Section 1: Week 2: Evaluate Data Mining Techniques

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Evaluate Data Mining Techniques

# Section I: Using Data Mining

The city of New York offers multiple data sets for businesses and researchers to explore and make discoveries. The Department of Health and Mental Hygiene publishes a daily feed of NYC Restaurant Inspection Results that enumerates all citations since July 2015 (DOHMH, 2020). Each establishment receives a grade of A, B, C, P(ending), N(ot available), or Z based on the severity of citations. According to NYC Health (2020), “a business must maintain a grade of A or B, or close until passing a future inspection.” Figure 1 displays the distribution of citations across the different boroughs for January 2019 through Feb 2020, with approximately 87.4% of locations maintain a high-quality rating, with only 5% receiving a grade of C. There are several outliers, such as Dunkan Donuts is consistently the most infractions, followed by McDonalds and Star Bucks, in part due to the number of locations. Specific ethnic categories, such as Chinese in Queens and Indian in the Bronx, have high infractions due to their concentration. Niche categories, such as Cajun-Creole, have an alarming rate of 22% non-compliance due to their only being 58 total businesses in the category.

Figure Citations by Borough

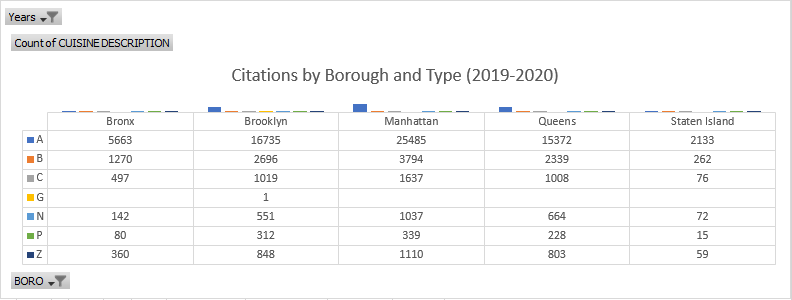
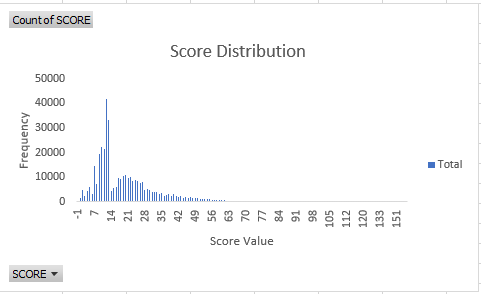
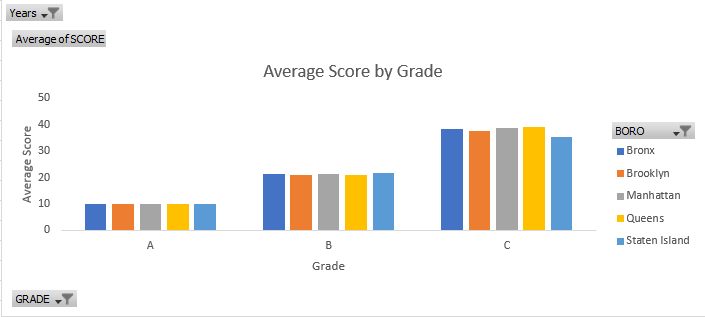


Table 1: Machine Learning Algorithms Used

|  |  |  |
| --- | --- | --- |
| Algorithm | Strategy Description | Comments |
| Logistic Regression | Maps numeric features to a numeric range. | The label-centric data set was not very applicable |
| Decision Tree Regression | Maps vectorized labels to a numeric range. | Effective with many guesses in general ballpark |
| PCA | Uses the correlation between features and combine columns | Improves runtime and accuracy of sparse data |
| Decision Tree Classifier | Maps vectorized labels to finite categories (e.g., value-ranges) | More accurate than DTR as general guesses are sufficient |
| Multilayer Perceptron Regressor | Uses backpropagation to build a fitting expression | Comparable to DTR performance |

The feed also details the violation code for the citation along with a numeric score that typically has a mean value of 20.4 and a standard deviation of 14.8 and a critical flag, with lower scores representing more minor infractions. A goal of the research is to predict the score that an organization would receive. First, the features Cuisine Description, Critical Flag, Violation Code, Inspection Type were One Hot Encoded into a 586 by 200730 matrix and fed into Scikit Learn’s Logistic Regression algorithm using a 50% split for testing/training data. The test data accuracy was 10.8%, making this strategy unusable. Next, the Borough, Critical Flag, Grade, Violation Code, and Inspection Type was One Hot Encoded into a 75 x 200730 matrix for the Decision Tree Regressor algorithm. This solution has an accuracy of 67.8% and was took significantly less time to train. MLPRegressor, a neural network-based algorithm was tested to have a 64.8% accuracy using the same feature set. Next, a Principal Components Analysis (PCA) over this same data frame was able to reduce the matrix dimensionality to 25 x 200730. This result did not change the accuracy results of either algorithm though it did speed up the training by 2-3x. Witten (2011) proposes a strategy called binning, which converts the regression problem into a classification scenario by making each bin represent a value range. The Decision Tree Classifier was able to predict the correct bucket with a 93.8% accuracy. In Figure 2, the score distribution suggests that value range partitions between -5 to 15, 16 to 25, 26 to 50, and 50 to 200 are effective—though the official documentation suggests that steps of 10 *should* be more accurate. The disconnect likely comes from erroneous values during the manual data entry. The Appendix section contains an example Python script that calculates these values and runs within the latest Docker container of jupyter/scipy-notebook. Additional analysis found that the Grade feature has the strongest influence, and its removal decreases the Decision Tree Classifier’s accuracy to only 51.7%. Removing both the Grade and PCA preprocessing increases the One Hot Encoded matrix from 10 x 190803 to 68 x 190803 with a total accuracy of only 0.03%. This test suggests that there is insufficient data for this strategy, and the boost from using PCA correlations is critical for the sparse data set.

Figure : Score Distribution

# Section II: Analyze the Process

## How can businesses use data mining in big data

Before an organization can operationalize predictive capabilities, they need first to identify the specific questions and what facts can support their answers. If the company starts with the sea of data, then how will they know these data points are relevant or fully encompass the problem? For instance, to provide restaurant recommendations requires evidence across different perspectives from the DOHMH to microbloggers (e.g., Twitter and Instagram). A company that only relies on a single source is bound to encounter distortion and bias towards their results. While the use of heterogeneous data sources can improve data mining, it also creates specific challenges, such as (1) mapping identifiers between systems, (2) handling inconsistent data schemas, (3) varying data publication cadences, and (4) provider-specific protocols to subscribe for updates. There are many highly reliable data ingestion tools, like Apache Kafka, NiFi, and Flume, to handle these scenarios (Matacuta & Popa, 2018). However, the business needs to consider beyond ingestion and towards their curation strategy. Perhaps the business needs Yelp customer reviews and has deployed Flume to load data into their data lake (e.g., Apache Hadoop or Amazon S3). Until feature extraction, record transformation, and deduplication processes have normalized these raw unstructured results, it can be challenging to analyze these results. The initial curation process also provides an opportunity to reduce the volume of records through aggregation (e.g., 1000 records a button click happened, versus a single summation record for the period).

After cleaning and curating the ingestion feed, these results need to flow into exploratory programs such as Microsoft Excel, OLAP data stores, Kibana, Jupyter Notebooks, and R Studio. These technologies allow the analysis to review the shape and attribute ranges without needing large time investments. Both Witten (2011) and Snee (2015) calls out the criticality of spending this time upfront and understanding what attribute means. As the volume of data increases, the variety of examples will also grow and lead to more edge cases. For instance, the documented range of the DOHMH score feature is between 0 to 100 though the maximum value is 164. Identifying and removing these erroneous records needs to happen before analysis, or it will skew the statistical model. However, simply truncating results outside of the range can cause important records to be lost, and there needs to be an investigation into the reason (e.g., missing case). After using the exploration tools to determine the filter rules, concise documentation needs to exist, or the analysis will not be reproducible.

Now each of the heterogeneous data sources is standardized, and erroneous records pruned the organization is ready to begin model training. This step requires choosing one or more categories of machine learning algorithms (e.g., regression and classification) and measuring its performance. Many big data scenarios require machine learning pipelines that combine multiple strategies into a final equation (Garreta, 2013). For instance, the pipeline might include steps (1) regularize value ranges to improve convergence, (2) use PCA to reduce dimensionality and training time, and (3) apply Gaussian noise to prevent over-fitting, among other actions. Each action within the pipeline has numerous parameters that can influence the accuracy of the results. Algorithms like GridSearch optimize these scenarios through automated parameter tuning, though the engineers need to be aware of these concepts.

Finally, data engineers need to bundle the model into an Application Programming Interface (API) so that it is accessible within the production environment. One approach is to serialize the model into a Scikit Pickle or Hierarchical Data Format (HDF5) and then deploy it into the cloud using Function as a Service (FaaS) technologies (e.g., Amazon Lambda or Azure Functions). FaaS solutions are highly economical and instantly scale to enormous workloads, such as integrating with existing streaming technologies and real-time analytics at the network edge. However, as the number of input features increases (e.g., speech to text and video processing), current FaaS technologies become ineffective for inference as the use-case needs General Purpose Graphics Processing Units (GPGPU), Field Programmable Gate Arrays (FPGA), or similar Application-specific Integrated Circuits (ASIC).

## What challenges does big data create

IoT, Cloud, Mobile, and Big Data (ICBM) increase the complexity to perform these steps as the volume, variety, velocity, and veracity add unique challenges. For instance, production datasets are commonly several factors of magnitude larger than the local resources of a single computer. Users need to either apply a sampling strategy or rely on distributed data stores, such as Azure Data Lake, Amazon DynamoDB, or Apache Hadoop. The time required to train a model can also introduce challenges, as it impacts the user’s ability to iterate. Consider the DOHMH dataset, where applying Logistic Regression to 586 by 200000 matrix took several minutes to converge. Cloud computing enables instant provisioning of elastic resources, though many instance-based learning algorithms require knowledge about their nearest neighbors to those examples propagate aggregate calculations (Witten, 2011, p. 312). This use-case limits the scalability of specific training algorithm categories to expensive vertically-scaled servers, over more economical horizontally-scaled patterns. Jassy (2019), CEO of AWS, recently stated that “after creating these models, substantial more processing power is typically necessary to run the inferences.” Google is addressing these challenges with custom hardware that runs at the network edge. By running machine learning algorithms at the edge, it removes the need to move across the network these massive workloads and also decreases latency. Minimizing network latency is critical for many machine learning solutions, such as health and safety monitoring or interactive user experiences, that need to react in real-time. Even after mitigating the physical resource constraints, other obstacles arise from the data variety. Sun et al. (2018) discuss the challenges of text-mining outside of academic scenarios due to spelling errors and locale-specific terms that are difficult to handle. Similarly, the wide adoption of micro-blogging (e.g., Twitter) requires data practitioners to both determine context and sentiment within 148 characters. These concepts are pushing the limits of machine learning algorithms as the ‘exceptions to the rule’ are becoming the norm.

## What non-technical constraints exist

Along with technical challenges, concerns exist around the security and privacy of user’s data in addition to reasonable use policies. People trust Facebook to facilitate private conversations between a billion people responsibly. When those same users learned how their connections become manipulated to influence elections, there was outrage as this usage did not align with their expectations (Media Buzz, 2018). Equifax collects sensitive financial information about 147 million people, and the breach of their security creates a permanent risk to nearly half of America (FTC, 2020). Countless other instances also exist, which cause a long-term impact on the brand and creates a lasting competitive disadvantage. Both national and international laws, such as the Health Insurance Portability and Accountability Act (HIPAA), the Family Education Rights and Privacy Act (FERPA), and the General Data Protection Regulation (GDPR)—give legislatures the ability to penalize negligence strictly. These legal requirements create both technical and procedural needs, like encrypting data at rest and in transit. Meeting these compliance constraints means limiting access to many interesting big data sets (e.g., electronic medical records), despite their high-value potential to research.

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# Appendix: Python Code

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# (c) Nate Bachmeier – 2020.02.16

# TIM-8130 Data Mining

# North Central University (NCU Phd CS)

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# Load the CSV file into Pandas

# This creates a DataFrame that allows efficient exploration

import pandas as pd

csv = pd.read\_csv('DOHMH\_New\_York\_City\_Restaurant\_Inspection\_Results.csv')

# This snippet creates the one-hot encoded data frame

# Garreta, R (2013). Learning sckit-learn machine learning in python

from sklearn import feature\_extraction

def one\_hot\_dataframe(data, cols, replace=False):

    vec = feature\_extraction.DictVectorizer()

    mkdict = lambda row: dict((col, row[col]) for col in cols)

    vecData = pd.DataFrame(vec.fit\_transform(

    data[cols].apply(mkdict, axis=1)).toarray())

    vecData.columns = vec.get\_feature\_names()

    vecData.index = data.index

    if replace:

        data = data.drop(cols, axis=1)

        data = data.join(vecData)

    return (data, vecData)

# Split the test and training data

train = csv[:200000][["BORO","CRITICAL FLAG","GRADE","VIOLATION CODE","INSPECTION TYPE","SCORE"]].dropna()

test = csv[200000:][["BORO","CRITICAL FLAG","GRADE","VIOLATION CODE","INSPECTION TYPE","SCORE"]].dropna()

# Build the train set

X\_train = train.drop(columns=['SCORE'])

Y\_train = train[["SCORE"]]

# Build the test set

X\_test = test.drop(columns=['SCORE'])

Y\_test = test[["SCORE"]]

# One Hot encode

x\_train\_hot = one\_hot\_dataframe(X\_train, ["BORO","CRITICAL FLAG","GRADE","VIOLATION CODE"], replace=True)

x\_test\_hot = one\_hot\_dataframe(X\_test, ["BORO","CRITICAL FLAG","GRADE","VIOLATION CODE"], replace=True)

# Drop these columns as they do not exist in both halfs

x\_train\_data = x\_train\_hot[1].drop(columns=["VIOLATION CODE=06H"])

x\_test\_data = x\_test\_hot[1].drop(columns=['VIOLATION CODE=02E','VIOLATION CODE=04I'])

from sklearn import tree

clf = tree.DecisionTreeRegressor()

clf.fit(x\_train\_data, Y\_train['SCORE'])

clf.score(x\_test\_data, Y\_test['SCORE'])

# 67%

from sklearn.decomposition import PCA

pca = PCA(n\_components=10)

pca = pca.fit(x\_train\_data, Y\_train['SCORE'])

x\_train\_pca = pca.transform(x\_train\_data)

x\_test\_pca = pca.transform(x\_test\_data)

from sklearn import tree

clf = tree.DecisionTreeRegressor()

clf.fit(x\_train\_pca, Y\_train['SCORE'])

clf.score(x\_test\_pca, Y\_test['SCORE'])

# 67%

bins = [-5, 15, 25,50,200]

Y\_train\_bins = pd.cut(Y\_train['SCORE'], bins=bins, labels=bins[0:-1])

Y\_test\_bins =  pd.cut(Y\_test['SCORE'], bins=bins, labels=bins[0:-1])

from sklearn.tree import DecisionTreeClassifier

clf = DecisionTreeClassifier()

clf.fit(x\_train\_pca, Y\_train\_bins)

clf.score(x\_test\_pca, Y\_test\_bins)

# 93.8%

import numpy as np

Y\_rand\_bins = pd.cut((np.random.random(Y\_test\_bins.shape)\*100), bins=bins, labels=bins[0:-1])

clf.score(x\_test\_pca, Y\_rand\_bins)

# 10.7%