A COMPARATIVE STUDY OF MACHINE LEARNING ALGORITHMS FOR PREDICTING BOSTON 311 RESPONSE TIME

DS504 FINAL PROJECT

YANG FU

2019-10-24

PROJECT DESCRIPTION

- BOS:311 provides Bostonians with access to report non-emergency issues and request services.
- The estimation of the processing time for a service request is barely found in the BOS:311 system but would be useful and preferred by users.
- In this project, I would like to explore the possibility of predicting the BOS:311 service request processing time using multiple machine learning algorithms.

GOALS

- Data processing.
- Exploratory data analysis.
- Modeling.
- Model evaluations and comparison.

DATA PROCESSING

- Dropped missing data.
- Extracted/Created potentially useful features/targets.
- Merged with the Boston weather dataset.

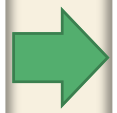
DATA PROCESSING - FEATURES

```
1 raw.shape
```

```
(1611147, 29)
```

```
1 raw.dtypes
```

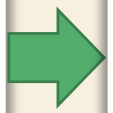
```
case_enquiry_id                  int64
open_dt                         object
target_dt                       object
closed_dt                       object
ontime                          object
case_status                     object
closure_reason                  object
case_title                      object
subject                         object
reason                          object
type                            object
queue                           object
department                      object
submittedphoto                  object
closedphoto                     object
location                        object
fire_district                   object
pwd_district                    object
city_council_district           object
police_district                 object
neighborhood                    object
neighborhood_services_district  object
ward                            object
precinct                        object
location_street_name            object
location_zipcode               float64
latitude                       float64
longitude                      float64
source                          object
dtype: object
```



```
In [8]: 1 w = pd.read_csv('weather.csv')
        2 w.head()
```

Out[8]:

	Year	Month	Day	Avg Temp (F)	Precip (in)
0	2013	1	1	29	0.0
1	2013	1	2	21	0.0
2	2013	1	3	16	0.0
3	2013	1	4	30	0.0
4	2013	1	5	35	0.0



```
1 new_df.shape
```

```
(936602, 13)
```

```
1 new_df.dtypes
```

```
reason                  object
department              object
neighborhood            object
latitude               float64
longitude              float64
source                  object
duration               float64
open_y                   int64
open_m                   int64
open_day_of_week         int64
Avg Temp (F)             int64
Precip (in)            float64
class                    int64
dtype: object
```

DATA PROCESSING - TARGET

- The target is the duration (processing time in hours) of a service request from open to close.
- The target is numeric by nature.

```
1  new_df.duration.describe()
```

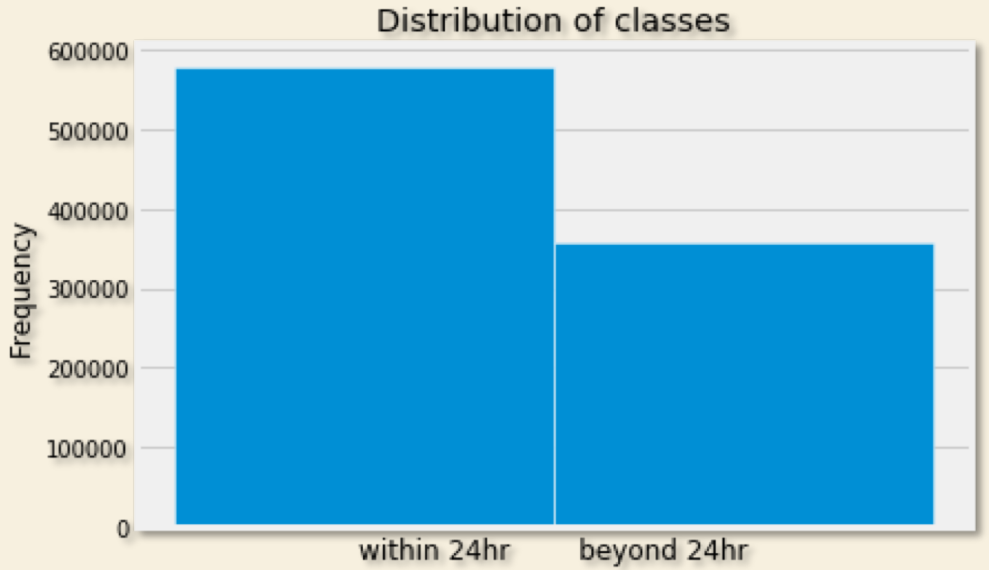
```
count    937454.000000
mean        226.835018
std        1092.388273
min           0.000000
25%           1.150000
50%          14.166944
75%          74.523333
max       54630.305556
Name: duration, dtype: float64
```

DATA PROCESSING - TARGET

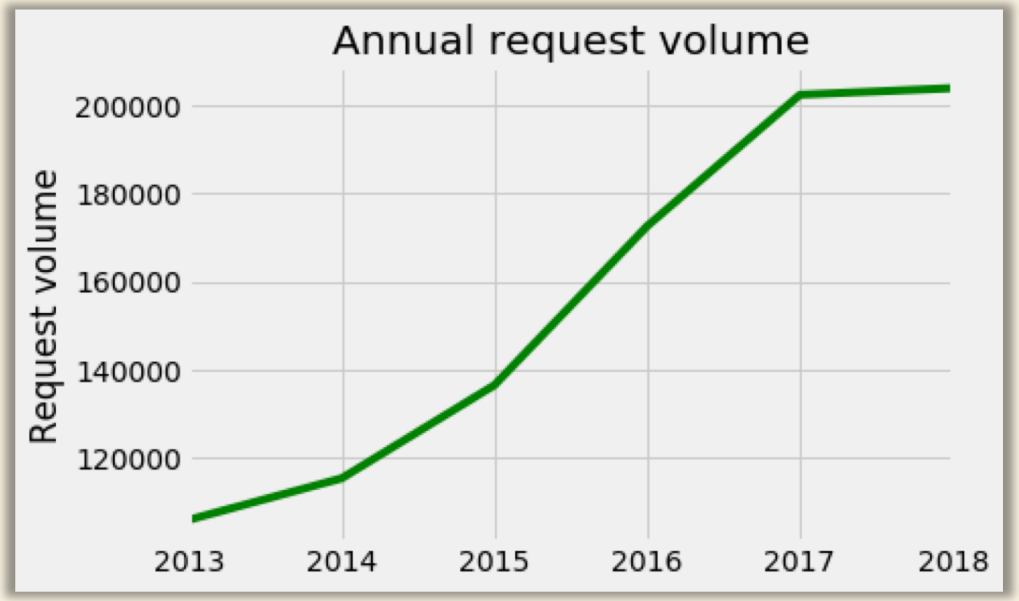
- The distribution of the target values is extremely skewed.
- The target were grouped into within/beyond 24hr classes.

```
1  new_df.duration.value_counts(bins=10)
```

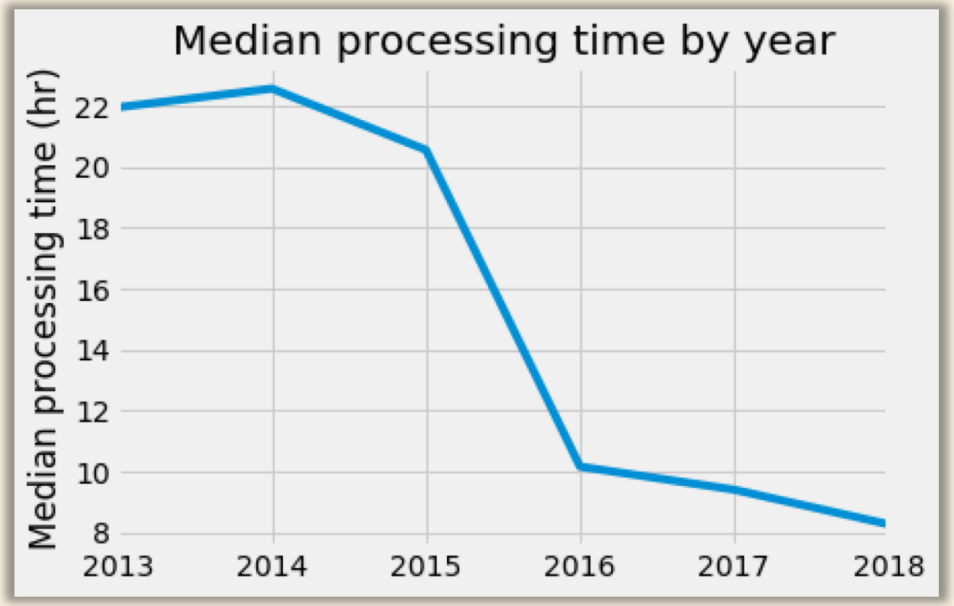
```
(-2.2769999999999997, 227.626]    927623
(227.626, 455.253]                  8360
(455.253, 682.879]                   970
(682.879, 910.505]                   275
(910.505, 1138.131]                  110
(1138.131, 1365.758]                  52
(1365.758, 1593.384]                  34
(1593.384, 1821.01]                   24
(2048.636, 2276.263]                   3
(1821.01, 2048.636]                    3
Name: duration, dtype: int64
```



EXPLORATORY DATA ANALYSIS

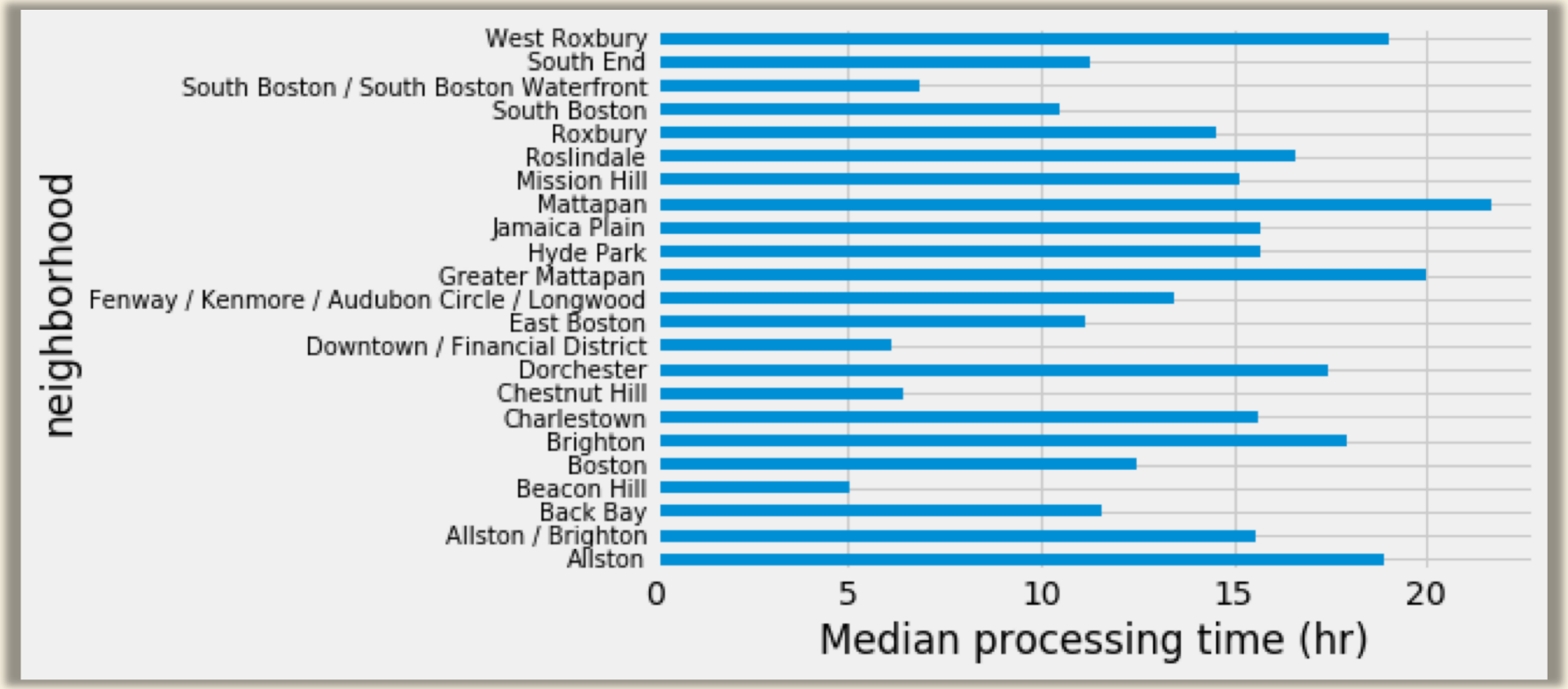


311 usage has been rising as the city introduced various 311 request channels.



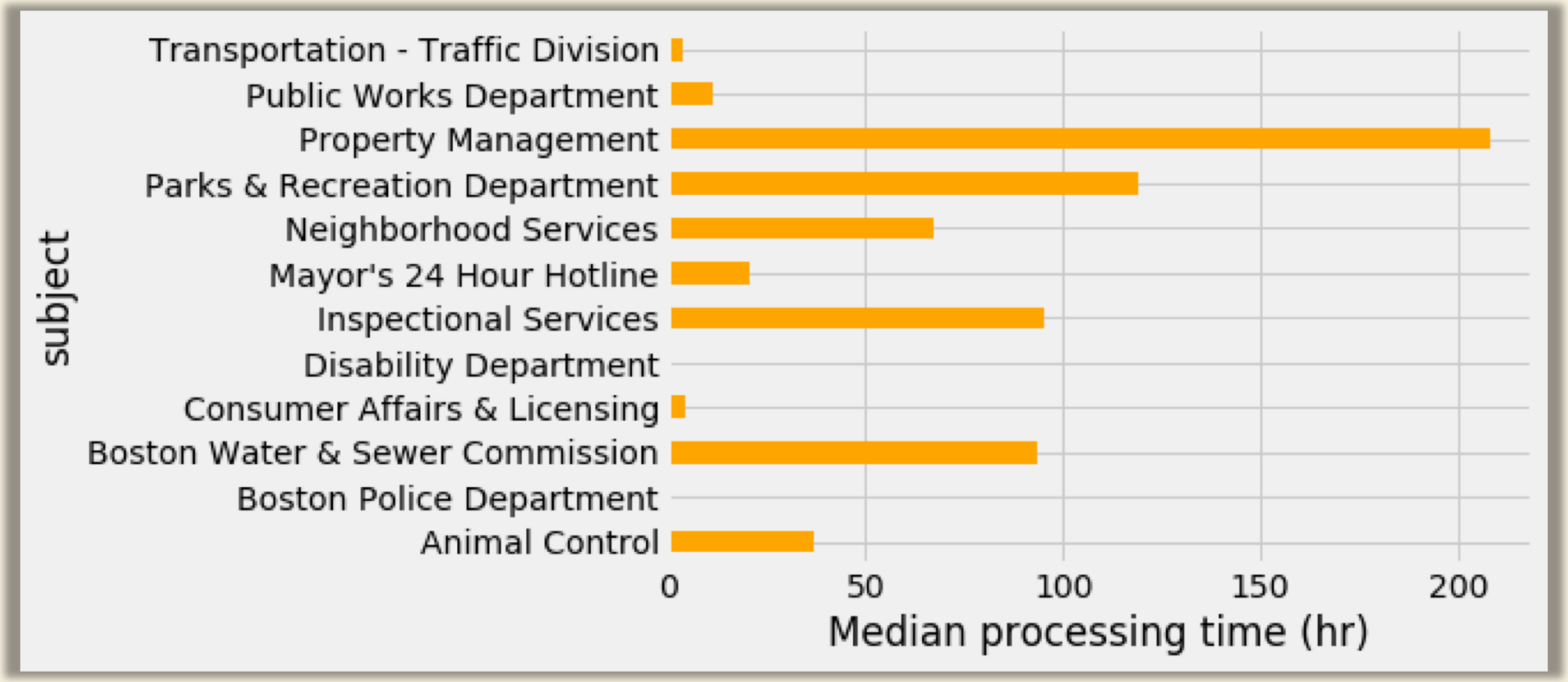
311 request processing time has been decreasing probably due to improved city services.

EXPLORATORY DATA ANALYSIS



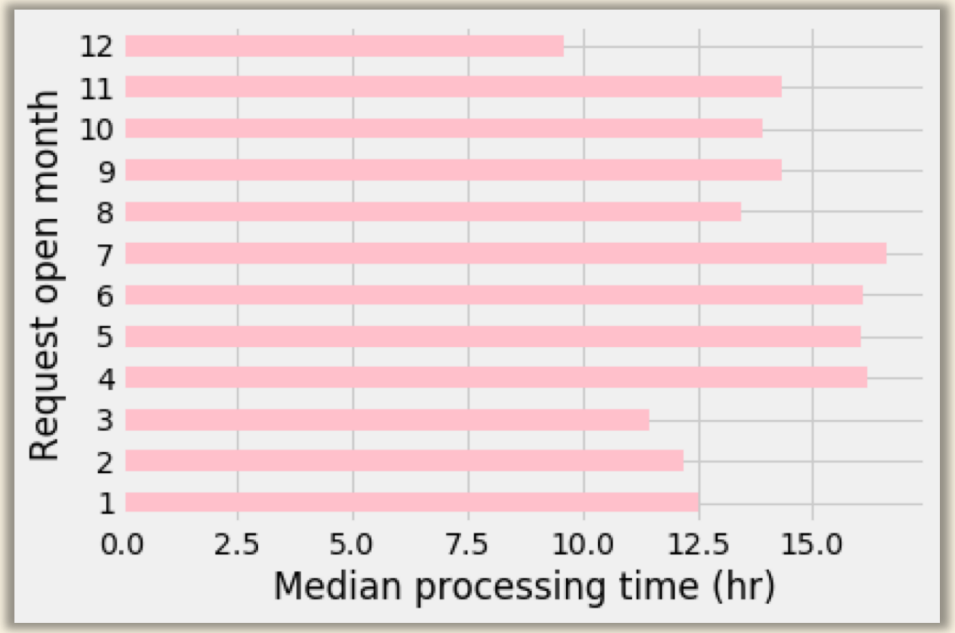
Processing times vary by neighborhood.
Chestnut Hill is the fastest while Charlestown is the slowest.

EXPLORATORY DATA ANALYSIS



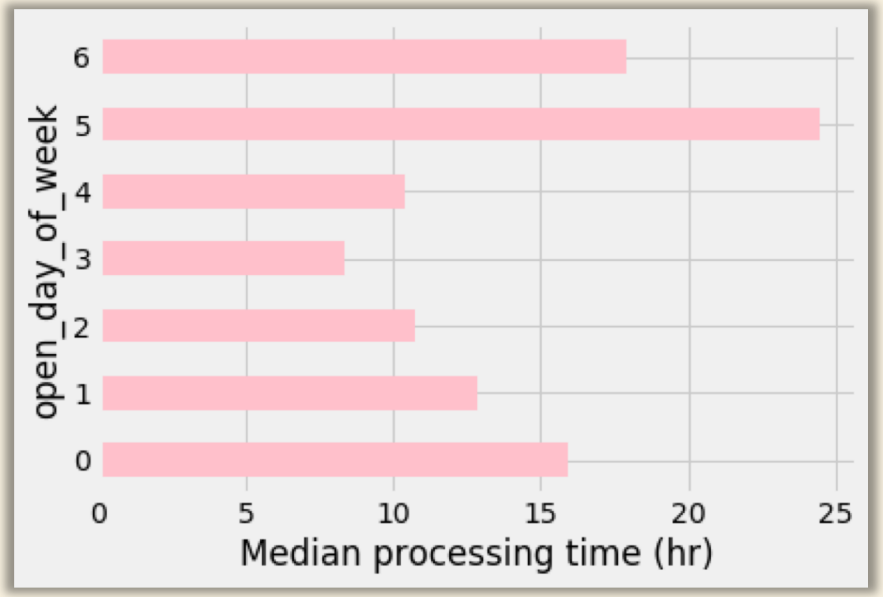
Processing times vary by subject.
Property Management related services were the most time-consuming.

EXPLORATORY DATA ANALYSIS



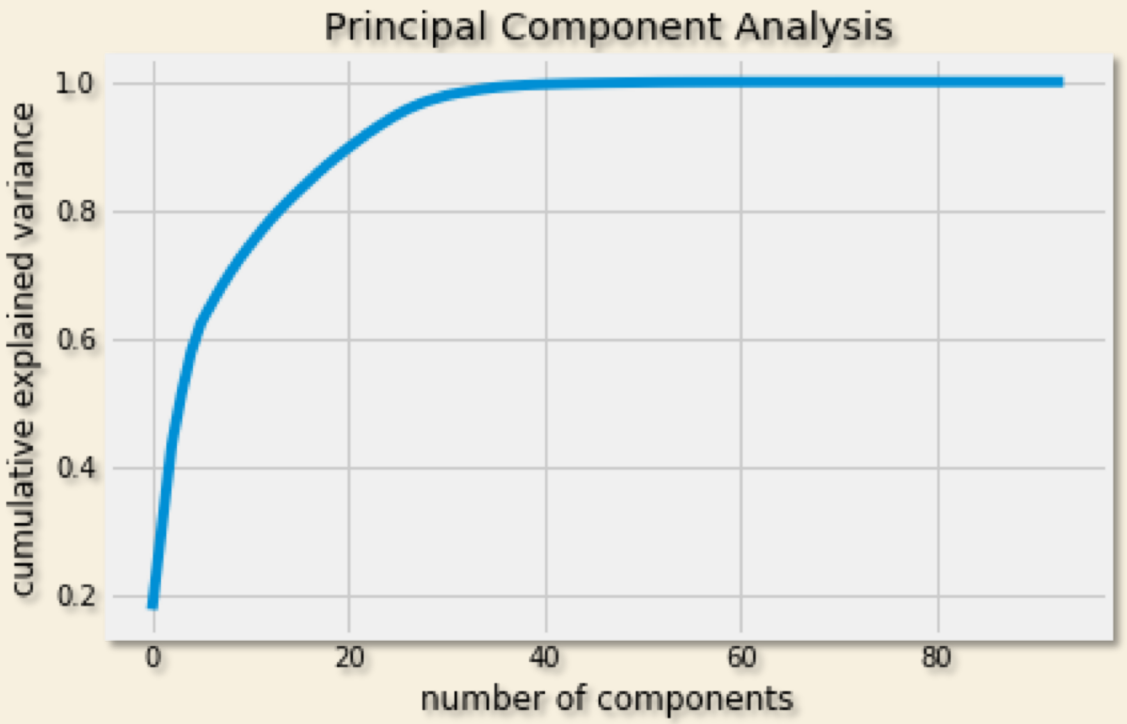
Processing times vary by request open month. Spring months were slower than winter months.

Processing times vary by open day of week. Weekend requests are processed faster.



PRINCIPAL COMPONENT ANALYSIS

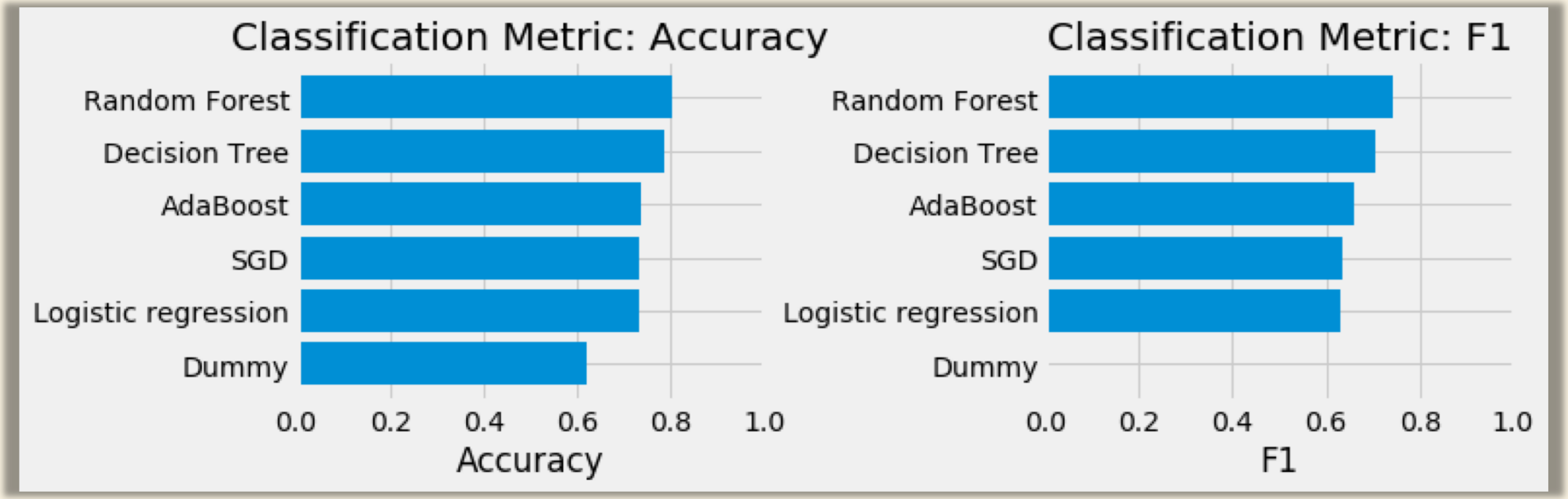
- The encoded dataset contains 107 features.
- The first 20 PCs can explain more than 90% variance.
- The first 20 PCs were applied to the classification modeling.



MODELING – CLASSIFICATION

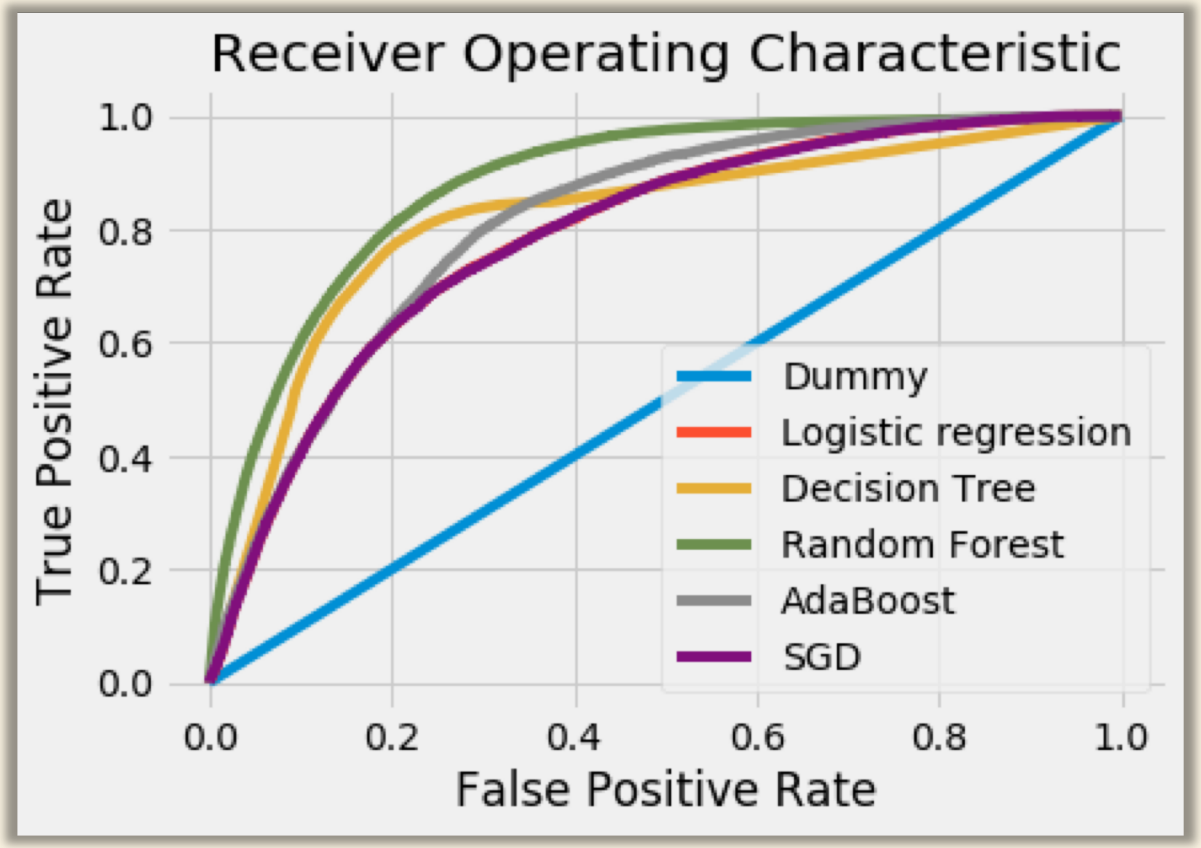
- **Predicted whether a request could be resolved in 24hr.**
- A dummy classifier was used as baseline control.
- All classifiers were briefly tuned by cross validation.
- Multiple error metrics were included to evaluate model performance:
  - Accuracy.
  - F1 score.
  - AUC.

MODELING – CLASSIFICATION



- The Random Forest classifier has the best performance, with an accuracy of 0.8, and a F1 score of 0.74.

MODELING – CLASSIFICATION



- The Random Forest classifier has the best performance, with the max area under ROC curve 0.79.

MODELING – REGRESSION

- Converted duration from hours to days.
- Focus on the most favorite service request 'reason' – Sanitation.
- Predicted how many DAYS are needed to resolve a Sanitation service request.

```
1  # convert duration from hours to days.
2  new_df['duration'] = new_df['duration']/24
3  new_df[(new_df['reason']=='Sanitation')]['duration'].describe()
```

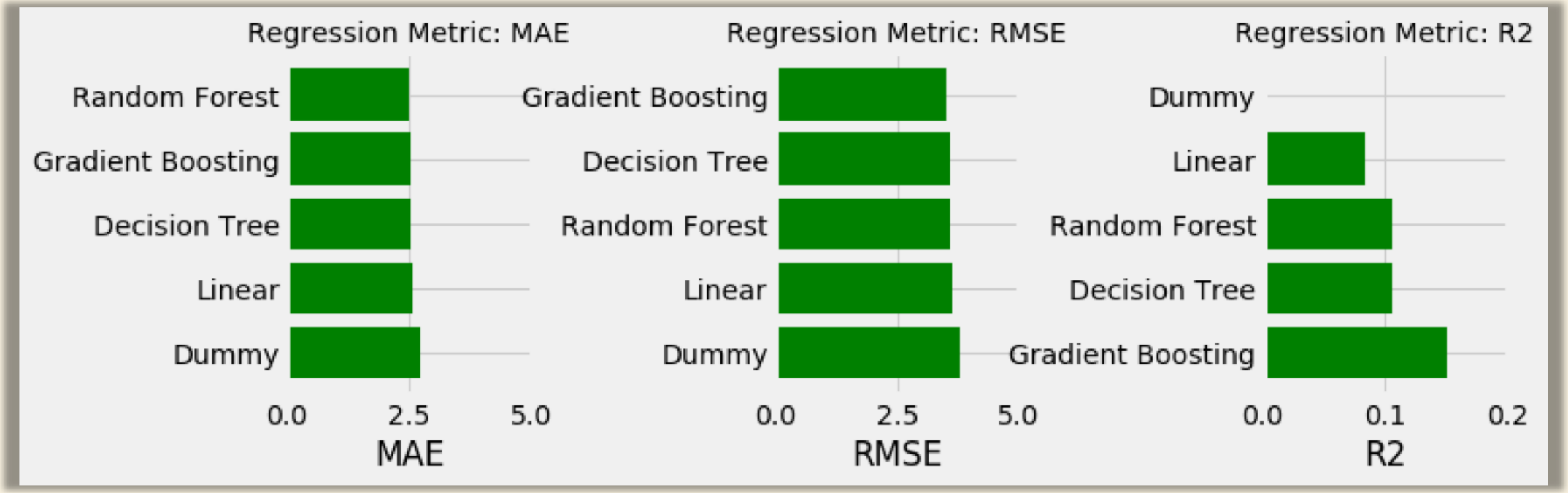
```
count    171069.000000
mean          3.386809
std           4.126719
min           0.000093
25%           0.651840
50%           2.287998
75%           5.327789
max         633.062025
Name: duration, dtype: float64
```

MODELING – REGRESSION

- A dummy regressor was used as baseline control.
- All regressors were briefly tuned by cross validation.
- Multiple error metrics were included to evaluate model performance.
  - Mean Absolute Error.
  - Root Mean Square Error.
  - R Square.

```
Dummy
Mean absolute error: 2.74
Mean squared error: 3.79
R2: -0.00
==================================
Decision Tree
Mean absolute error: 2.53
Mean squared error: 3.59
R2: 0.11
==================================
Random Forest
Mean absolute error: 2.49
Mean squared error: 3.59
R2: 0.11
==================================
Gradient Boosting
Mean absolute error: 2.52
Mean squared error: 3.49
R2: 0.15
==================================
Linear
Mean absolute error: 2.58
Mean squared error: 3.63
R2: 0.08
==================================
```

MODELING – REGRESSION



- In general, regressors failed this task.
- The min MAE is as large as 2.5, the min RMSE is as large as 3.5, and the max R2 is as tiny as 15%.

PYSPARK ON DATABRICKS

- The same project was rewritten in PySpark and run on Databricks, without feature scaling and PCA.
- Very similar results were observed.

Classifiers

```
Logistic regression
Accuracy: 0.77
====================
Random forest
Accuracy: 0.75
====================
GBT
Accuracy: 0.80
====================
MPC
Accuracy: 0.77
====================
```

Regressors

```
Linear regression
R2: 0.11
====================
Decision tree
R2: 0.08
====================
Random forest
R2: 0.09
====================
GBT
R2: 0.14
====================
```

CONCLUSIONS

- Among all the **classifiers** tested, the Random Forest classifier performs the best in deciding whether a request can be resolved within 24 hrs with an accuracy of 0.8 and an F1 score of 0.74.

- All **regressors** tested fail to explain the variance in this dataset. However, the MAE and RMSE could still be used as references when predicting the processing time of a service request under certain 'reason'.

FUTURE DIRECTIONS

- Predicting BOS:311 service request processing time using various machine learning algorithms is doable but the results are not so great in this project. (And I now understood why such information is missing in the system.)

- Future work could focus on better feature engineering, as the current dataset contains too little numeric features.

REFERENCES

- Data source:
  - https://data.boston.gov/dataset/311-service-requests
  - https://www.kaggle.com/jqpeng/boston-weather-data-jan-2013-apr-2018
- Code: https://github.com/ilovemanu/ds504_big_data_analytics
- Tutorials:
  - https://spark.apache.org/docs/latest/ml-classification-regression.html
  - https://docs.databricks.com/getting-started/index.html

THANKS