Team 2
Chicago Car Accidents Assessment Utilizing Clustering Analysis

1st Hodgetts, Michael
Electrical Engineering Dept
EE-695 - Machine Learning
Hoboken, NJ
mhodgetts@comcast.net

2nd Paladugu, Rithvika
Computer Engineering
EE 695 - Machine Learning
Hoboken, NJ
paldugurithvika@gmail.com

***Abstract*—Practice as a team to analyse unsupervised data by exploring various clustering methods (k-means, k-modes, kprototype, Gaussian and DBSCAN) on Chicago Accident database.**

I. Introduction

Utilizing two datasets from Chicago Department website (Crashes and People related to Crashes), we like to find areas/neighborhoods within the city that have different characteristics in terms of the attributes available. Dataset is large (750K rows) so we decided to look at only 2 years (2021 and 2022) which reduces to about 250K. There is a good amount of prep to get data suitable for cluster analysis (ETL, Hot Encoding, data cleanup) We will try at least 3 different methods and compare the results. Since the data his mixed we have limited methods to do cluster analysis. We'll choose the better model and create an optimum number of clusters to analyze. We will illustrate some of the main differences these assigned clusters present. Provide a summary of each cluster characteristics to illustrate the main differences between them. You'll see in this report we have already started this plan.

II. Related Work

There are many examples on how clustering solves problems in various business use cases. Segmentation analysis, anomoly detection and a form of classification are some of the use cases. The analysis here could be useful to identify hot areas of accidents due to poor signage, road conditions, and other conditions that could be improved to reduce accidents or injuries in the Chicago area. Practicing how to get meaningful insights is essential in the business world.

III. Our Solution

Since the data is large and has many attributes (both numerical and categorical), reducing the number of attributes will be critical. Also, minimizing the number of clusters needed is beneficial to ensure each cluster has meaningful differences and similar volume. Heatmaps showing differences will be provided to help show major allocation of attributes to each cluster. Another issue is we have a lot of category data as well as continous. k-modes was explored first since it handles categorical data and kmeans covers numerical. K-Prototypes covers both at the same time. We tried to use Gaussian Mixture but that seems to not be appropriate and gave us unusual results. Another method is DBSCAN which can handle hot encoding but so far find it difficult to gain the necessary clusters needed, very sensitive to noise (EPS) and size of data. kprototype so far has the best results with the mixed data. We will show Heatmaps to illustrate our results and provide summary description of the final clustering results.

A. Description of Dataset

The dataset can be found here: Chicago Crashe Data, Two datasets; one for crashes in Chicago and the other are the people characteristics of those crashes. The 'Crash ID' is the key attribute to join the 2 datasets. We reduced the size to only years 2021 and 2022 which still leaves about 250K rows and 68 columns. We used Knime (ETL software) to help do this join and ensure it was properly achieved. Here is the workflow using KNIME ETL software:

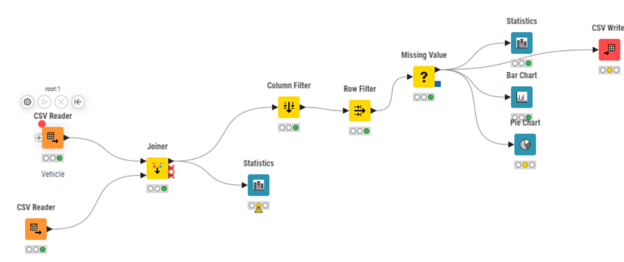


Fig. 1. Chicago Dataset prep

Data had very few problems with missing data but we removed as necessary or added average values as needed. We separated the dataset into two parts, categorical and numerical. Performed Hot Encoding on the categorical and scaling on the numberical (0,1), then combined them back together as one file. New Shape of the file is now 248K by 111 columns with hot encoding. We created another dataset for k-prototypes which has 31 columns based on what attributes we deemed valuable. Pie charts were useful in this particular dataset since most attributes are categorical. Many Attributes had too many categories that represented less than 1 percent of the size so we create algorithm to gather them up into a 'Remainder' for each category to help reduce the number of hot columns needed. Below is the list of columns we are working with in the dataset. Some have been removed since they will not contribute to the model performance.

```
df.columns
```

```
Index(['CRASH_RECORD_ID', 'RD_NO', 'CRASH_DATE', 'POSTED_SPEED_LIMIT',
       'TRAFFIC_CONTROL_DEVICE', 'DEVICE_CONDITION', 'WEATHER_CONDITION',
       'LIGHTING_CONDITION', 'FIRST_CRASH_TYPE', 'TRAFFICWAY_TYPE',
       'ALIGNMENT', 'ROADWAY_SURFACE_COND', 'ROAD_DEFECT', 'REPORT_TYPE',
       'CRASH_TYPE', 'INTERSECTION_RELATED_I', 'NOT_RIGHT_OF_WAY_I',
       'HIT_AND_RUN_I', 'DAMAGE', 'DATE_POLICE_NOTIFIED',
       'PRIM_CONTRIBUTORY_CAUSE', 'SEC_CONTRIBUTORY_CAUSE', 'STREET_NO',
       'STREET_DIRECTION', 'STREET_NAME', 'BEAT_OF_OCCURRENCE', 'NUM_UNITS',
       'MOST_SEVERE_INJURY', 'INJURIES_TOTAL', 'INJURIES_FATAL',
       'INJURIES_INCAPACITATING', 'INJURIES_NON_INCAPACITATING',
       'INJURIES_REPORTED_NOT_EVIDENT', 'INJURIES_NO_INDICATION',
       'INJURIES_UNKNOWN', 'CRASH_HOUR', 'CRASH_DAY_OF_WEEK', 'CRASH_MONTH',
       'LATITUDE', 'LONGITUDE', 'LOCATION', 'PERSON_ID', 'PERSON_TYPE',
       'CRASH_RECORD_ID (right)', 'RD_NO (right)', 'VEHICLE_ID',
       'CRASH_DATE (right)', 'CITY', 'STATE', 'ZIPCODE', 'SEX', 'AGE',
       'DRIVERS_LICENSE_STATE', 'DRIVERS_LICENSE_CLASS', 'SAFETY_EQUIPMENT',
       'AIRBAG_DEPLOYED', 'EJECTION', 'INJURY_CLASSIFICATION', 'HOSPITAL',
       'EMS_AGENCY', 'DRIVER_ACTION', 'DRIVER_VISION', 'PHYSICAL_CONDITION',
       'PEDPEDAL_ACTION', 'PEDPEDAL_VISIBILITY', 'PEDPEDAL_LOCATION',
       'BAC_RESULT', 'BAC_RESULT VALUE'],
      dtype='object')
```

Fig. 2. Chicago Dataset

EDA

Here we show a sampling of some of the attributes classes for the categorical data and numerical. There are many columns so we will just show a sample of some. You can see more in the code readout.

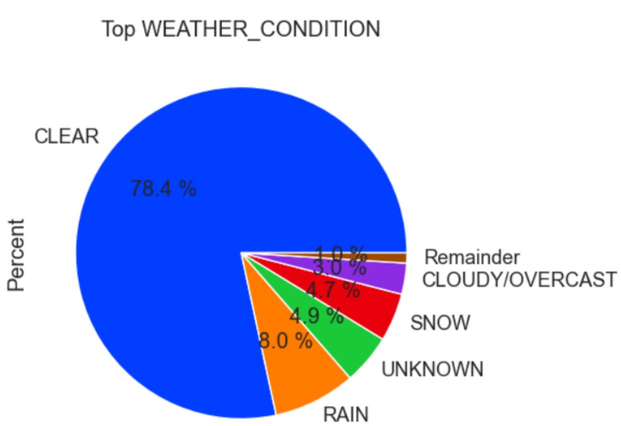
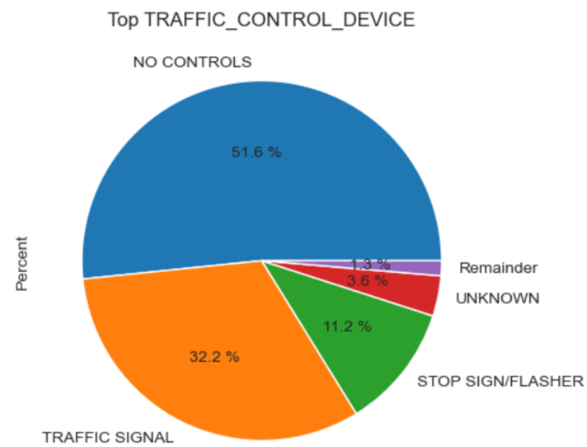


Fig. 3. Categorical Pie Charts (Sampling View)

Here are some of the numeric attributes to examine note:

B. Machine Learning Algorithms

Our data is raw and has no classification or specific purpose so it lends itself to utilize unsupervised data techniques. We



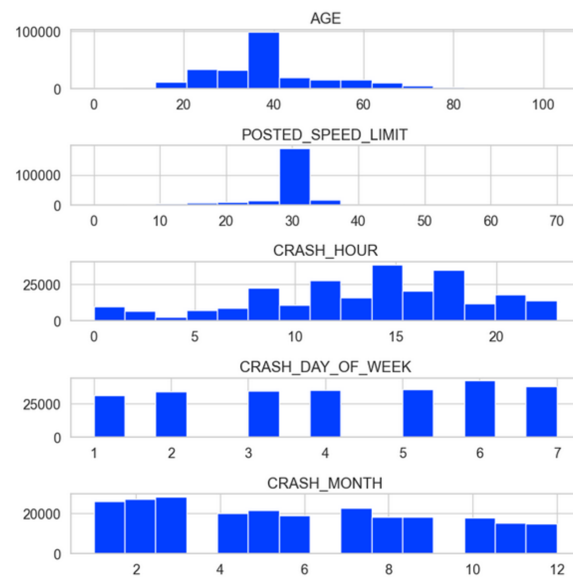


Fig. 5. Numeric Histograms (Sampling View)

explored K-modes, kmeans, kprototype and DBSCAN and will investigate other possible methods to find insights. kprototype is our best hope so far to get good results since it handles both categorical and numeric attributes. Kmodes can only handle category and kmeans does numerical. Noticed Kprototype takes a very long time to process the model. Elbow curve took over 24 hours. Since we have a large dataset, training take a good length of time for all model types. We created elbow curves for both K-modes and Kprototypes in the figures below: linebreak

From figures 2 and 3 you can see 4 clusters would be reasonable. We currently picked 4 clusters as a start. The difficulty is assessing the cluster characteristics with so many attributes. We did some Chi Testing on the attributes to find any that were not relevate but all picked were significant. We uUtilized pspark to use groupby by clusters by percent of occurence to see what patterns emerge. We may have to

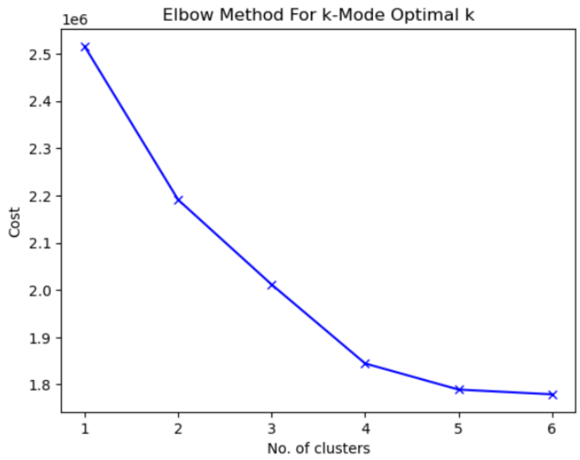


Fig. 6. k-means

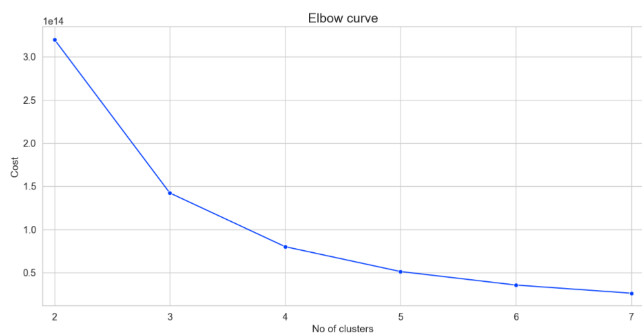


Fig. 7. k-prototype

	variable	chi2_test_stat	p_value	dof
34	INJURIES_UNKNOWN	0.000000e+00	1.000000e+00	0
41	PERSON_ID	1.243115e+06	4.985663e-01	1243110
67	BAC_RESULT VALUE	5.929951e+02	2.216402e-39	205
45	VEHICLE_ID	1.219355e+06	1.280826e-45	1197360
36	CRASH_DAY_OF_WEEK	8.620735e+02	5.757343e-162	30
...	...	...	...	...
30	INJURIES_INCAPACITATING	1.071638e+04	0.000000e+00	30
31	INJURIES_NON_INCAPACITATING	5.991988e+04	0.000000e+00	55
32	INJURIES_REPORTED_NOT_EVIDENT	2.847958e+04	0.000000e+00	40
33	INJURIES_NO_INDICATION	4.908476e+04	0.000000e+00	135
68	Cluster	1.243115e+06	0.000000e+00	25

Fig. 8. Chi Square Testing View

build this view outside of Python to get a good illustrative view ith excel. At the current time, we're assessing how to describe these these clusters and find recommendations to provide back to the city of Chicago. This figure below issustrates the comparison we are doing with 4 clusters verses the categorical columns. You can see clearly differences in of how the clustering divided up the percent allocation. Percent allocation is based total population so we can compare to each different attribute. Will do the same for the numerical but it will look a little different since we will use averages.

IV. Comparison

In this section we'll discuss the results of each method and show more in detail the best solution results. The table below shows a summary of the different clustering algorithms.

Team 2 Model Summary

Method	Application	Model Training Speed	Cluster Volumes	Error	Results/Notes
kmodes	Categorical	7.5 minutes	1) 32.1% 2) 30.4% 3) 23.4% 4) 14%	1375000	kmodesand kPrototypes were similar in categorization but kmode had higher error
kmeans	Numerical	1.8 seconds	1) 25% 2) 25% 3) 25% 4) 25%	1 x10^15	equal distribution but can only be used for numerical
GMM	Both	5 seconds	1) 58% 2) 28.2% 3) 11.8% 4) 1.7%	AIC=-1.33x10^7	One cluster dominated in the distribution, results were not as good as KP
DBSCAN	Numerical	5.5 seconds	1) 70.3% 2) 17.5% 3) 6.3% 4) 6%		One cluster dominated in the distrubution and results didn't look reasonable
Kprototype	Both	51 minutes	1) 28.4% 2) 27.4% 3) 23.5% 4) 20.6%	128000	Best of All, Reasonable results but took much longer to train

Kmodes

Kmodes is designed for categorical data only and it a can take the data without hot encoding. K-modes was successful and did a good job of clustering but you have to take out the numerical data and run that on kmeans. The cluster allocation is similar to K-prototype and its error was also one of the lowest

Kmeans

Kmeans above in the chart reflects the numerical data only, you can try to run the categorical data with hot encoding but it accuracy or abilityto cluster diminishes.

GMM

We used both numeric scaling and hot encoding here but we think that GMM is suited better with only numerical data. Here the cluster allocation was skewed towards one cluster that has the majority of volume. This was not our ideal solution.

DBSCAN

DBSCAN was very sensitive to the amount of data and columns. Only numerical data was used here and finding the EPS and min sample values was a challenge, Had to iterate through 50 different EPS values to find a sweet spot. By changing EPS by only 0.01 increments at that sweet spot changed clusters size and number of cluster significantly. The results were not optimal and we saw again high allocation to one cluster. Also this could not be used effectively with categorical data.

K-prototype

KPrototype was our best soluton in that we can use all the data and train at the same time. This took significantly longer to train as you can see compared to others in the table. The volume allocation was similar to kmodes. So we can use kmeans for numerical and kmodes for categorical and combine them but KP does it together. We'll use KP to explain the main difference we see in the 4 clusters we trained on

Cluster-Characteristics

Below is a partial view of the KP Heatmap for the 4 clusters

Sum of perc_of_count_total	Column Labels								
Row Labels	0	1	2	3	Grand Total	Note			
ALIGNMENT	**17.1056**	**26.1112**	**25.3148**	**30.9176**	**99.4492**	min	max	major change	
Remainder	0.212	0.1844	0.2132	0.3968	1.0064	2	4	0.388354	
STRAIGHT AND LEVEL	16.6004	25.6088	24.6852	30.1252	97.0196	1	4	0.232093	
STRAIGHT ON GRADE	0.2932	0.318	0.4164	0.3956	1.4232	1	3	0.167097	
CRASH_TYPE	**17.1056**	**26.1112**	**25.3148**	**30.9176**	**99.4492**	1	4	0.230585	
INJURY AND / OR TOW DUE TO CRASH	5.0084	4.3912	16.3424	6.006	31.748	2	3	0.710969	xx
NO INJURY / DRIVE AWAY	12.0972	21.72	8.9724	24.9116	67.7012	3	4	0.449096	
DAMAGE	**17.1056**	**26.1112**	**25.3148**	**30.9176**	**99.4492**	1	4	0.230585	
$500 OR LESS	1.86	2.4584	1.8864	2.9004	9.1052	1	4	0.21936	
$501 - $1,500	4.25	7.0856	3.7328	8.7424	23.8108	3	4	0.398638	
OVER $1,500	10.9956	16.5672	19.6956	19.2748	66.5332	1	3	0.24084	
DEVICE_CONDITION	**17.1056**	**26.1112**	**25.3148**	**30.9176**	**99.4492**	1	4	0.230585	
FUNCTIONING PROPERLY	5.496	5.0384	21.6872	6.8172	39.0388	2	3	0.818401	xx
NO CONTROLS	10.3228	18.8628	1.8648	21.4664	52.5168	3	4	0.677187	xx
Remainder	0.2916	0.3168	0.4916	0.3888	1.4888	1	3	0.240796	
UNKNOWN	0.9952	1.8932	1.2712	2.2452	6.4048	1	4	0.356245	
FIRST_CRASH_TYPE	**17.1056**	**26.1112**	**25.3148**	**30.9176**	**99.4492**	1	4	0.230585	
ANGLE	2.054	2.2632	6.3104	2.7872	13.4148	1	3	0.594899	xx
FIXED OBJECT	0.6588	0.666	0.5636	1.2012	3.0896	3	4	0.375001	
HEAD ON	0.1988	0.266	0.316	0.318	1.0988	1	4	0.203957	
PARKED MOTOR VEHICLE	1.5084	10.1572	0.3744	2.4624	14.5024	3	2	1.223868	xxx
PEDALCYCLIST	0.2192	0.1828	0.6348	0.3844	1.4212	2	3	0.579652	
PEDESTRIAN	0.4892	0.4324	1.1116	0.3732	2.4064	4	3	0.570616	
REAR END	5.0976	3.3412	4.2936	11.9844	24.7168	2	4	0.637001	
REAR TO FRONT	0.3344	0.4976	0.1596	0.7072	1.6988	3	4	0.549776	
Remainder	0.538	0.5256	0.244	0.894	2.2016	3	4	0.483789	
SIDESWIPE OPPOSITE DIRECTION	0.344	0.5164	0.2248	0.5592	1.6444	3	4	0.377447	
SIDESWIPE SAME DIRECTION	3.1616	4.9012	2.3192	6.0188	16.4008	3	4	0.407513	
TURNING	2.5016	2.3616	8.7628	3.2276	16.8536	2	3	0.725445	xx
HIT_AND_RUN_I	**17.1056**	**26.1112**	**25.3148**	**30.9176**	**99.4492**	1	4	0.230585	
N	0.1872	0.4448	0.3756	0.3824	1.39	1	2	0.320322	
none	14.7576	6.5256	19.2136	26.7872	67.284	2	4	0.503631	
Y	2.1608	19.1408	5.7256	3.748	30.7752	1	2	1.009827	xx
INTERSECTION_RELATED_I	**17.1056**	**26.1112**	**25.3148**	**30.9176**	**99.4492**	1	4	0.230585	
N	0.2192	0.2308	0.4376	0.3072	1.1948	1	3	0.336432	
none	13.5644	23.7784	6.3476	28.1152	71.8056	3	4	0.548782	
Y	3.322	2.102	18.5296	2.4952	26.4488	2	3	1.204015	xx

Fig. 10. Example of Cluster Heatmap for Categorical Attributes

Cluster 1 -In general 1 has the lowest occurance of crash attributes -lowest occurance of any damage level -Volume is lowest -unlikely for Hit and run -first 1-3 day of week occurance

Cluster 2 -In general 2 has the second lowest occurance of crash attributes -Likely to see Parked Vehicle Crash -likely Hit and Run -overindex on Sex X -overindex on Sex F -first 1-3 day of week occurance

Cluster 3 -Overindex on Crash Injury -Overindex turning related crash type -Overindex on Interection related crash -Overindex incapaciting injury -Overindex disregarding traffic signals -Overindex device condition functioning properly -Overindex disregarding stop sign -Overindex likely to report on scene -likely to occur in the first 6 months of years

Cluster 4 -Volume is highest -Overindex Parked Motor Vehicle -Overindex on no injury -Overindex no control for device condition (non traffic light) -Overindex to be rear ended -Overindex for follow to closely crash type -Overindex for months 7-12

V. Future Directions

We still need to try other methods and see if the allocations are significantly different. We'll describe each cluster characteristics in more detail. We like to show so mapping features of how the clusters map over Chicago but find this difficult so far to accomplish. There another method call Squeezer which can be used with mixed data but has little documentaion. Deep learning techniques utilaing autoencoders can be examined. We'll add to this section for our final report

VI. Conclusions

We'll add our conclusions at the final report

References

1) https://scottmduda.medium.com/categorical-clustering-of-pittsburgh-car-accidents-using-k-modes-7c842cc15d87
2) https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3if
3) https://www.freecodecamp.org/news/8-clustering-algorithms-in-machine-learning-that-all-data-scientists-should-know/
4) https://scikit-learn.org/stable/auto$_e xamples/cluster/plot_d bscan.html$
5)$https : //antonsruberts.github.io/kproto - audience/$