

Denver 2016 B-cycle

Data Exploration
Regression Machine Learning
Classification Machine Learning

Harpreet Bhasin

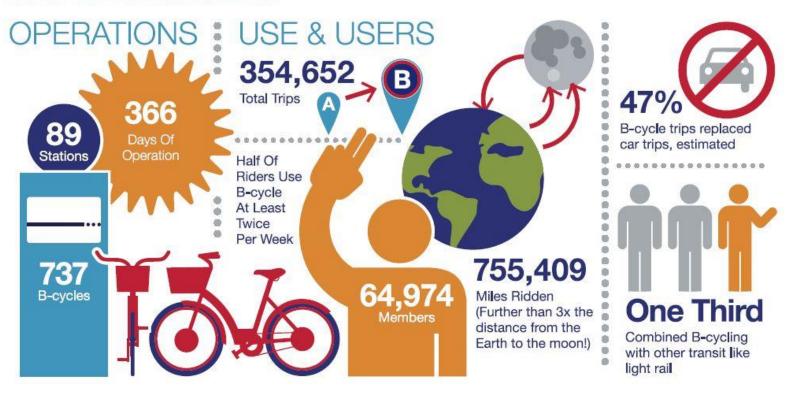
Denver B-cycle



- Non-profit public organization
- Owns and operates an automated public bike sharing system
- Has 737 bicycles and 89 kiosks located throughout downtown Denver and nearby areas
- Complements and integrates with Denver's comprehensive metropolitan transportation
- Contributes to Denver becoming the healthiest and greenest city in America
- Encourages the replacement of short car trips for recreational, social and functional purposes

Denver Bike Share

2016 SUCCESSES

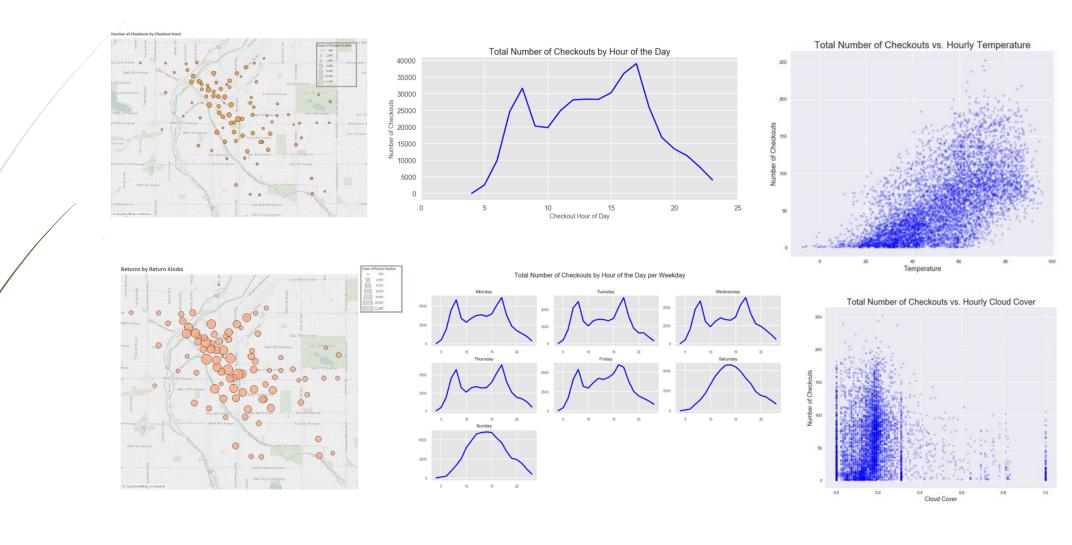


Source: https://denver.bcycle.com/docs/librariesprovider34/default-document-library/dbs_annualreport_2016_05.pdf

The Objective

- Explore the publicly available 2016 Trips dataset and visualize the data to provide useful and interesting information
- Deploy a variety of regression machine learning models to predict number of bike checkouts using a combination of calendar, clock and weather attributes
- Deploy variety of classification machine learning models to predict number of bike checkouts using a combination of calendar, clock and weather attributes
- Provide and/or present findings to Denver B-cycle executives to improve future ridership

Step 1- Data Exploration



Step 2 – Regression Models

- Predict number of bike checkouts using the following models
 - Linear Regression
 - Most widely used statistical and machine learning technique to model relationship between two sets of variables typically using a straight line. Simple to use and fast performance but lacks high accuracy when compared to non-linear models.
 - Lasso Regression
 - ► A type of linear regression that uses shrinkage to reduce data values toward the mean. Well suited for automating feature selection..
 - Ridge Regression
 - ▶ Well suited for data that suffers from multicollinearity, i.e. features with high correlation.
 - Bayesian Ridge Regression
 - ► An approach to linear regression in which the statistical analysis is undertaken using Bayesian inference.
 - Decision Tree Regression
 - Uses a tree like structure to derive a final decision on the outcome of the analysis.
 - Random Forest Regression
 - An ensemble learning method that operates by constructing a multitude of decision trees to arrive at the mean prediction.
 - Extra Trees Regression
 - ► An extremely randomized tree regressor. Builds a totally random decision tree.
 - Nearest Neighbors Regression
 - A simple algorithm that uses a similarity measure (e.g. distance between neighbors) to predict the outcome.

Step 3 – Classification Models

- Predict number of bike checkouts using the following models
 - Logistic Regression Classification
 - Similar to linear regression but used for classification.
 - Decision Tree Classification
 - Uses a tree like structure to derive a final decision on the outcome of the analysis.
 - Random Forest Classification
 - Similar to random forest regression but used for classification.
 - Extra Trees Classification
 - Similar to extra trees regression but used for classification.
 - Naïve Bayes Classification
 - Uses the Bayes' Theorem (i.e. assumes that the presence of a particular feature is unrelated to the presence of any other feature).
 - Gradient Boosting Classification
 - A machine learning method that produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees.
 - Nearest Neighbors Regression
 - Similar to nearest neighbors regressor but used for classification
 - Multi-Layer Perceptron Classification
 - A feedforward artificial neural network mode that maps sets of input data onto a set of appropriate outputs.

Results – Regression Models

Regression Modeling Summary – Categorical Feature Set

| | Linear | Lasso | Ridge | Bayesian | Decision | Random | Extra | Nearest |
|----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|------------|
| | Lilleai | Lasso | niuge | Ridge | Tree | Forest | Trees | Neighbors |
| Training | | | | | | | | |
| Test | 0.676 | 0.676 | 0.676 | 0.676 | 1.000 | 0.969 | 1.000 | 0.575 |
| Score | | | | | | | | |
| Test Set | 0,696 | 0.696 | 0.696 | 0.696 | 0.718 | 0.825 | 0.840 | 0.476 |
| Score | 0.090 | 0.030 | 0.030 | 0.090 | 0.718 | 0.825 | 0.840 | 0.476 |
| R | 0.034510 | 0.024457 | 0.024457 | 0.024440 | 0.047276 | 0.000443 | 0.016370 | 0.600040 |
| Squared | 0.834519 | 0.834457 | 0.834457 | 0.834448 | 0.847276 | 0.908443 | 0.916278 | 0.690249 |
| RMSE | 627.95439 | 628.16826 | 628.16826 | 628.19832 | 583.57445 | 361.43485 | 331.86035 | 1082.98114 |
| | | | | | | | | |

- Extra Trees is best performing regressor with 44 features
- Random Forest is pretty close

Regression Modeling Summary – Numerical Feature Set

| | Linear | Lasso | Ridge | Bayesian Ridge | Decision Tree | Random Forest | Extra Trees | Nearest Neighbors |
|------------------------|----------|----------|----------|-------------------|------------------|------------------|-------------|----------------------|
| Training Test Score | 0.433 | 0.433 | 0.433 | 0.433 | 1.000 | 0.975 | 1.000 | 0.880 |
| Test Set Score | 0.448 | 0.447 | 0.447 | 0.447 | 0.741 | 0.854 | 0.838 | 0.646 |
| R Squared | 0.669090 | 0.668243 | 0.668243 | 0.668785 | 0.861079 | 0.924077 | 0.915609 | 0.803447 |
| RMSE | 1142.475 | 1144.818 | 1144.818 | 1143.319 | 534.800 | 302.172 | 334.397 | 733.229 |

- Random Forest is best performing regressor with 9 features
- Either Extra Trees or Random Forest regressor is recommended for 44 or 9 features

Regressor Test on Unseen Samples

| Sample Number | Actual Number of Checkouts | Predicted Number of Checkouts | +/- |
|---------------|----------------------------|----------------------------------|-----|
| 1 | 92 | 96 | +4 |
| 2 | 12 | 13 | +1 |
| 3 | 55 | 56 | +1 |
| 4 | 111 | 112 | +1 |
| 5 | 76 | 72 | -4 |
| 6 | 41 | 37 | -4 |
| 7 | 8 | 14 | +6 |
| 8 | 81 | 99 | +18 |
| 9 | 65 | 64 | -1 |
| 10 | 14 | 14 | 0 |

- Random Forest Regressor with 92.4% accuracy predicted 9 out of 10 unseen samples well within 7.6%.
- Of the remaining 1 sample, its prediction was off by 22%.

Results – Classification Models - 1

Classification Modeling Summary – Categorical Feature Set

| | Logistic | Decision Tree | Random Forest | Extra Trees | Naïve Bayes | Nearest Neighbors | Gradient Boosting | Multi- Layer Perceptron |
|-------------------------|-----------|------------------|------------------|----------------|----------------|----------------------|----------------------|-------------------------------|
| Accuracy | 0.662281 | 0.640838 | 0.705653 | 0.712693 | 0.347466 | 0.545809 | 0.665205 | 0.689571 |
| F1 (macro) | 0.500343 | 0.535669 | 0.580615 | 0.597661 | 0.277657 | 0.316936 | 0.540916 | 0.488650 |
| F1 (micro) | 0.662281 | 0.640838 | 0.705653 | 0.712693 | 0.347466 | 0.545809 | 0.665205 | 0.689571 |
| Precision (macro) | 0.547424 | 0.534911 | 0.611702 | 0.609287 | 0.353727 | 0.426109 | 0.551274 | 0.600202 |
| Precision (micro) | 0.662281 | 0.640838 | 0.705653 | 0.712693 | 0.347466 | 0.545809 | 0.665205 | 0.689571 |
| Recall (macro) | 0.488317 | 0.538071 | 0.565099 | 0.590623 | 0.399370 | 0.314355 | 0.532883 | 0.514250 |
| Recall (micro) | 0.662281 | 0.640838 | 0.705653 | 0.712693 | 0.347466 | 0.545809 | 0.665205 | 0.689571 |
| Cross Validation | 0.654620 | 0.639123 | 0.695088 | 0.708480 | 0.350292 | 0.552339 | 0.652398 | 0.665322 |
| Execution Time (sec) | 15.989999 | 0.337216 | 4.064112 | 3.654782 | 0.211667 | 0.980936 | 137.870316 | 9.564595 |

- Extra Trees Classifier is best performing classifier with 44 features
- Random Forest Classifier is pretty close

Results – Classification Models - 2

Classification Modeling Summary – Numerical Feature Set

| | Logistic | Decision Tree | Random Forest | Extra Trees | Naïve Bayes | Nearest Neighbors | Gradient Boosting | Multi- Layer Perceptron |
|-------------------------|-----------|------------------|------------------|----------------|----------------|----------------------|----------------------|-------------------------------|
| Accuracy | 0.571637 | 0.654483 | 0.702242 | 0.700780 | 0.462476 | 0.608187 | 0.670565 | 0.585283 |
| F1 (macro) | 0.317235 | 0.536431 | 0.565431 | 0.571989 | 0.288432 | 0.400182 | 0.551396 | 0.314778 |
| F1 (micro) | 0.571637 | 0.654483 | 0.702242 | 0.700780 | 0.462476 | 0.608187 | 0.670565 | 0.585283 |
| Precision (macro) | 0.329322 | 0.534468 | 0.605005 | 0.591664 | 0.366608 | 0.462348 | 0.567401 | 0.368854 |
| Precision (micro) | 0.571637 | 0.654483 | 0.702242 | 0.700780 | 0.462476 | 0.608187 | 0.670565 | 0.585283 |
| Recall (macro) | 0.330366 | 0.538836 | 0.549900 | 0.560451 | 0.331956 | 0.392413 | 0.539238 | 0.342865 |
| Recall (micro) | 0.571637 | 0.654483 | 0.702242 | 0.700780 | 0.462476 | 0.608187 | 0.670565 | 0.585283 |
| Cross Validation | 0.573450 | 0.649181 | 0.691696 | 0.690877 | 0.470760 | 0.605263 | 0.660643 | 0.580409 |
| Execution Time (sec) | 14.257541 | 0.217554 | 4.202843 | 3.353612 | 0.128580 | 0.957223 | 76.372264 | 4.313864 |

- Random Forest is best performing classifier with 9 features
- Extra Trees Classifier is pretty close

Classifier Test on Unseen Samples

| Sample Number | Actual Number of Checkouts | Class Number | Predicted Number of Checkouts | Class Number |
|------------------|----------------------------|--------------|-------------------------------|--------------|
| 1 | Between 51 and 100 | 1 | Between 51 and 100 | 1 |
| 2 | Between 1 and 50 | 0 | Between 1 and 50 | 0 |
| 3 | Between 51 and 100 | 1 | Between 1 and 50 | 0 |
| 4 | Between 101 and 150 | 2 | Between 101 and 150 | 2 |
| 5 | Between 51 and 100 | 1 | Between 51 and 100 | 1 |
| 6 | Between 1 and 50 | 0 | Between 1 and 50 | 0 |
| 7 | Between 1 and 50 | 0 | Between 1 and 50 | 0 |
| 8 | Between 51 and 100 | 1 | Between 1 and 50 | 0 |
| 9 | Between 51 and 100 | 1 | Between 51 and 100 | 1 |
| 10 | Between 1 and 50 | 0 | Between 1 and 50 | 0 |

- Random Forest Classifier with 79.3% accuracy predicted 8 out of 10 unseen samples accurately
- Of the remaining 2 samples, it predicted one class below the actual class in both samples.

Use of Regressor and Classifier for Denver B-cycle

- ► Help predict number of bike checkouts in 2017 based on 2016 trips dataset.
- Drill down on calendar variables (month and weekday), clock variable (checkout hour) and weather variables (temperature, cloud clover, humidity, wind speed and visibility) to predict number of bike checkouts in 2017.
- Optimize number of available bikes at checkout kiosks.
- Use the Random Forest Regressor to predict a number of bike checkouts.
- Use the Random Forest Classifier to predict number of bike checkouts within a range (1 to 50, 51 to 100, 101 to 150 and 151 to 252).

Next Steps

- Undertake similar project for Boulder B-cycle
- Longmont, CO has just introduced its bike sharing system this study could be useful