Analyzing Temporal, Spatial, and Historical Data in Rating Prediction Algorithms: A Comparative Study

***Abstract*— User reviews of a business have become an integral part of our quotidian lives. We decide places to visit, restaurants to dine, and services to utilize based on these reviews. Furthermore, the general population and their sentiments about a business have a huge impact on the performance of the business. In this project, we utilize the *Google Local Reviews* data set to predict the potential rating a user will give to a business. Specifically, we compare and contrast the effects of including temporal and spatial aspects of the data in our models for the task at hand.**

***Index Terms*— Google Business Reviews, Regression, Machine Learning, Deep Learning, Data Modelling, Information Systems, Personalized Recommendation.**

I. Introduction

The Google Local Reviews data set [1]–[3] consists of three files that contain information specific to users, businesses, and reviews, respectively, along with their metadata. Here, we intend to use this data set to predict what rating a person will give to a business based on the time of year (the *temporal* aspect of the data set), the past ratings of the user (the *historical* aspect of the data set), and the geographical coordinates of the business (the *spatial* aspect of the data set).

We start by performing exploratory data analysis and data visualization to find any interesting trends, patterns, and seasonalities in the data. Based on that, we transform and prune our data. Further, we perform feature engineering on the pruned data set to create meaningful features for optimizing the regression problem at hand. We propose the design of several baseline (intuitive) models and a few machine and deep learning models, along with the evaluation metrics. Our aim is to create a model that fits the data and generates precise predictions.

Our report is structured as follows: Section 2 discusses existing literature on the topic; Section 3 details data-preprocessing, exploratory data analysis, data visualization, and feature engineering techniques; Sections 4 and 5 define the predictive task, the design of models and experiments; and Section 6 concludes our report with results and outcomes.

II. Literature Review

Several regression based problems exist in literature for such data sets. Similar data sets studied in the past include Google Play Store Apps Reviews [4] data set which was used in finding sentimental analysis of a particular app based on reviews. OpinRank Review data set [5] is also very useful data set that has users rating on cars and hotels around the world. Understanding the users trends from these dataset can heavily benefit the businesses . State-of-the-art models found for understanding spatial and temporal data set include Recurrent Neural Network (RNN) as it can learn highly complex correlations between features very well and adapts itself based on change in location and timestamp. This is something which most of the machine learning models fails to learn.

III. Exploratory Data Analysis & Insights

In this section, we describe the exploratory data analysis carried out on the raw version of the Google Local Reviews data set (hereinafter referred to as 'data set'). Here, our aim is to bring about the notions of data completeness, sparseness, and cardinality to optimize our next steps. Additionally, we intend to find any interesting trends, patterns, and seasonalities in the data.

A. Data Pre-processing

Following pre-processing operations were performed on the dataset:

1) We merge the 'user' ,'places' and 'review' data tables from the raw data set, using the foreign keys: `gPlusUserId` and `gPlusPlaceId`, and obtain a 'merged' table. As shown in Figure 1, it has 11 columns: `userName`, `gPlusUserId`, `gPlusPlaceId`, `rating`, `reviewText`, `categories`, `unixReviewTime`, `name`, `price`, `gps`, and `closed`.
2) We define 3 new terms:
   - **Completeness**: Fraction of non-null values over total values.

```
merged.head()
```

	userName	gPlusUserId	rating	reviewText	categories	gPlusPlaceId	unixReviewTime	name	price	gps	closed
0	an lam	100000010817154263736	3.0	Chất lượng tạm ổn	[Giải Trí - Café]	108103314380004200232	1.372687e+09	Cà Phê Thăng Long	None	[10.852044, 106.65971]	False
1	hoang long nguyen	101659842775092396018	5.0	Good coffee, nice and peaceful place	[Giải Trí - Café]	108103314380004200232	1.354888e+09	Cà Phê Thăng Long	None	[10.852044, 106.65971]	False
2	Hong Le	107574994242995460712	2.0	Cho heo	[Giải Trí - Café]	108103314380004200232	1.352015e+09	Cà Phê Thăng Long	None	[10.852044, 106.65971]	False
3	HALİL TURGUT	100000013500285534661	5.0	Wc si temiz duzenli..	[Turkish Cuisine]	102194128241608748649	1.342871e+09	Selale Restaurant	None	[37.8037, 29.2209]	False
4	Akudosoft Yazılım	105271324704942360981	5.0	None	[Turkish Cuisine]	102194128241608748649	1.373148e+09	Selale Restaurant	None	[37.8037, 29.2209]	False

Fig. 1. Merged Dataframe

- **Distinctness**: Fraction of distinct non-null values over total non-null values.
- **Uniqueness**: Fraction of unique values over the number of all non-null values of a column. Unique values occur exactly once. For example, $[a, a, b]$ contains one unique value b, so uniqueness is $1/3$.

We drop all the columns that have extremely low completeness values or extremely high uniqueness values as they would skew our data and could result in sub-optimal models. We further prune the data set by dropping columns with excessive `NaN` values and perform `NaN` imputation on relevant columns like `gps`. The resulting dataframe has $8,649,011$ rows and 11 columns.

3) We expand the `gps` column to `lat` and `lon` indicating the latitude and the longitude of the place. We filter these latitudes and longitudes to keep only the businesses present in the United States of America. Now, we have a cleaned data set, called the 'pruned' data set, with $1,299,688$ rows and 13 columns.

We utilize this pruned data set and geolocations to create a mapping of the various types of ratings that we see across all businesses/places in the US.

1) We compute the completeness, distinctness, and uniqueness statistics on the entire data set and on every column in the data set. We also compute the following basic stats (Figures **??** & **??**):
   a) Mean
   b) Standard deviation
   c) Minimum
   d) Maximum
   e) Percentiles
   f) Entropy

Columns	Number of Nulls
`userName`	0
`gPlusUserId`	0
`rating`	0
`reviewText`	2649295
`categories`	135813
`gPlusPlaceId`	0
`unixReviewTime`	42698
`name`	0
`price`	6782945
`gps`	27431
`closed`	0

TABLE I

Completeness	57.04435
Missingness	42.9556

TABLE II

We infer that columns with high entropy (high degree of randomness) can be removed. Moreover, based on the min. and max. values, we perform data normalization.

2) Next, we perform outlier detection to remove skewed entries in our data. We employed the following outlier detection techniques:
   - **Z-score outliers**: Here, we compute the z-score on the `reviewTextLength` feature (details in subsequent sections). z-score is

Column	Entropy
`rating`	1.4216
`unixReviewTime`	13.9288
`reviewTextLength`	6.4236

TABLE III

defined as: $(x-\mu)/\sigma$. We retain only the rows where $-2 \leq$ z-score ≤ 2. For example, users who give only 1-10 or 1000-2000 character reviews are usually junk reviews and can bias our model extensively. Such reviews are considered outliers and are removed.

- **99-100 percentile outliers**: The data contains 99-100 percentile outliers if the difference between the 99.999^{th} percentile and 100^{th} percentile exceeds a certain threshold. We remove all the data points that have `reviewTextLength` exceeding this threshold.
- **Cardinality based pruning**: We drop columns with extremely low ($\sim$ 0) and extremely high cardinalities ($\sim$ 1 million) based on empirically-chosen thresholds.
- **Timestamp based filtering**: We noticed that there were some extremely old and irrelevant/out-of-trend reviews, such as a review from 1990 and a review from 2001, while the most recent review for the specific place was circa 2014. It makes sense to keep only the most recent reviews and not reviews that were given $\sim$ 2 decades ago.

B. Data Visualizations & Inferences

In this step, we utilize data visualization techniques to derive meaningful patterns in our data. The resulting inferences are subsequently used in data set localization and feature extraction/engineering.

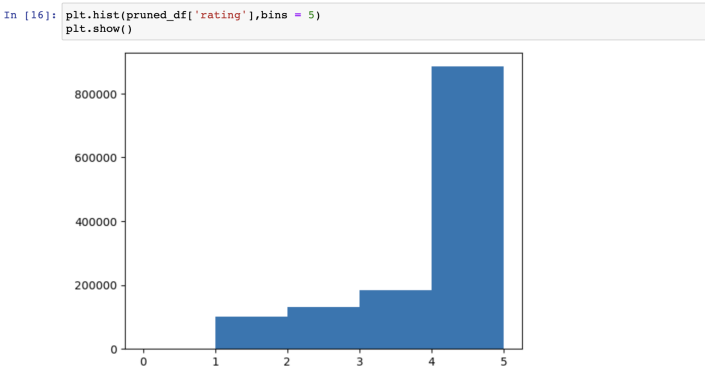

Fig. 2. Rating distribution cross-population

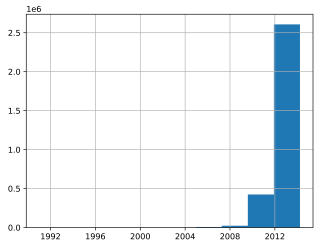

Fig. 3. No. of Ratings available year-wise

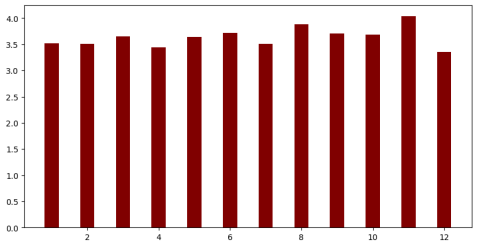

Fig. 4. Month Wise Rating Distribution in U.S.

Fig. 5. Correlation Map of features for all data

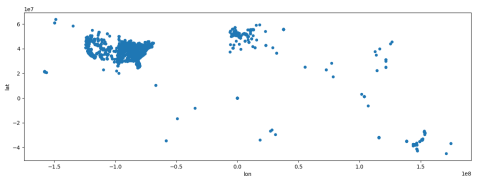

Fig. 6. World Map of Locations present in Places data

Fig. 7. Correlation Map of features of ratings data across the US

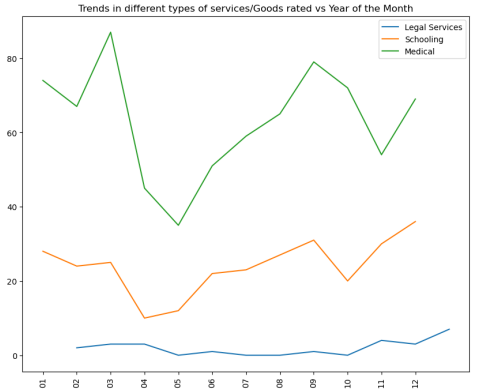

Fig. 8. Monthly Trends in Rating of Various Services

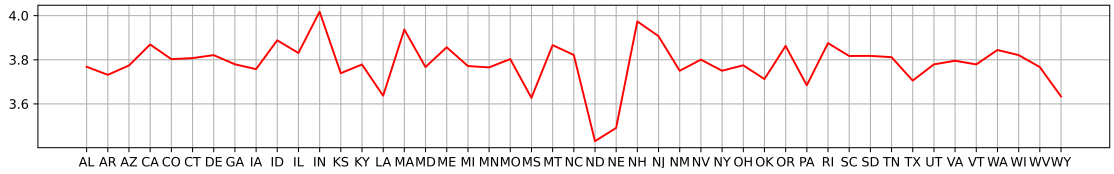

Fig. 9. US state-wise average rating across all services

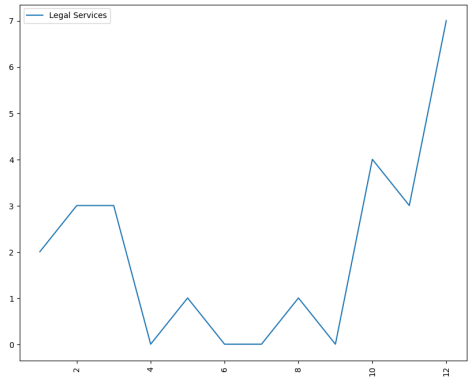

Fig. 10. Monthly Trends in Rating of Legal Services

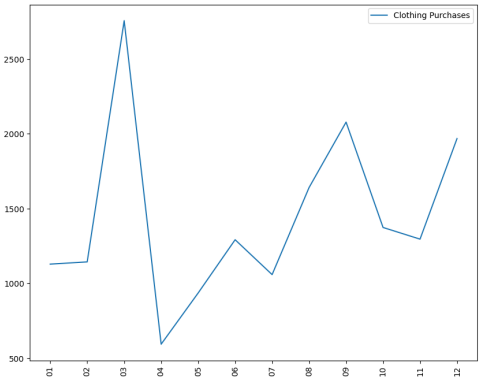

Fig. 11. Monthly Trends in Rating of Cloth Purchases

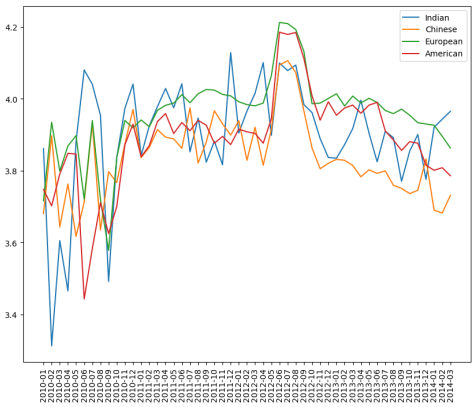

Fig. 12. Temporal rating trends in 4 Types of Restaurants

Fig. 13. User rating trends for a subset of users

1) Majority of the `ratings` ($> 62.5\%$) tend to be on the higher side of 4-5 stars (Figure 2). This indicates that users tend to be more biased towards higher ratings than lower.
2) We see from the world map distribution (Figure 6) that there is a dense set ($\sim$ 8 million) of ratings in the United States alone, which we can further localize into states to obtain state-wise business/place ratings.
3) The `categories` column has a strong correlation on the type of people that rate a business and the influence of categories are dynamic over the years (Figure 8, 10 & 11).
4) We see from temporal visualizations that the ratings tend to vary drastically based on the time of the year (Figures 4 & 3). This means that the `year-month` feature is a strong indicator of user ratings.
5) The `categories` can be clubbed together. By training a *word2vec* [6], [7] model on the temporally sorted business categories, we obtain an N-dimensional vector for each category in our data set. Further, running clustering on top of it, we group several categories into a single category.
6) The location of a specific business has a huge impact on the business' rating (Figures 9 & 12), on the business' performance (i.e., the chances of a business getting shut down), and on user sentiments.

7) It is also evident from the visualizations that though the sentiments/ratings of 2 individuals for the same place/business in a large populous may vary drastically based on their tastes (Figure 13). The general rating trend for two countries (or large populations) as a whole are collective and are similar in distribution. The ratings are consistent over time.
8) Demand, utilization and rating of certain services or businesses such as 'Gift Shops', 'Hospitals', 'Schools', and 'Legal Services' vary greatly based on the time of the year and a trend in the data is noticed across countries as well.

C. Feature Engineering

1) First, we reduce the scope of our data set to account for only interactions (i.e., user-business ratings) that occurred within the United States. This gave us about $\sim$ 3 million data points to work with. We achieve this by constraining the latitudes and longitudes of the GPS data.
2) We write python scripts to find the *Geospatial distance* in miles from the latitude and longitude of our business/place to the center (latitude and longitude) of each state in the US. Using the nearest neighbour approach, we zero-in on the closest state in the US for the said business. Thus, we add new column `state` as an indicator of the rating given to a place.
3) Since it is evident from our temporal correlation analysis that the column `unixReviewTime` is highly relevant, we extract the `year-month` information from it (in `YYYY-MM` format) and create `month` and `year` features.
4) In our EDA on the `categories` column, we had shown that several categories can be clubbed into a single category. For every cluster identified, we resort to a customized category grouping technique using 'word' similarities (i.e., of all the categories that a particular place/business belongs to, which category best describes the place). We posit that there exists 10 such mutually exclusive categories that we can optimally 'bin' our places into. These are as follows: 'Associations/Organizations', 'Entertainment', 'Legal Services', 'Medical', 'Public', 'Restaurant', 'School', 'Shops and Stores', 'Venues', and 'Others'.
5) Additionally, our category-wise user rating prediction analysis in the visualizations showed a strong dependency of average user rating for a category with the places that belong to those categories. Therefore, we systematically generated the "User Average Ratings" for every business grouped "Category-Wise" and included that as another data point in the parameter vector.
6) Finally, we perform a one-hot-encoding of the columns `year`, `month`, `state`, `final-category`.

The resulting data set has 84 columns: `gPlusUserId`, `gPlusPlaceId`, `userCategoryAvgRating`, `month_[01, 02, 03, 04, 05, 06, 07, 08, 09, 10, 11, 12]`, `year_[1990, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014]`, `final_category_[AssocOrgs, Entertainment, Legal, Medical, Others, Public, Restaurant, School, ShopsStores, Venues]`, and `state_[AL, AR, AZ, CA, CO, CT, DE, GA, IA, ID, IL, IN, KS, KY, LA, MA, MD, ME, MI, MN, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NV, NY, OH, OK, OR, PA, RI, SC, SD, TN, TX, UT, VA, VT, WA, WI, WV, WY]`.

IV. Predictive Modelling & Tasks Identification

Following are a few possible predictive tasks for our data set:

1) Given user and place metadata, predict what rating a user would give to a business.
2) Given the location and historical user ratings of a place, predict whether a business would fail or succeed.
3) Predicting the top-k most similar users for a particular user given the way they rated different places in different categories.

In this report, we discuss the implementation, experiments and analysis of first task.

Problem Statement: Predict what rating a user will give to a business based on the time of year (the *temporal* aspect of the data set), the past ratings of the user (the *historical* aspect of the data set), and the geographical coordinates of the business (the *spatial* aspect of the data set).

We propose regression-based techniques to develop solutions to this problem as we need to make real-valued predictions in the range 1-5 (star ratings). Multivariate regression is the ideal way to approach this

problem. So, initially, we start by building some intuitive baselines and then suggest a few machine and deep learning models. We perform a comparative analysis of the performance of these models by evaluating them on suitable evaluation metrics. We also attempt to avoid over-fitting by exploring various techniques of regularization. Finally, we explore cold-start issue as well.

V. Model Selection & Experiments

A. Experimental Setup

1) Data is split into 3 subsets: 'train', 'validation', and 'test' in the ratio $60 : 20 : 20$.
2) Regularization is done wherever applicable ensuring to optimize the validation loss.
3) If the loss between any two subsequent epochs is less than 0.0001 (tolerance value), we argue that the model has converged.
4) Simpler models are tried first and then, more intricate models.

B. Baseline Models

1) Always Predict Mean: Our first naive baseline is predicting the mean rating of all businesses for all users satisfying a particular condition, such as falling within a specific state or category. The different variants of this baseline are as follows:

- **Always Predict Mean Per State**: Find average rating of all businesses per `state` and return this value as the predicted rating based on the `state` of the input test data point.
- **Always Predict Mean Per Category**: Do the same as above but based on `category` of the test data point.
- **Always Predict Mean Per Unit of Time**: Do the same as above but based on `month` and `year` of the test data point.

2) Based on Most Popular: An alternative baseline can be to always predict the mean rating of the most popular place/business satisfying a particular condition. Here, we hypothesize that a place/business is popular if it has the most number of reviews. The different variants of this baseline are as follows:

- **Based on Most Popular Per State**: Find the average rating for the most popular place in every `state` and return this value as the predicted rating based on the `state` of the input test data point.
- **Based on Most Popular Per Category**: Do the same as above but based on `category` of the test data point.
- **Based on Most Popular Per Unit of Time**: Do the same as above but based on `month` and `year` of the test data point.

Table IV summarizes the baseline performances.

C. Machine & Deep Learning Models

1) **Linear Regression**: Simple multi-variate linear regression with no regularization. We use `sklearn.linear_model.LinearRegression` here.
2) **Ridge Regression with Regularization**: A variant of linear regression which regularizes given the L2-norm. Here, we find the optimal `alpha` (regularization term) by tuning the same on our validation data set. This comes out to be 100. We use `sklearn.linear_model.Ridge` here.
3) **Random Forest Regression**: Random forest regression with the following hyper-parameters: `n_estimators`: 100 and `min_samples_split`: 250. We use `sklearn.ensemble.RandomForestRegressor` here.
4) **XGBoost Regression**: A Gradient Boosted Decision Tree (GBDT) algorithm that does extremely well for sparse data. We use `xgboost.XGBRegressor` here, with `reg_lambda`: 2.0 and `learning_rate`: 0.1.
5) **Bayesian Personalized Ranking (BPR)**: A personalized ranking technique, where we pass only the user-place interaction pairs and the model learns user-features based on the rating that a user gave to a specific place. This is a simple model with just user/place biases (α, β_u, and β_i).
6) **BPR with Latent Factors**: This model not only takes in the user/place biases but also utilizes a γ term which models the latent factors of users and items. The resulting function we train has the parameters α, β_u, β_i, γ_u, and γ_i.
7) **TensorFlow DNN**: A feed-forward deep-neural network trained on TensorFlow with 5 dense layers and 4 dropout layers for regularization [8]. The sequential model is described in Figure 14.

D. Evaluation Metrics

Since our task involves regression, we use the following evaluation metrics:

- **Mean Absolute Error (MAE)**: This is the arithmetic average of absolute errors, i.e., the absolute

Baseline Model	Type of Data Passed to Model	MSE	MAE
Always Predict Mean			
Per state	No Spatial or Temporal Features	2.5374	1.3143
	SpatioTemporal Features (No Timestamp sorting)	1.6746	1.6709
	Temporally Sorted Spatial	2.5295	1.312
Per category	No Spatial or Temporal Features	2.5374	1.3143
	SpatioTemporal Features (No Timestamp sorting)	1.673	1.067
	Temporally Sorted Spatial	2.518	1.312
Per unit of time	No Spatial or Temporal Features	2.5374	1.3143
	SpatioTemporal Features (No Timestamp sorting)	1.6616	1.0711
	Temporally Sorted Spatial	N/A	N/A
Based on Most Popular			
Per State	No Spatial or Temporal Features	2.5374	1.3143
	SpatioTemporal Features (No Timestamp sorting)	2.3346	1.1808
	Temporally Sorted Spatial	2.8617	1.3497
Per category	No Spatial or Temporal Features	2.5374	1.3143
	SpatioTemporal Features (No Timestamp sorting)	1.8017	1.0675
	Temporally Sorted Spatial	2.7617	1.3474
Per unit of time	No Spatial or Temporal Features	2.5374	1.3143
	SpatioTemporal Features (No Timestamp sorting)	2.6878	1.198
	Temporally Sorted Spatial	N/A	N/A

TABLE IV
BASELINE MODEL PERFORMANCE

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (484576, 512)             43520

 dropout (Dropout)           (484576, 512)             0

 dense_1 (Dense)             (484576, 256)             131328

 dropout_1 (Dropout)         (484576, 256)             0

 dense_2 (Dense)             (484576, 64)              16448

 dropout_2 (Dropout)         (484576, 64)              0

 dense_3 (Dense)             (484576, 16)              1040

 dropout_3 (Dropout)         (484576, 16)              0

 dense_4 (Dense)             (484576, 1)               17

=================================================================
Total params: 192,353
Trainable params: 192,353
Non-trainable params: 0
_________________________________________________________________
```

Fig. 14. TensorFlow DNN Model

difference between the model's predicted rating and the actual rating, *viz.*, MAE $= \sum_{n=1}^{N} |\hat{y} - y|/N$

- **Mean Squared Error (MSE)**: This is the arithmetic average of the square of errors, i.e., the square of the difference between the model's predicted rating and the actual rating, *viz.*, MSE $= \sum_{n=1}^{N} (\hat{y} - y)^2/N$. MSE penalizes heavily for large deviations and very little for smaller deviations.

Table V depicts the performance of each of these models on the test data set.

E. Cold Start Problem

In the data set, almost 70% of reviews are given by unique users, i.e., a large number of users have reviewed only 1 place/business. Predicting the rating for these users is a massive challenge as we do not have extensive information about them. Any similarity function will not work as there is no feature through which we can compare users. Therefore for a new user, we predict the mean rating of the business as the potential rating.

Regression Model	Type of Data Passed to Model	MSE	MAE
Linear Regression	No Spatial or Temporal Features	Same as Baseline	Same as Baseline
	SpatioTemporal Features (No Timestamp sorting)	0.4172	0.35666
	Temporally Sorted Spatial	0.36095	0.27726
Ridge Regression with Regularization	No Spatial or Temporal Features	Same as Baseline	Same as Baseline
	SpatioTemporal Features (No Timestamp sorting)	0.4172	0.3565
	Temporally Sorted Spatial	0.3609566893	0.2772278664
Random Forest	No Spatial or Temporal Features	Same as Baseline	Same as Baseline
	SpatioTemporal Features (No Timestamp sorting)	0.4245	0.3616
	Temporally Sorted Spatial	0.36589232	0.27512476
XGBoost	No Spatial or Temporal Features	Same as Baseline	Same as Baseline
	SpatioTemporal Features (No Timestamp sorting)	0.4173	0.3555
	Temporally Sorted Spatial	0.36252784	0.27383018
Bayesian Personalized Ranking	No Spatial or Temporal Features	Same as Baseline	Same as Baseline
	SpatioTemporal Features (No Timestamp sorting)	1.590519363	1.023491638
	Temporally Sorted Spatial	2.554251616	1.31015079
BPR with Latent Factors	No Spatial or Temporal Features	Same as Baseline	Same as Baseline
	SpatioTemporal Features (No Timestamp sorting)	1.673983	1.06955
	Temporally Sorted Spatial	2.535442192	1.313966471
TensorFlow – Deep Neural Network	No Spatial or Temporal Features	Same as Baseline	Same as Baseline
	SpatioTemporal Features (No Timestamp sorting)	0.4166	0.36540286
	Temporally Sorted Spatial	0.36148914	0.27371245

TABLE V
PERFORMANCES OF VARIOUS REGRESSION MODELS

VI. RESULTS & CONCLUSION

A. Results & Outcomes

From our experimental analyses, we infer that several forms of regression perform reasonably well on the data set. We see that the *Tensorflow based Deep Neural Network* with Dropout regularization performs the best on the data if MSE is considered as the evaluation metric. In terms of MAE, *XGBoost Regressor* is the best-performing model. While the performance of all models are reasonably close, we see that Bayesian Personalized Ranking both with and without Latent Factors perform worse on the data. This is predominantly due to the fact that our data is sparse (as detailed in the Cold Start section), which renders a personalized ranking strategy ineffective.

B. Conclusion & Future Work

We explored several data cleaning, pruning, and encoding techniques. Our data visualizations and inferences allowed to extract essential features and create several baselines. We designed a few machine and deep learning regression models and tried overfitting by introducing regularization wherever necessary. We also handled the cold-start problem.

Future work on the realm of predictive analysis and modelling on the data set could include the prediction of places/businesses shutting down, predicting similar users, development of recommendation engines based on user ratings, modelling the review text data and finding N-most-similar reviews/places based on user sentiment, N-most similar places based on the place description and category.

In conclusion, we believe that multiple inherent characteristics exist in the data set that can be put to great use in development of future models. We see that identifying and exploiting subtle relations and correlations in the data go a long way in the development of optimal Machine Learning predictive models.

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