Smart Prediction for Shared Bicycles (Data Bootcamp Final Project) by Ray Xie

Introduction:

In recent years, there has been the rise of the shared bike programs as an environmental and trendy form of transportation within cities around the world. The way of commuting reduces traffic jam, carbon emissions, and improves users' health. So far, Washington D.C., New York City, and Beijing are some of the major cities that currently enjoy extensive bike-share systems with thousands of daily users.

One of the key questions for these sharing systems is: Can we accurately forecast the number of bike rentals on a given day? In my final report, I'm gonna focus on forecasting daily rental counts (cnt) from variables such as weather, season, and calendar variables. I believe accurate demand forecasts are required for planning operations because they can help city planners and service providers to allocate bikes efficiently, schedule maintenance, and adjust fleet size. For instance, miscalculating demand on a hot holiday can lead to empty stations and lost money, but overestimating on a rainy, cold workday can trigger unfilled bikes and additional operating expense.

Why this prediction is important to consider:

First, it enhances urban planning efforts by helping city officials anticipate transportation needs and promote sustainable alternatives to private-car use.

Second, it enables operational efficiency by allowing bike-sharing companies to adjust supply levels and maintenance schedules based on expected demand.

Lastly, predictive insights can support policy analysis, shedding light on how factors like holidays, seasonal changes, or traffic interventions influence public transportation system.

The content of this project:

My goal is to forecast daily bike rentals model using historical data from Washington D.C.'s bike-sharing system. The content includes:

1. Building and comparing Linear Regression, KNN, Random Forest, and Decision Tree models.
2. Evaluating model performance using RMSE and R square.
3. Interpreting results and next steps to understand key drivers of rental behavior.

Data Description:

This 2011-2012 dataset comes from the UCI Machine Learning Repository and initially collected

by the Capital Bikeshare System in Washington D.C.. The data is aggregated on a daily basis and supplemented with weather and calendar information, making it a qualified resource for my predictive modeling.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 731 entries, 0 to 730
Data columns (total 15 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   dteday      731 non-null    object
 1   season      731 non-null    int64
 2   yr          731 non-null    int64
 3   mnth        731 non-null    int64
 4   holiday     731 non-null    int64
 5   weekday     731 non-null    int64
 6   workingday  731 non-null    int64
 7   weathersit  731 non-null    int64
 8   temp        731 non-null    float64
 9   atemp       731 non-null    float64
 10  hum         731 non-null    float64
 11  windspeed   731 non-null    float64
 12  casual      731 non-null    int64
 13  registered  731 non-null    int64
 14  cnt         731 non-null    int64
dtypes: float64(4), int64(10), object(1)
memory usage: 85.8+ KB
```

```
[ ] # Confirm that 'cnt' is the sum of 'casual' and 'registered'
    # This validates the definition of our target variable
    (df['cnt'] == df['casual'] + df['registered']).all()

    np.True_

[ ] # Check unique values for key categorical variables
    # This supports our earlier point that variables like 'season', 'holiday', and
    'weathersit' are categorical with discrete levels
    df['season'].unique(), df['weathersit'].unique(), df['holiday'].unique(), df
    ['workingday'].unique()

    (array([1, 2, 3, 4]), array([2, 1, 3]), array([0, 1]), array([0, 1]))

    # Validate normalized weather-related variables
    # These should be between 0 and 1, as mentioned in the dataset description
    df[['temp', 'atemp', 'hum', 'windspeed']].agg(['min', 'max'])
```

	temp	atemp	hum	windspeed
min	0.059130	0.079070	0.0000	0.022392
max	0.861667	0.840896	0.9725	0.507463

	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
0	2011-01-01	1	0	1	0	6	0	2	0.344167	0.363625	0.805833	0.160446	331	654	985
1	2011-01-02	1	0	1	0	0	0	2	0.363478	0.353739	0.696087	0.248539	131	670	801

Analyzing the above 2 screenshots, the dataset contains 731 daily observations. Each row represents a single day and includes the target variable cnt as well as several predictors related to calendar events, weather conditions, and user behavior:

1. *Calendar-related variables* include the season (1=spring to 4=winter), year (0=2011, 1=2012), month, weekday, holiday status, and whether it was a working day.
2. *Weather-related variables* capture both categorical and continuous aspects of the environment, such as weathersit (ranging from 1 for clear days to 4 for extreme conditions), normalized temperature (temp), perceived temperature (atemp), humidity (hum), and wind speed (windspeed).
3. *User behavior variables* include the number of casual users (casual), registered users (registered), and their sum (cnt), which serves as the main prediction target.

Strength of this dataset:

Each variable has been carefully engineered. Specifically, temperatures are normalized using the min-max range for interpretability, and binary indicators like holiday or workday clearly define whether the day belongs to a weekend or holiday.

The dataset also captures human activity patterns. The separation of registered and casual users, for instance, allows researchers to distinguish between commuter usage and recreational use. On this project, I treat cnt as a whole to avoid data leakage.

Beyond that, there are no missing values in the data, which simplifies the preprocessing step.

Models and Methods:

Before introducing complex models, I first establish a baseline for comparison, which predicts the average number of daily rentals (cnt) for every observation. This naive approach provides a reference mean squared error that more advanced models must exceed.

```
from sklearn.metrics import mean_squared_error
import numpy as np
# Calculate the baseline prediction: Use the mean of y
y = df['cnt']
baseline_preds = np.ones(len(y)) * y.mean()
mean_squared_error(y, baseline_preds)
```

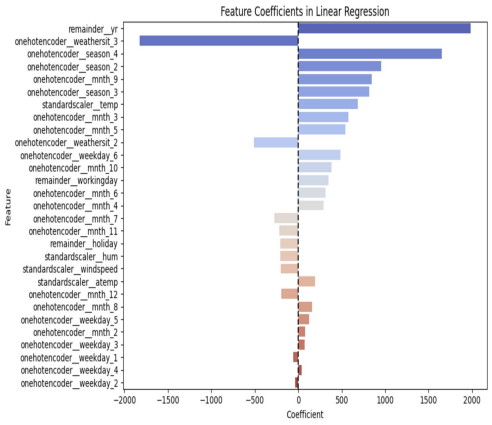
```
3747654.4350841474
```

The baseline model yields a high MSE of 3,747,654.44. This is expected as cnt typically ranges in thousands and MSE penalizes errors quadratically. Despite the model ignores all input features and daily variability, its poor performance makes it a valuable benchmark for assessing the effectiveness of more sophisticated models.

Linear Regression Model:

I begin with a linear regression model due to its simplicity, speed, and interpretability. It provides a useful baseline and helps reveal how features like temperature, season, and humidity relate to rental volume. Each coefficient offers clear insight into variable influence, making it ideal for building initial intuition. However, linear regression assumes linear relationships and can struggle with multicollinearity and outlier, which are limitations that more advanced models can address.

	Feature	Coefficient
26	remainder__yr	1981.834582
10	onehotencoder__weathersit_3	-1826.372063
2	onehotencoder__season_4	1654.242956
0	onehotencoder__season_2	951.858211
18	onehotencoder__mnth_9	847.680102
1	onehotencoder__season_3	819.071721
22	standardscaler__temp	686.298246
12	onehotencoder__mnth_3	578.428177
14	onehotencoder__mnth_5	540.876304
9	onehotencoder__weathersit_2	-508.438725
8	onehotencoder__weekday_6	486.677266
19	onehotencoder__mnth_10	383.093660
28	remainder__workingday	348.905685
15	onehotencoder__mnth_6	313.362932
13	onehotencoder__mnth_4	290.190864
16	onehotencoder__mnth_7	-274.881371
20	onehotencoder__mnth_11	-218.126336
27	remainder__holiday	-206.136140
24	standardscaler__hum	-204.787259
25	standardscaler__windspeed	-198.408092
23	standardscaler__atemp	195.466120
21	onehotencoder__mnth_12	-194.501085
17	onehotencoder__mnth_8	161.478733
7	onehotencoder__weekday_5	123.870510
11	onehotencoder__mnth_2	79.776198
5	onehotencoder__weekday_3	71.187696
3	onehotencoder__weekday_1	-58.946740
6	onehotencoder__weekday_4	40.554224
4	onehotencoder__weekday_2	-33.896144



By looking at the linear regression coefficients, I got a clearer sense of what drives bike rentals:

The most influential factor turns out to be yr, which reflects whether the day is in 2011 or 2012. Rentals in 2012 are nearly 2000 higher than in 2011, possibly because of increased awareness, expanded bike availability, or growing popularity over time.

As we expected, bad weather still has a major negative impact. When the weather shifts to category 3 (light snow or heavy rain), rental volume drops by over 1200. That fits with real-life experience—fewer people want to ride in unpleasant conditions.

On the flip side, summer (season 4) boosts rentals by about 1650, and higher temperatures add another 686 rentals per standard deviation. Warm and sunny days clearly get more people out on bikes.

To my surprise, July (mnth_7) showing a slight negative effect of around -275. I expected July to

be a peak month, but maybe it's too hot or fewer people are commuting due to vacations.

Overall, the model picks up patterns that mostly match real-world expectations: good weather brings out the bikes, and bad weather keeps them away. It's a simple model, but it already gives a helpful breakdown of what's pushing rentals up or down.

```
RMSE: 796.46
MAE: 583.02
R²: 0.842
```

Performance Summary:

The linear regression model achieves an RMSE of 796.46, meaning that on average, our predictions are off by around 796 rentals. The MAE is 583.02, suggesting that most errors stay within a few hundred bikes. An R square of 0.842 means the model explains about 84% of the variance in daily rental counts, which is quite strong. While it's not perfect, this is a solid performance for a simple linear model and makes it a reliable starting point before moving on to more advanced approaches.

KNN:

While linear regression offers a strong starting point and helped identify key predictors like weather and seasonality, it struggles with more complex relationships in the data. The biggest limitation is the assumption of linearity, which is something that rarely holds in real-world scenarios like our bike rentals case.

Let's first analyze temperature variable. In real-life, people tend to avoid biking in both extreme heat and cold, which creates a U-shape preference curve that linear models can't capture. Additionally, linear regression misses interactions among variables, like how humidity might affect ridership differently depending on the season.

To address these issues, I adopt the K-Nearest Neighbors model. Unlike linear regression, KNN makes no assumptions about the form of the relationship between features and the target. It simply finds the most similar days in the data based on inputs.

This flexibility makes KNN well-suited for capturing non-linear trends and hidden interactions. It can naturally learn that rentals drop off at both ends of the temperature scale without needing to model that curve explicitly.

Coding Method:

I start by splitting the data into 80% training and 20% testing sets using train test split, ensuring that evaluation is based on unseen data. Categorical features (season, month, and weather) are encoded, while numerical features (temperature and windspeed) are standardized using standard scale. These preprocessing steps are organized using a ColumnTransformer.

Then, I build a pipeline that combines both preprocessing and the K-Nearest Neighbors regressor. To further tune the model, I run a grid search over different values of n_neighbors (ranging from 5

to 50) with 5-fold cross-validation.

	Feature	Importance
1	yr	0.276075
7	temp	0.198414
8	atemp	0.173283
9	hum	0.153083
0	season	0.041637
10	windspeed	0.035172
6	weathersit	0.032999
5	workingday	0.020639
2	mnth	0.019801
3	holiday	-0.001151
4	weekday	-0.015679

```
Train MSE: 628336.48
Test MSE: 887765.53
Train MAE: 617.59
Test MAE: 733.39
R²: 0.779
```

Performance Summary:

To interpret what drives KNN's predictions, I use permutation importance, which shows how much model performance drops when each feature is randomly shuffled. The larger the drop, the more the model depends on that feature.

The most important predictor turns out to be yr, suggesting that bike usage increased significantly from 2011 to 2012. Weather-related features like temp, atemp, and hum also rank highly, which is consistent with the linear regression model: people tend to ride more when the weather is warm and comfortable. Meanwhile, variables like windspeed and weather conditions had moderate impact, while holiday and weekday showed little to no influence—indicating that the KNN model didn't rely much on the calendar variables.

In terms of performance, KNN outperformed the baseline (MSE > 3.7 million) but did not beat the linear regression model this time. Its test MSE is around 887,766, and the MAE is 733.39, meaning predictions were typically off by about 733 rentals. The R^2 score of 0.779 shows that the model explains roughly 78% of the variance in daily rental counts. While slightly weaker than linear regression in this case, KNN still captures some nonlinear patterns.

Random Forest Model:

While KNN offers a clear improvement over linear regression, it comes with notable limitations. One key issue is that it treats all neighbors equally. This can lead to overly smooth or noisy predictions, especially in dense regions where small variations in inputs are averaged together. For example, extremely cold or rainy days often lead to sharp drops in bike rentals. But KNN might blur these patterns by averaging them with nearby days, producing overly optimistic predictions. Additionally, KNN struggles in high-dimensional spaces, where irrelevant features can distort the notion of "closeness" and weaken prediction accuracy.

To address these challenges, I turn to a more powerful model: Random Forest. Like KNN, it captures nonlinear relationships, but it does so by building an ensemble of decision trees trained on random subsets of the data and features. This randomness helps the model generalize better and reduces overfitting. It also offers reliable feature importance scores, giving clearer insight into what truly drives bike rental behavior.

Coding Method:

To ensure fair comparison, I use the same 80/20 train test split and similar preprocessing steps: categorical features were one-hot encoded, and numerical features were standardized. These transformations were combined with a RandomForestRegressor in a pipeline.

I then applied GridSearchCV with 5-fold cross-validation to tune the number of trees. This setup helps prevent overfitting, ensures robust performance, and keeps the workflow clean.

```
Train MSE: 75,739.08
Test MSE: 514,496.11
Train MAE: 195.40
Test MAE: 467.17
R²: 0.872
```

	Feature	Importance
25	remainder__temp	0.348292
3	onehotencoder__yr_1	0.278237
26	remainder__atemp	0.167306
27	remainder__hum	0.061510
2	onehotencoder__season_4	0.045674
28	remainder__windspeed	0.031430
24	onehotencoder__weathersit_3	0.010914
22	onehotencoder__workingday_1	0.005454
23	onehotencoder__weathersit_2	0.005328
0	onehotencoder__season_2	0.004844
11	onehotencoder__mnth_9	0.004358
4	onehotencoder__mnth_2	0.004136
21	onehotencoder__weekday_6	0.003915
12	onehotencoder__mnth_10	0.003448
6	onehotencoder__mnth_4	0.003000
15	onehotencoder__holiday_1	0.002947
14	onehotencoder__mnth_12	0.002651
19	onehotencoder__weekday_4	0.002456
17	onehotencoder__weekday_2	0.002203
5	onehotencoder__mnth_3	0.002056
16	onehotencoder__weekday_1	0.001908
18	onehotencoder__weekday_3	0.001525
7	onehotencoder__mnth_5	0.001367
20	onehotencoder__weekday_5	0.001344
8	onehotencoder__mnth_6	0.001229
10	onehotencoder__mnth_8	0.000995
13	onehotencoder__mnth_11	0.000655
1	onehotencoder__season_3	0.000417
9	onehotencoder__mnth_7	0.000400

Performance Summary:

To evaluate model performance, I analyze three metrics:

1. MSE captures average squared error. In our case, a test MSE of 488,000 is a major drop from the baseline (3.7 million) and linear regression (1.9 million), showing much better accuracy.
2. Test MAE reflects average prediction error. At 449, it means predictions are off by about 449 rentals per day.
3. R square indicates how much variance the model explains. A score of 0.878 means Random Forest accounts for nearly 88% of rental fluctuations, far stronger than the linear model (0.53).

Feature importance analysis shows that instant is by far the most influential variable. This is followed by temp and atemp, reinforcing earlier findings from KNN and linear regression's prediction that people prefer to biking more in moderate, comfortable weather. Variables like humidity and windspeed also contribute while calendar-based features such as individual months, weekdays, season, or holiday show minimal importance. This suggests that Random Forest focuses more on real-time numeric signals rather than static or repetitive categories.

Despite its strong performance, Random Forest comes with trade-offs. This model makes it difficult to interpret how specific variables influence individual predictions. It also tends to smooth out changes, such as sudden drops in ridership due to extreme weather on a holiday, by averaging across trees. As a result, it may underestimate rare but impactful events. Moreover, when uncommon combinations of inputs appear (a hot Monday holiday in spring), the model might misrepresent them and cause error.

Decision Tree Model:

Unlike Random Forest, Decision Tree offers full transparency as showing exactly how predictions are made at each split. While it's more prone to overfitting, this can actually be useful for exploring sharp behavioral shifts or rare cases in the data. For this special step, the goal isn't for optimal performance, but interpretability to see how the tree structures decisions and which features it relies on when predictions aren't averaged across models.

Coding Method:

In the modeling step, I train a Decision Tree Regressor using the same 80/20 train-test split and pipeline structure to ensure consistency across models. A grid search with 5-fold cross-validation was used to tune key parameters: max_depth, min_samples_split, and min_samples_leaf to minimize Mean Squared Error.

```
Train MSE: 305,645.79
Test MSE: 847,672.15
Train MAE: 400.93
Test MAE: 652.91
R²: 0.789
```

	Feature	Importance
25	remainder__temp	0.348292
3	onehotencoder__yr_1	0.278237
26	remainder__atemp	0.167306
27	remainder__hum	0.061510
2	onehotencoder__season_4	0.045674
28	remainder__windspeed	0.031430
24	onehotencoder__weathersit_3	0.010914
22	onehotencoder__workingday_1	0.005454
23	onehotencoder__weathersit_2	0.005328
0	onehotencoder__season_2	0.004844
11	onehotencoder__mnth_9	0.004358
4	onehotencoder__mnth_2	0.004136
21	onehotencoder__weekday_6	0.003915
12	onehotencoder__mnth_10	0.003448
6	onehotencoder__mnth_4	0.003000
15	onehotencoder__holiday_1	0.002947
14	onehotencoder__mnth_12	0.002651
19	onehotencoder__weekday_4	0.002456
17	onehotencoder__weekday_2	0.002203
5	onehotencoder__mnth_3	0.002056
16	onehotencoder__weekday_1	0.001908
18	onehotencoder__weekday_3	0.001525
7	onehotencoder__mnth_5	0.001367
20	onehotencoder__weekday_5	0.001344
8	onehotencoder__mnth_6	0.001229
10	onehotencoder__mnth_8	0.000995
13	onehotencoder__mnth_11	0.000655
1	onehotencoder__season_3	0.000417
9	onehotencoder__mnth_7	0.000400

Performance Summary:

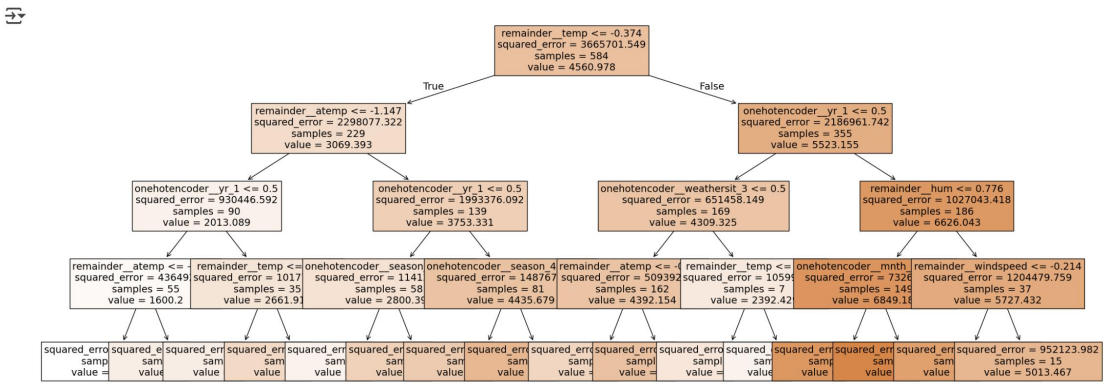
This model achieves a test MSE of 847,672 and a MAE of roughly 653, meaning predictions are, on average, off by about 653 rentals. The R square of 0.789 shows that the model explains about 79% of the variance in rental counts, which is slightly behind the linear regression and KNN models.

Compared to previous models, the decision tree performs quite well, especially given its simplicity. The gap between training and test errors suggests some overfitting issue, but not a severe one. More importantly, it offers full transparency. We can see exactly how features drive predictions at each split. While less accurate than more complex models, this model is still helpful for understanding rental patterns.

Then by analyzing the feature importance, the pattern reinforces previous findings: temperature (temp) is the most influential feature, followed closely by yr, which reflects temporal growth in ridership. Perceived temperature (atemp) and humidity (hum) also play meaningful roles. Their influence makes sense as warmer and more comfortable weather tends to drive more bike usage.

On the other hand, categorical calendar variables like weekday, holiday, and even specific months contribute very little as most scoring below 0.002 in importance. This suggests that once broader weather conditions and long-term trends are captured, fine-grained calendar details add little

incremental value. In this case, my decision tree confirms a clear hierarchy: bike rentals are primarily driven by temperature, time trends, and overall weather comfort, while calendar-based features are secondary.



Decision Tree Structure Interpretation:

I analyze the structure of the decision tree from top to bottom. At the top, the first split is based on remainder__temp, meaning the model's very first decision is whether the day was relatively cold. This aligns with our earlier finding that temperature is the most important driver of bike rentals.

On the left side, the tree focuses on colder or less comfortable days, splitting on variables like atemp, hum, and even calendar features such as mnth_4. For instance, when perceived temperature drops below a certain threshold, predicted rentals fall to around 1745, which is consistent with lower demand during uncomfortable weather. This side of the tree is deeper, showing the model needs more rules to handle variability under less favorable conditions.

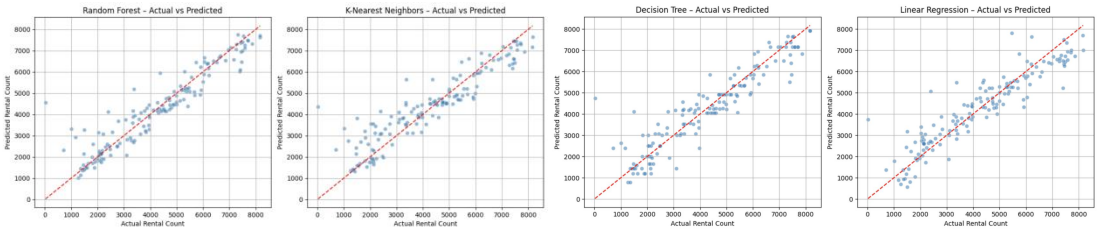
On the right side, the splits center around variables like yr, hum, and windspeed, covering warmer and more stable days. These branches are shallower and converge to higher rental predictions, highlighting the model's confidence under ideal biking conditions.

All in all, the tree structure suggests this: on colder, less predictable days, bike usage requires more nuanced decision paths. But under warm dry conditions, usage is stable and high, and the model can predict it with fewer splits.

Result & Interpretation:

To better understand how the four models differ in structures and behaviors, I created 4 visual comparisons that highlights each of their characteristics.

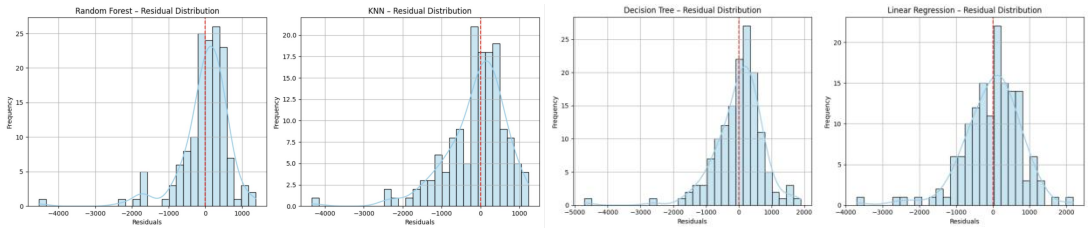
Actual vs Predicted Graph:



The scatter plots show how closely each model's predictions align with actual rental counts:

1. Random Forest produces the tightest fit along the diagonal, indicating accurate and balanced predictions across all demand levels.
2. KNN shows increasing spread as rental counts rise, suggesting it struggles with high-demand days.
3. Decision Tree performs better than KNN, though still shows some noise due to its segmented prediction structure.
4. Linear Regression deviates the most from the diagonal, underestimating high values and overestimating lows.

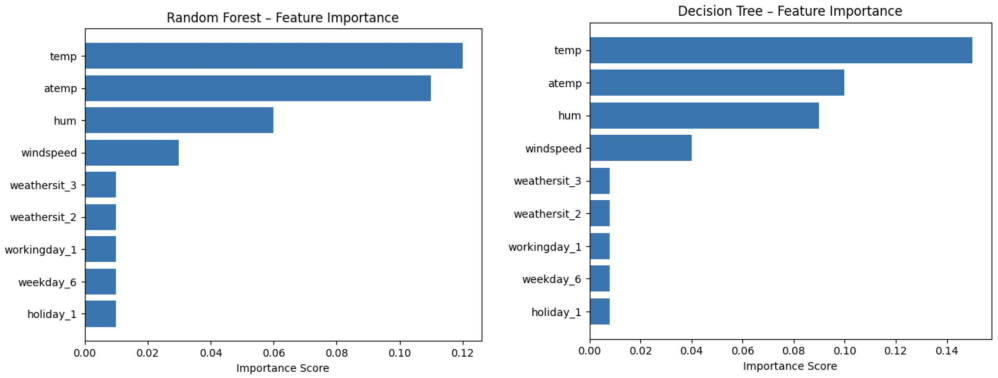
Histogram of Residuals:



These plots show how each model's prediction errors are distributed: closer to zero indicates better accuracy and stability.

1. Random Forest: Residuals are tightly concentrated with a sharp peak near zero and thin tails, showing high accuracy and few extreme errors. Slight right skew, but overall very consistent.
2. KNN: Broader spread and slight left skew suggest less stability. Errors are more variable, especially on outlier days.
3. Decision Tree: Symmetrical and relatively compact residuals. Moderate variance, supporting its solid but not top-tier performance.
4. Linear Regression: Classic bell shape, centered at zero, but with fatter tails. It captures the average trend but struggles with high-variance or extreme cases due to its linear constraints.

Feature Importance Graph:



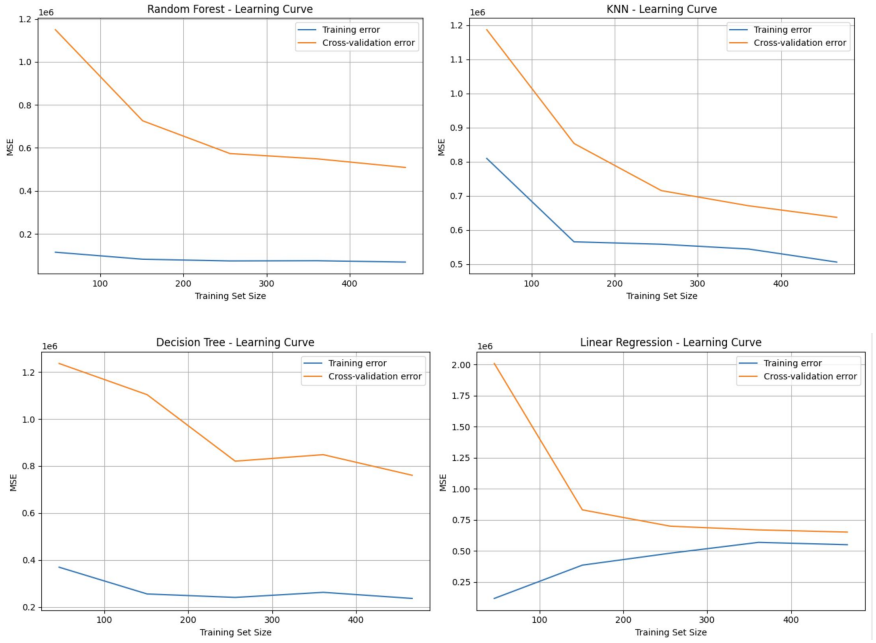
KNN and Linear Regression don't really give us traditional feature importance scores—KNN doesn't learn any weights, and linear regression relies on coefficients that aren't directly comparable unless everything is standardized first.

But with Random Forest and Decision Tree, we can see that in both cases, weather dominates. Temperature (temp), perceived temperature (atemp), and humidity (hum) top the list. That matches what we've been seeing all along: people are way more likely to ride when the weather feels good.

Other variables like wind speed and weather conditions have much smaller effect. This suggests that once general weather conditions are accounted for, the model doesn't rely heavily on granular calendar variables.

Compared to Random Forest, the Decision Tree model gives a slightly more balanced view across temperature-related variables, which may indicate it captures temporal variation with less overfitting to specific patterns. Overall, both models confirm that weather comfort is the most reliable and consistent driver of bike demand.

From my extra knowledge: Learning Plot



The learning curves illustrate how each model adapts to more training data and handles generalization:

1. Random Forest shows consistently low training error and declining validation error, indicating a low bias and moderate variance.
2. KNN has higher training error and a wide gap between training and validation curves. The slight improvement with more data suggests high variance and limited capacity to generalize from local patterns.
3. Decision Tree exhibits classic overfitting: near-zero training error but stubbornly high validation error. The model memorizes training data well but fails to improve with scale.
4. Linear Regression reflects high bias. Training error increases with more data, and validation error stays flat and high. The small gap between the two indicates underfitting issue.

Conclusion and Next Steps:

Overall, my project compared four predictive models (Linear Regression, KNN, Decision Tree, and Random Forest) to forecast daily bike rental counts using the unbiased Bike Sharing dataset. Through a comprehensive analysis that included evaluation metrics, residual plots, feature importance, and learning curves, each model revealed distinct strengths and weaknesses.

Which Model Performs The Best?

Among the above 4 models, Random Forest consistently delivers the best overall performance. It achieves the lowest test MSE, the highest R square score (0.878), and produces residuals that are tightly clustered around zero. Its learning curve shows a steady improvement with more data, suggesting strong generalization ability and low variance.

Decision Tree and KNN also capture non-linear patterns but suffer from higher variance and less stability, as seen in their noisier residuals and wider gaps between training and validation errors.

Linear Regression, while easy to interpret and respond fast, underestimates the data significantly.

Based on the metrics analysis, **Random Forest** can handle both general trends and day-to-day variability very well so does it achieve **the best balance between accuracy, stability, and flexibility**, making it the most reliable model for our predictive task.

Speaking to general drawbacks, all 4 models rely solely on historical data and don't account for real-world shocks like holidays, public events, or sudden weather changes. Also, the dataset only reflects city-level rental totals, which limits spatial insight into station-level behavior or regional patterns.

Next Step:

1. Move from daily to hourly prediction by using the hour.csv dataset. This would help the model capture short-term fluctuations in bike demand more effectively, such as rush hour peaks or midday drops.
2. Integrate external data sources/API, including weather forecasts, public event schedules, or unexpected disruptions (e.g., holidays or road closures). These inputs can improve the model's adaptability to real-world changes that aren't visible in historical patterns alone.
3. Deploy the model in an interactive environment, such as an online-version dashboard with auto-updating function. This would allow users to explore predictions dynamically, adjust inputs in real time, and use the model as a practical decision-making tool for fleet allocation or demand forecasting.

Dataset Reference:

"Bike Sharing." UCI Machine Learning Repository,
archive.ics.uci.edu/dataset/275/bike+sharing+dataset. Accessed 1 May 2025.