that of the unknown and the women.

4. Results

In this project, we utilized Apache Hive, a data warehousing tool built on Hadoop, to conduct a comprehensive analysis of crime data. Hive is highly suitable for processing large datasets due to its use of MapReduce programming, allowing us to efficiently handle vast volumes of data. By leveraging Hive's SQL-like querying language, we could retrieve meaningful insights that would be otherwise challenging to extract manually or through traditional databases. This enabled us to identify patterns, correlations, and trends within the dataset, helping to bring clarity to complex crime data in an accessible and organized manner.

Our findings provide insights that can inform targeted interventions, such as implementing youth awareness programs and enhancing community safety initiatives. Observations about trends by age group, offense type, and temporal factors indicate specific areas where proactive measures may mitigate crime. For instance, identifying peak hours of offenses and demographic-specific trends highlights key risk periods and populations that could benefit from preventive actions, like educational outreach or increased patrolling during specific times and in specific areas. Such data-driven decision-making can improve resource allocation, making crime prevention efforts both more efficient and effective.

Finally, for data visualization, we used Python, a versatile tool for graphical representation that allowed us to transform raw, complex data into clear, visually engaging charts and graphs. This approach made our findings more accessible and easier to interpret compared to traditional tabular formats, providing a more intuitive understanding of crime trends and risk factors. Visualizations like bar charts, line graphs, and heatmaps made it possible to spot patterns briefly, fostering a better grasp of the data's story. This combination of Hive's processing power and Python's visualization capabilities allowed us to convert large-scale data into actionable insights, providing valuable contributions to research on crime prevention and community safety

5. Concluding Remarks

This report provides an analysis of crime data utilizing Hive for data processing and PySpark for visualization, emphasizing the extraction of insights related to crime trends and demographics. The primary objective was to leverage Hive's capabilities to efficiently analyze large datasets while employing PySpark to create visually impactful representations of the findings.

The analysis produced several key insights:

Data Insights: The investigation revealed critical trends in crime occurrences, revealing how various demographic factors and types of offenses correlate with crime rates. Specific demographics were found to be associated with higher instances of certain crimes, such as domestic violence and firearm usage, highlighting the need for targeted community responses.

Visualization Impact: By employing PySpark for visualization, complex datasets were transformed into clear, engaging graphics that enhance understanding. Visualizations such as bar charts, heatmaps, and trend lines effectively communicated the underlying narratives, making it easier for stakeholders to grasp essential patterns and relationships.

Practical Implications: The insights gleaned from this analysis can inform targeted interventions aimed at crime reduction, such as awareness campaigns for at-risk groups and enhanced security measures in identified hotspots. The integration of efficient data processing through Hive with compelling visualizations in PySpark not only deepens our understanding of crime dynamics but also supports the formulation of proactive strategies for crime prevention and community engagement.

6. Future Work

For future work, there are several potential avenues to explore:

- Predictive Modelling: Develop machine learning models to forecast crime occurrences
 using historical data. By leveraging variables like time, location, and demographics, these
 models can enhance resource allocation for law enforcement and inform proactive
 measures.
- 2. **Geospatial Analysis**: Utilize Geographic Information Systems (GIS) to visualize crime hotspots and spatial patterns. This analysis helps identify high-crime areas, enabling targeted interventions and community policing efforts.
- 3. **Real-Time Data Integration**: Create a system to incorporate real-time crime data from various sources, such as police reports and social media. This approach allows for timely analysis and improves situational awareness for law enforcement.
- 4. **Socioeconomic Data Enrichment**: Integrate external datasets like socioeconomic indicators to analyse correlations with crime rates. This can provide insights into the underlying causes of crime and guide community development strategies.
- 5. **Crime Severity Index Development**: Establish an index to assess crime severity, combining factors like offense nature and victim impact. This helps law enforcement prioritize cases and allocate resources effectively.
- 6. **Temporal Analysis of Crime Patterns**: Investigate crime trends based on time of day and seasonality. Identifying peak crime times can inform patrol strategies and community engagement efforts.
- 7. **Community Outreach Programs**: Design community outreach initiatives focused on crime prevention based on data analysis findings. These programs can empower residents and foster collaboration with law enforcement.
- 8. **Collaboration with Urban Planning**: Partner with urban planners to explore the relationship between neighbourhood design and crime rates. Insights can guide urban development strategies to reduce crime opportunities.
- 9. **Longitudinal Studies on Crime Trends**: Conduct studies to observe how crime patterns evolve over time. This research can evaluate intervention effectiveness and provide insights for future prevention strategies.

10. **Public Policy Recommendations**: Develop recommendations for policymakers based on data analysis findings. This could involve assessing legislation impacts on crime rates and advocating for community-based safety approaches.

7. References

- 1. https://data.kcmo.org/browse?category=Crime
- $2. \underline{https://colab.research.google.com/drive/1y19B8Rlv3pzSjx2QpjExyC084hH7r74W?} \\ \underline{usp=sharing}$
- 3. https://cwiki.apache.org/confluence/display/Hive/