

```
# IMPORTANT: SOME KAGGLE DATA SOURCES ARE PRIVATE
# RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES.
import kagglehub
kagglehub.login()

# IMPORTANT: RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES,
# THEN FEEL FREE TO DELETE THIS CELL.
# NOTE: THIS NOTEBOOK ENVIRONMENT DIFFERS FROM KAGGLE'S PYTHON
# ENVIRONMENT SO THERE MAY BE MISSING LIBRARIES USED BY YOUR
# NOTEBOOK.

trishalakarmacharya_kaggle_json_path = kagglehub.dataset_download('trishalakarmacharya/kaggle-json')
trishalakarmacharya_environment_path = kagglehub.dataset_download('trishalakarmacharya/environment')
trishalakarmacharya_bike_sharing_demand_path = kagglehub.dataset_download('trishalakarmacharya/bike-sharing-demand')

print('Data source import complete.')
```

✓ Predict Bike Sharing Demand with AutoGluon Template

✓ Project: Predict Bike Sharing Demand with AutoGluon

This notebook is a template with each step that you need to complete for the project.

Please fill in your code where there are explicit ? markers in the notebook. You are welcome to add more cells and code as you see fit.

Once you have completed all the code implementations, please export your notebook as a HTML file so the reviews can view your code. Make sure you have all outputs correctly outputted.

File-> Export Notebook As... -> Export Notebook as HTML

There is a writeup to complete as well after all code implementation is done. Please answer all questions and attach the necessary tables and charts. You can complete the writeup in either markdown or PDF.

Completing the code template and writeup template will cover all of the rubric points for this project.

The rubric contains "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. The stand out suggestions are optional. If you decide to pursue the "stand out suggestions", you can include the code in this notebook and also discuss the results in the writeup file.

✓ Install packages

```
!pip install -U pip
!pip install pandas
!pip install kaggle
!pip install -U setuptools wheel
!pip install -U "mxnet<2.0.0" bokeh==2.0.1
!pip install autogluon --no-cache-dir
!pip install unzip
# Without --no-cache-dir, smaller aws instances may have trouble installing
!pip install python-dotenv
```

```
Requirement already satisfied: pip in /opt/conda/lib/python3.7/site-packages (22.3.1)
Collecting pip
  Downloading pip-24.0-py3-none-any.whl (2.1 MB)
    2.1/2.1 MB 31.5 MB/s eta 0:00:00a 0:00:01
Installing collected packages: pip
  Attempting uninstall: pip
    Found existing installation: pip 22.3.1
    Uninstalling pip-22.3.1:
      Successfully uninstalled pip-22.3.1
  Successfully installed pip-24.0
WARNING: Running pip as the 'root' user can result in broken permissions and conflicting behaviour with the system package manager. It
Requirement already satisfied: pandas in /opt/conda/lib/python3.7/site-packages (1.3.5)
Requirement already satisfied: python-dateutil>=2.7.3 in /opt/conda/lib/python3.7/site-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.7/site-packages (from pandas) (2022.7.1)
Requirement already satisfied: numpy>=1.17.3 in /opt/conda/lib/python3.7/site-packages (from pandas) (1.21.6)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.7/site-packages (from python-dateutil>=2.7.3->pandas) (1.16.0)
WARNING: Running pip as the 'root' user can result in broken permissions and conflicting behaviour with the system package manager. It
```

```

Requirement already satisfied: kaggle in /opt/conda/lib/python3.7/site-packages (1.5.12)
Requirement already satisfied: six>=1.10 in /opt/conda/lib/python3.7/site-packages (from kaggle) (1.16.0)
Requirement already satisfied: certifi in /opt/conda/lib/python3.7/site-packages (from kaggle) (2022.12.7)
Requirement already satisfied: python-dateutil in /opt/conda/lib/python3.7/site-packages (from kaggle) (2.8.2)
Requirement already satisfied: requests in /opt/conda/lib/python3.7/site-packages (from kaggle) (2.28.2)
Requirement already satisfied: tqdm in /opt/conda/lib/python3.7/site-packages (from kaggle) (4.63.0)
Requirement already satisfied: python-slugify in /opt/conda/lib/python3.7/site-packages (from kaggle) (8.0.0)
Requirement already satisfied: urllib3 in /opt/conda/lib/python3.7/site-packages (from kaggle) (1.26.14)
Requirement already satisfied: text-unidecode>=1.3 in /opt/conda/lib/python3.7/site-packages (from python-slugify->kaggle) (1.3)
Requirement already satisfied: charset-normalizer<4,>=2 in /opt/conda/lib/python3.7/site-packages (from requests->kaggle) (2.1.1)
Requirement already satisfied: idna<4,>=2.5 in /opt/conda/lib/python3.7/site-packages (from requests->kaggle) (3.4)
WARNING: Running pip as the 'root' user can result in broken permissions and conflicting behaviour with the system package manager. It
Requirement already satisfied: setuptools in /opt/conda/lib/python3.7/site-packages (59.8.0)
Collecting setuptools
  Downloading setuptools-68.0.0-py3-none-any.whl.metadata (6.4 kB)
Requirement already satisfied: wheel in /opt/conda/lib/python3.7/site-packages (0.38.4)
Collecting wheel
  Downloading wheel-0.42.0-py3-none-any.whl.metadata (2.2 kB)
  Downloading setuptools-68.0.0-py3-none-any.whl (804 kB)
----- 804.0/804.0 kB 16.8 MB/s eta 0:00:00:01
  Downloading wheel-0.42.0-py3-none-any.whl (65 kB)
----- 65.4/65.4 kB 3.1 MB/s eta 0:00:00
Installing collected packages: wheel, setuptools
Attempting uninstall: wheel
  Found existing installation: wheel 0.38.4
  Uninstalling wheel-0.38.4:
    Successfully uninstalled wheel-0.38.4
Attempting uninstall: setuptools
  Found existing installation: setuptools 59.8.0
  Uninstalling setuptools-59.8.0:
    Successfully uninstalled setuptools-59.8.0
ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is the source
google-cloud-spanner 3.27.0 requires google-api-core[grpc]!=2.0.*,!=2.1.*,!=2.10.*,!=2.2.*,!=2.3.*,!=2.4.*,!=2.5.*,!=2.6.*,!=2.7.*,!=2
jupyter-console 6.6.1 requires jupyter-core!=5.0.*,>=4.12, but you have jupyter-core 4.11.1 which is incompatible.
tensorflow 2.11.0 requires protobuf<3.20,>=3.9.2, but you have protobuf 3.20.3 which is incompatible.
tensorflow-serving-api 2.11.0 requires protobuf<3.20,>=3.9.2, but you have protobuf 3.20.3 which is incompatible.
tfx-bsl 1.12.0 requires google-api-python-client<2,>=1.7.11, but you have google-api-python-client 2.79.0 which is incompatible.
Successfully installed setuptools-68.0.0 wheel-0.42.0
WARNING: Running pip as the 'root' user can result in broken permissions and conflicting behaviour with the system package manager. It
Requirement already satisfied: mxnet<2.0.0 in /opt/conda/lib/python3.7/site-packages (1.9.1)

```

Setup Kaggle API Key

```

# Fill in your user name and key from creating the kaggle account and API token file
import json
from dotenv import dotenv_values
CONFIG = dotenv_values('/kaggle/input/environment/.env')
kaggle_username = CONFIG['KAGGLE_USERNAME']
kaggle_key = CONFIG['KAGGLE_KEY']
# Save API token the kaggle.json file
with open("kaggle.json", "w") as f:
    f.write(json.dumps({"username": kaggle_username, "key": kaggle_key}))

```

Download and explore dataset

Go to the [bike sharing demand competition](#) and agree to the terms


kaggle6.png

```

!mkdir -p ~/.kaggle
!cp /kaggle/input/kaggle-json/kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json

```

!kaggle datasets list

 Warning: Looks like you're using an outdated API Version, please consider updating (server 1.7.4.2 / client 1.5.12)

ref	title	size	lastUpdated
rakeshkapilavai/extrovert-vs-introvert-behavior-data	Extrovert vs. Introvert Behavior Data	31KB	2025-06-13 14:
bismasajjad/global-ai-job-market-and-salary-trends-2025	Global AI Job Market & Salary Trends 2025	517KB	2025-06-01 07:
adilshamin8/social-media-addiction-vs-relationships	Students' Social Media Addiction	8KB	2025-05-10 14:
prajwaldongre/loan-application-and-transaction-fraud-detection	Loan Application & Transaction: Fraud Detection	8MB	2025-06-10 08:

shalmamuji/personality-prediction-data-introvert-extrovert	Personality prediction data introvert extrovert	160KB	2025-06-12 10:
therohithanand/used-car-price-prediction	Used Car Price Prediction	141KB	2025-06-09 08:
brendanartley/openfwi-preprocessed-72x72	OpenFWI Preprocessed 72x72	21GB	2025-06-02 17:
samanfatima7/2020-2025-apple-stock-dataset	2020-2025 Apple Stock Dataset	51KB	2025-06-03 11:
sahilislam007/shopping-trends-and-customer-behaviour-dataset	Shopping Trends And Customer Behaviour Dataset	78KB	2025-05-25 13:
sahilislam007/sales-dataset	Sales Dataset	9KB	2025-05-27 07:
abhishekdave9/digital-habits-vs-mental-health-dataset	Screen Time Impact on Mental Health	546KB	2025-06-13 11:
adilshamim8/rock-paper-scissors	Rock Paper Scissors SXS: Hand Gesture Detection	201MB	2025-05-28 04:
chaitu20/ipl-dataset2008-2025	IPL Dataset(2008-2025)	6MB	2025-06-06 17:
hbugrae/best-selling-steam-games-of-all-time	Best-Selling Steam Games of All Time	154KB	2025-06-12 11:
dansbecker/melbourne-housing-snapshot	Melbourne Housing Snapshot	451KB	2018-06-05 12:
skullagos5246/upi-transactions-2024-dataset	UPI Transactions 2024 Dataset	5MB	2025-06-14 21:
anirudhsub/twizzlerdata	Popularity of Twizzlers Dataset	996B	2025-06-13 22:
datasnaek/youtube-new	Trending YouTube Video Statistics	201MB	2019-06-03 00:
zyncide/wine-reviews	Wine Reviews	51MB	2017-11-27 17:
datasnaek/chess	Chess Game Dataset (Lichess)	3MB	2017-09-04 03:

```
# Download the dataset, it will be in a .zip file so you'll need to unzip it as well.
!kaggle competitions download -c bike-sharing-demand
# If you already downloaded it you can use the -o command to overwrite the file
import zipfile
with zipfile.ZipFile('bike-sharing-demand.zip','r') as z:
    z.extractall()
```

 Downloading bike-sharing-demand.zip to /kaggle/working

0%

100%


0.00/189k

189k/189k

[00:00<?, ?B/s]

[00:00<00:00, 52.3MB/s]

```
!pip install autogluon.tabular --quiet
```

 WARNING: Error parsing requirements for jsonschema: [Errno 2] No such file or directory: '/opt/conda/lib/python3.7/site-packages/jsonsch

DEPRECATION: torch-lightning 1.7.7 has a non-standard dependency specifier torch>=1.9.*. pip 24.1 will enforce this behaviour change.

WARNING: Running pip as the 'root' user can result in broken permissions and conflicting behaviour with the system package manager. It is

```
import pandas as pd
from autogluon.tabular import TabularPredictor
```

```
# Create the train dataset in pandas by reading the csv
# Set the parsing of the datetime column so you can use some of the `dt` features in pandas later
train = pd.read_csv('train.csv',parse_dates = ['datetime'])
train.head()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0	1	1

```
# Simple output of the train dataset to view some of the min/max/varition of the dataset features.
train.describe()
```

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	regist
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000
mean	2.506614	0.028569	0.680875	1.418427	20.23086	23.655084	61.886460	12.799395	36.021955	155.55
std	1.116174	0.166599	0.466159	0.633839	7.79159	8.474601	19.245033	8.164537	49.960477	151.03
min	1.000000	0.000000	0.000000	1.000000	0.82000	0.760000	0.000000	0.000000	0.000000	0.00
25%	2.000000	0.000000	0.000000	1.000000	13.94000	16.665000	47.000000	7.001500	4.000000	36.00
50%	3.000000	0.000000	1.000000	1.000000	20.50000	24.240000	62.000000	12.998000	17.000000	118.00
75%	4.000000	0.000000	1.000000	2.000000	26.24000	31.060000	77.000000	16.997900	49.000000	222.00
max	4.000000	1.000000	1.000000	4.000000	41.00000	45.455000	100.000000	56.996900	367.000000	886.00

```
# Create the test pandas dataframe in pandas by reading the csv, remember to parse the datetime!
test = pd.read_csv('test.csv',parse_dates = ['datetime'])
test.head()
```

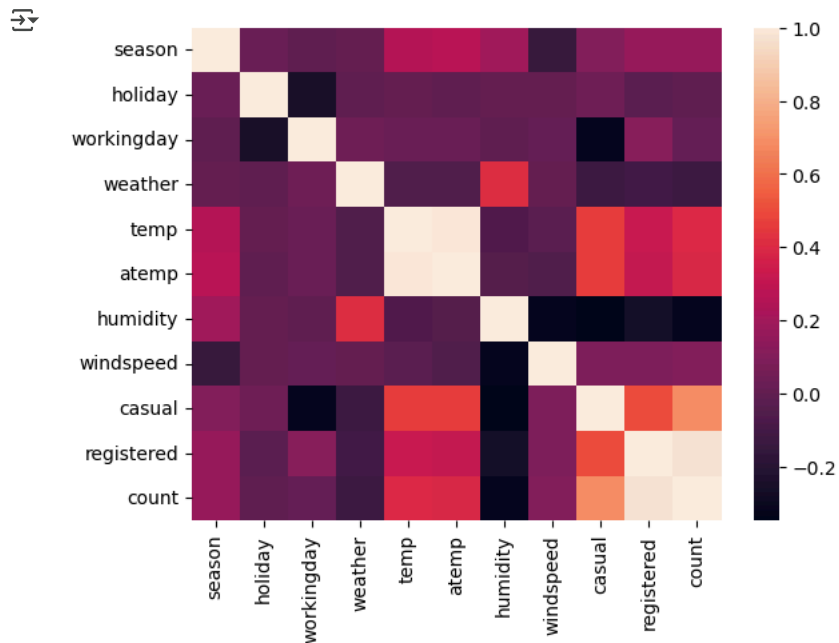
	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed
0	2011-01-20 00:00:00	1	0	1	1	10.66	11.365	56	26.0027
1	2011-01-20 01:00:00	1	0	1	1	10.66	13.635	56	0.0000
2	2011-01-20 02:00:00	1	0	1	1	10.66	13.635	56	0.0000
3	2011-01-20 03:00:00	1	0	1	1	10.66	12.880	56	11.0014
4	2011-01-20 04:00:00	1	0	1	1	10.66	12.880	56	11.0014

```
# Same thing as train and test dataset
submission = pd.read_csv('sampleSubmission.csv',parse_dates = ['datetime'])
submission.head()
```

	datetime	count
0	2011-01-20 00:00:00	0
1	2011-01-20 01:00:00	0
2	2011-01-20 02:00:00	0
3	2011-01-20 03:00:00	0
4	2011-01-20 04:00:00	0

```
import matplotlib.pyplot as plt
import seaborn as sns
```

```
sns.heatmap(train.corr());
```



Step 3: Train a model using AutoGluon's Tabular Prediction

Requirements:

- We are predicting `count`, so it is the label we are setting.
- Ignore `casual` and `registered` columns as they are also not present in the test dataset.
- Use the `root_mean_squared_error` as the metric to use for evaluation.
- Set a time limit of 10 minutes (600 seconds).
- Use the preset `best_quality` to focus on creating the best model.

```


import warnings
warnings.filterwarnings('ignore')
predictor = TabularPredictor(label='count',eval_metric = 'root_mean_squared_error',
                             learner_kwargs = {"ignored_columns": ["casual", "registered"]}).fit(train_data = train,
                                                    time_limit =300,
                                                    presets = 'best_quality')

```

 No path specified. Models will be saved in: "AutogluonModels/ag-20250616_160321/"
 Presets specified: ['best_quality']
 Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8, num_bag_sets=20
 Beginning AutoGluon training ... Time limit = 300s
 AutoGluon will save models to "AutogluonModels/ag-20250616_160321/"
 AutoGluon Version: 0.6.2
 Python Version: 3.7.12
 Operating System: Linux
 Platform Machine: x86_64
 Platform Version: #1 SMP PREEMPT_DYNAMIC Sun Nov 10 10:07:59 UTC 2024
 Train Data Rows: 10886
 Train Data Columns: 11
 Label Column: count
 Preprocessing data ...
 AutoGluon infers your prediction problem is: 'regression' (because dtype of label-column == int and many unique label-values observed)
 Label info (max, min, mean, stddev): (977, 1, 191.57413, 181.14445)
 If 'regression' is not the correct problem_type, please manually specify the problem_type parameter during predictor init (You
 Using Feature Generators to preprocess the data ...
 Dropping user-specified ignored columns: ['casual', 'registered']
 Fitting AutoMLPipelineFeatureGenerator...
 Available Memory: 32115.89 MB
 Train Data (Original) Memory Usage: 0.78 MB (0.0% of available memory)
 Inferring data type of each feature based on column values. Set feature_metadata_in to manually specify special dtypes of the
 Stage 1 Generators:
 Fitting AsTypeFeatureGenerator...
 Note: Converting 2 features to boolean dtype as they only contain 2 unique values.
 Stage 2 Generators:
 Fitting FillNaFeatureGenerator...
 Stage 3 Generators:
 Fitting IdentityFeatureGenerator...
 Fitting DatetimeFeatureGenerator...
 Stage 4 Generators:
 Fitting DropUniqueFeatureGenerator...
 Types of features in original data (raw dtype, special dtypes):
 ('datetime', []) : 1 | ['datetime']
 ('float', []) : 3 | ['temp', 'atemp', 'windspeed']
 ('int', []) : 5 | ['season', 'holiday', 'workingday', 'weather', 'humidity']
 Types of features in processed data (raw dtype, special dtypes):
 ('float', []) : 3 | ['temp', 'atemp', 'windspeed']
 ('int', []) : 3 | ['season', 'weather', 'humidity']
 ('int', ['bool']) : 2 | ['holiday', 'workingday']
 ('int', ['datetime_as_int']) : 5 | ['datetime', 'datetime.year', 'datetime.month', 'datetime.day', 'datetime.dayofweek']
 0.5s = Fit runtime
 9 features in original data used to generate 13 features in processed data.
 Train Data (Processed) Memory Usage: 0.98 MB (0.0% of available memory)
 Data preprocessing and feature engineering runtime = 0.57s ...
 AutoGluon will gauge predictive performance using evaluation metric: 'root_mean_squared_error'
 This metric's sign has been flipped to adhere to being higher_is_better. The metric score can be multiplied by -1 to get the m
 To change this, specify the eval_metric parameter of Predictor()
 AutoGluon will fit 2 stack levels (L1 to L2) ...
 Fitting 11 L1 models ...
 Fitting model: KNeighborsUnif_BAG_L1 ... Training model for up to 199.57s of the 299.43s of remaining time.
 -101.5737 = Validation score (-root_mean_squared_error)
 1.23s = Training runtime
 0.06s = Validation runtime
 Fitting model: KNeighborsDist_BAG_L1 ... Training model for up to 194.65s of the 294.5s of remaining time.
 -84.14 = Validation score (-root_mean_squared_error)

▼ Review AutoGluon's training run with ranking of models that did the best.

```
predictor.fit_summary()
```

 *** Summary of fit() ***
 Estimated performance of each model:

	model	score_val	pred_time_val	fit_time	pred_time_val_marginal	fit_time_marginal	stack_level	can_infer	fi
0	LightGBMXT_BAG_L2	-60.774946	84.855869	271.904273	24.929981	84.181874	2	True	fi
1	WeightedEnsemble_L3	-60.774946	84.856793	271.909829	0.000925	0.005555	3	True	
2	KNeighborsDist_BAG_L1	-84.139994	0.054230	0.024892	0.054230	0.024892	1	True	
3	WeightedEnsemble_L2	-84.139994	0.055197	0.378629	0.000967	0.353737	2	True	
4	KNeighborsUnif_BAG_L1	-101.573722	0.056528	1.226576	0.056528	1.226576	1	True	
5	LightGBM_BAG_L1	-131.054162	12.058094	58.968965	12.058094	58.968965	1	True	
6	LightGBMXT_BAG_L1	-131.460909	47.757036	127.501967	47.757036	127.501967	1	True	

Number of models trained: 7

```

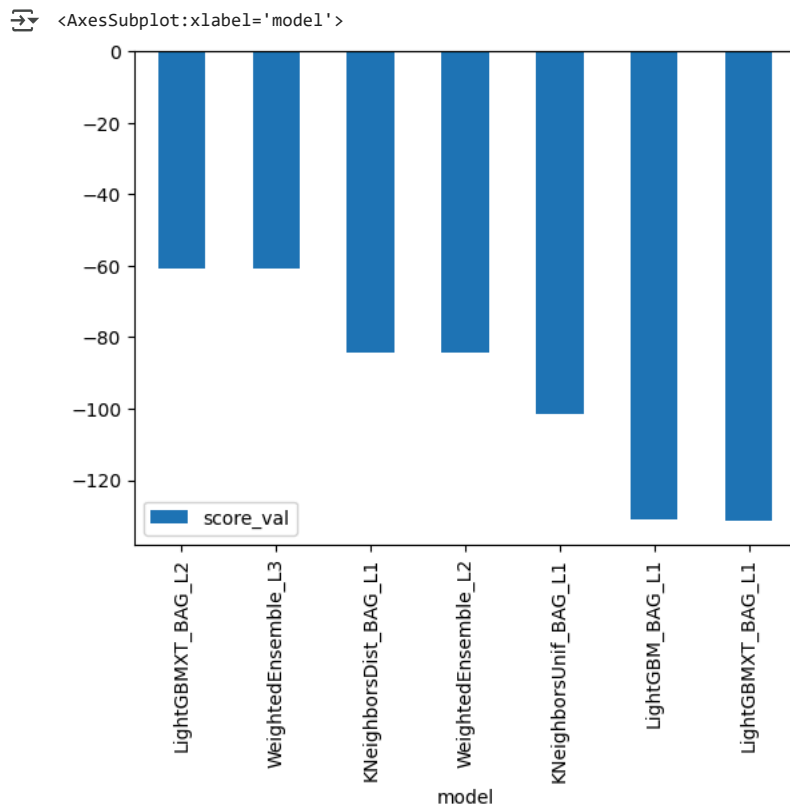
Types of models trained:
{'StackerEnsembleModel_LGB', 'WeightedEnsembleModel', 'StackerEnsembleModel_KNN'}
Bagging used: True (with 8 folds)
Multi-layer stack-ensembling used: True (with 3 levels)
Feature Metadata (Processed):
(raw dtype, special dtypes):
('float', []) : 3 | ['temp', 'atemp', 'windspeed']
('int', []) : 3 | ['season', 'weather', 'humidity']
('int', ['bool']) : 2 | ['holiday', 'workingday']
('int', ['datetime_as_int']) : 5 | ['datetime', 'datetime.year', 'datetime.month', 'datetime.day', 'datetime.dayofweek']
*** End of fit() summary ***
{'model_types': {'KNeighborsUnif_BAG_L1': 'StackerEnsembleModel_KNN',
'KNeighborsDist_BAG_L1': 'StackerEnsembleModel_KNN',
'LightGBMX_T_BAG_L1': 'StackerEnsembleModel_LGB',
'LightGBM_BAG_L1': 'StackerEnsembleModel_LGB',
'WeightedEnsemble_L2': 'WeightedEnsembleModel',
'LightGBMX_T_BAG_L2': 'StackerEnsembleModel_LGB',
'WeightedEnsemble_L3': 'WeightedEnsembleModel'},
'model_performance': {'KNeighborsUnif_BAG_L1': -101.57372218106647,
'KNeighborsDist_BAG_L1': -84.13999364278118,
'LightGBMX_T_BAG_L1': -131.46090891834504,
'LightGBM_BAG_L1': -131.054161598899,
'WeightedEnsemble_L2': -84.13999364278118,
'LightGBMX_T_BAG_L2': -60.77494566213506,
'WeightedEnsemble_L3': -60.77494566213506},
'model_best': 'WeightedEnsemble_L3',
'model_paths': {'KNeighborsUnif_BAG_L1': 'AutogluonModels/ag-20250616_160321/models/KNeighborsUnif_BAG_L1/',
'KNeighborsDist_BAG_L1': 'AutogluonModels/ag-20250616_160321/models/KNeighborsDist_BAG_L1/',
'LightGBMX_T_BAG_L1': 'AutogluonModels/ag-20250616_160321/models/LightGBMX_T_BAG_L1/',
'LightGBM_BAG_L1': 'AutogluonModels/ag-20250616_160321/models/LightGBM_BAG_L1/',
'WeightedEnsemble_L2': 'AutogluonModels/ag-20250616_160321/models/WeightedEnsemble_L2/',
'LightGBMX_T_BAG_L2': 'AutogluonModels/ag-20250616_160321/models/LightGBMX_T_BAG_L2/',
'WeightedEnsemble_L3': 'AutogluonModels/ag-20250616_160321/models/WeightedEnsemble_L3/'},
'model_fit_times': {'KNeighborsUnif_BAG_L1': 1.2265760898590088,
'KNeighborsDist_BAG_L1': 0.02489161491394043,
'LightGBMX_T_BAG_L1': 127.50196695327759,
'LightGBM_BAG_L1': 58.96896505355835,
'WeightedEnsemble_L2': 0.35373735427856445,
'LightGBMX_T_BAG_L2': 84.18187355995178,
'WeightedEnsemble_L3': 0.005555391311645508},
'model_pred_times': {'KNeighborsUnif_BAG_L1': 0.05652761459350586,
'KNeighborsDist_BAG_L1': 0.0542302131652832,
'LightGBMX_T_BAG_L1': 47.757035970687866,
'LightGBM_BAG_L1': 12.058093786239624,
'WeightedEnsemble_L2': 0.0009672641754150391,
'LightGBMX_T_BAG_L2': 24.929980993270874,

```

```

predictor.leaderboard(silent = True).plot(kind = 'bar', x = 'model', y = 'score_val')

```



▼ Create predictions from test dataset

```
predictor.get_model_names()
```

```
['KNeighborsUnif_BAG_L1',
 'KNeighborsDist_BAG_L1',
 'LightGBMXt_BAG_L1',
 'LightGBM_BAG_L1',
 'WeightedEnsemble_L2',
 'LightGBMXt_BAG_L2',
 'WeightedEnsemble_L3']
```

```
predictions = predictor.predict(test)
predictions.head()
```

```
0    34.372520
1    42.365173
2    48.134609
3    52.555149
4    54.487957
Name: count, dtype: float32
```

▼ NOTE: Kaggle will reject the submission if we don't set everything to be > 0.

```
# Describe the `predictions` series to see if there are any negative values
predictions.describe()
```

```
count    6493.000000
mean     106.363449
std       101.880005
min       -4.437493
25%       15.039785
50%       62.662796
75%      187.099335
max      403.451935
Name: count, dtype: float64
```

```
# How many negative values do we have?
predictions[predictions < 0].count()
```


AutoGluon infers your prediction problem is: 'regression' (because dtype of label-column == int and many unique label-values observed)
 Label info (max, min, mean, stddev): (977, 1, 191.57413, 181.14445)
 If 'regression' is not the correct problem_type, please manually specify the problem_type parameter during predictor init (You
 Using Feature Generators to preprocess the data ...
 Fitting AutoMLPipelineFeatureGenerator...
 Available Memory: 31539.84 MB
 Train Data (Original) Memory Usage: 0.78 MB (0.0% of available memory)
 Inferring data type of each feature based on column values. Set feature_metadata_in to manually specify special dtypes of the
 Stage 1 Generators:
 Fitting AsTypeFeatureGenerator...
 Note: Converting 2 features to boolean dtype as they only contain 2 unique values.
 Stage 2 Generators:
 Fitting FillNaFeatureGenerator...
 Stage 3 Generators:
 Fitting IdentityFeatureGenerator...
 Fitting DatetimeFeatureGenerator...
 Stage 4 Generators:
 Fitting DropUniqueFeatureGenerator...
 Types of features in original data (raw dtype, special dtypes):
 ('datetime', []) : 1 | ['datetime']
 ('float', []) : 3 | ['temp', 'atemp', 'windspeed']
 ('int', []) : 5 | ['season', 'holiday', 'workingday', 'weather', 'humidity']
 Types of features in processed data (raw dtype, special dtypes):
 ('float', []) : 3 | ['temp', 'atemp', 'windspeed']
 ('int', []) : 3 | ['season', 'weather', 'humidity']
 ('int', ['bool']) : 2 | ['holiday', 'workingday']
 ('int', ['datetime_as_int']) : 5 | ['datetime', 'datetime.year', 'datetime.month', 'datetime.day', 'datetime.dayofweek']
 0.3s = Fit runtime
 9 features in original data used to generate 13 features in processed data.
 Train Data (Processed) Memory Usage: 0.98 MB (0.0% of available memory)
 Data preprocessing and feature engineering runtime = 0.36s ...
 AutoGluon will gauge predictive performance using evaluation metric: 'root_mean_squared_error'
 This metric's sign has been flipped to adhere to being higher_is_better. The metric score can be multiplied by -1 to get the m
 To change this, specify the eval_metric parameter of Predictor()
 AutoGluon will fit 2 stack levels (L1 to L2) ...
 Fitting 1 L1 models ...
 Fitting model: XGBoost_BAG_L1 ... Training model for up to 199.71s of the 299.63s of remaining time.
 Fitting 8 child models (S1F1 - S1F8) | Fitting with ParallelLocalFoldFittingStrategy
 E0616 16:11:32.111737671 450 http2_transport.cc:1150] Received a GOAWAY with error code ENHANCE_YOUR_CALM and debug data equal
 -131.6247 = Validation score (-root_mean_squared_error)
 88.15s = Training runtime
 2.25s = Validation runtime
 Completed 1/20 k-fold bagging repeats ...

predictor_hp0.fit_summary()

```

*** Summary of fit() ***
Estimated performance of each model:
      model  score_val  pred_time_val  fit_time  pred_time_val_marginal  fit_time_marginal  stack_level  can_infer  fit_
0      XGBoost_BAG_L2 -130.590563      8.014871  193.770850      5.766083      105.617150          2      True
1  WeightedEnsemble_L3 -130.590563      8.015826  193.776682      0.000956      0.005832          3      True
2      XGBoost_BAG_L1 -131.624665      2.248787   88.153700      2.248787      88.153700          1      True
3  WeightedEnsemble_L2 -131.624665      2.249693   88.163722      0.000906      0.010021          2      True
Number of models trained: 4
Types of models trained:
{'StackerEnsembleModel_XGBoost', 'WeightedEnsembleModel'}
Bagging used: True (with 8 folds)
Multi-layer stack-ensembling used: True (with 3 levels)
Feature Metadata (Processed):
(raw dtype, special dtypes):
('float', []) : 3 | ['temp', 'atemp', 'windspeed']
('int', []) : 3 | ['season', 'weather', 'humidity']
('int', ['bool']) : 2 | ['holiday', 'workingday']
('int', ['datetime_as_int']) : 5 | ['datetime', 'datetime.year', 'datetime.month', 'datetime.day', 'datetime.dayofweek']
*** End of fit() summary ***
{'model_types': {'XGBoost_BAG_L1': 'StackerEnsembleModel_XGBoost',
  'WeightedEnsemble_L2': 'WeightedEnsembleModel',
  'XGBoost_BAG_L2': 'StackerEnsembleModel_XGBoost',
  'WeightedEnsemble_L3': 'WeightedEnsembleModel'},
 'model_performance': {'XGBoost_BAG_L1': -131.62466543942023,
  'WeightedEnsemble_L2': -131.62466543942023,
  'XGBoost_BAG_L2': -130.59056321268582,
  'WeightedEnsemble_L3': -130.59056321268582},
 'model_best': 'WeightedEnsemble_L3',
 'model_paths': {'XGBoost_BAG_L1': 'AutogluonModels/ag-20250616_161131/models/XGBoost_BAG_L1/',
  'WeightedEnsemble_L2': 'AutogluonModels/ag-20250616_161131/models/WeightedEnsemble_L2/',
  'XGBoost_BAG_L2': 'AutogluonModels/ag-20250616_161131/models/XGBoost_BAG_L2/',
  'WeightedEnsemble_L3': 'AutogluonModels/ag-20250616_161131/models/WeightedEnsemble_L3/'},
 'model_fit_times': {'XGBoost_BAG_L1': 88.15370011329651,
  'WeightedEnsemble_L2': 0.010021448135375977,
  'XGBoost_BAG_L2': 105.61714959144592,
  'WeightedEnsemble_L3': 0.0058324337005615234},
 'model_pred_times': {'XGBoost_BAG_L1': 2.2487874031066895,

```

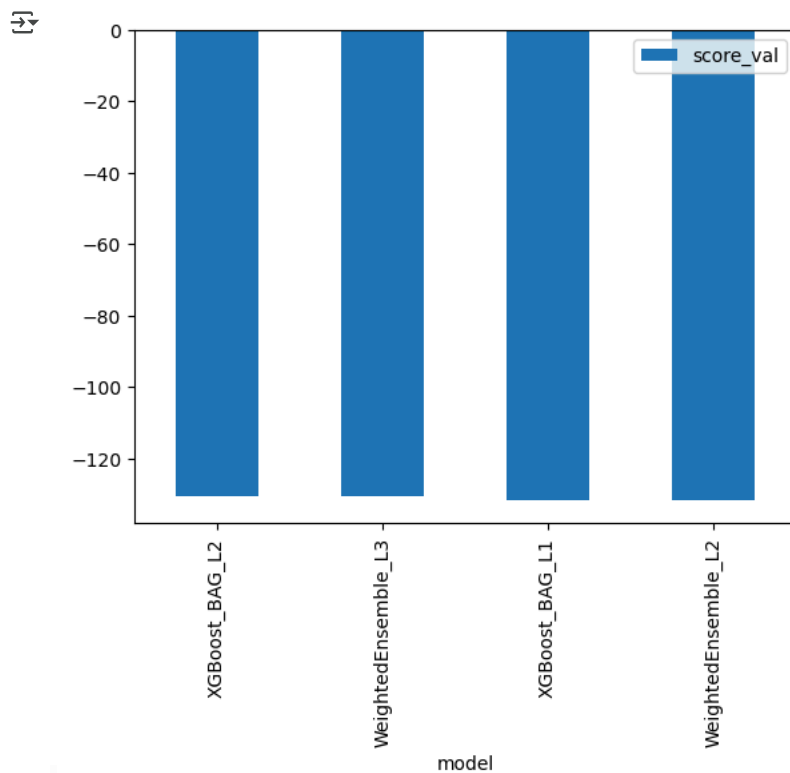
```

'WeightedEnsemble_L2': 0.0009057521820068359,
'XGBoost_BAG_L2': 5.766083240509033,
'WeightedEnsemble_L3': 0.0009555816650390625},
'num_bag_folds': 8,
'max_stack_level': 3,
'model_hyperparams': {'XGBoost_BAG_L1': {'use_orig_features': True,
'max_base_models': 25,
'max_base_models_per_type': 5,
'save_bag_folds': True},
'WeightedEnsemble_L2': {'use_orig_features': False,
'max_base_models': 25,
'max_base_models_per_type': 5,
'save_bag_folds': True},
'XGBoost_BAG_L2': {'use_orig_features': True,
'max_base_models': 25,
'max_base_models_per_type': 5,
'save_bag_folds': True},
'WeightedEnsemble_L3': {'use_orig_features': False,
'max_base_models': 25,
'max_base_models_per_type': 5.

```

#Displaying models which perform best.

```
predictor_hp0.leaderboard(silent = True).plot(kind = 'bar',x = 'model',y = 'score_val');
```



#fitting model.

```
predictions_hp0 = predictor_hp0.predict(test,model = 'WeightedEnsemble_L2')
```

#making sure there is no negative value.

```
predictions_hp0.describe()
```

```

count    6493.000000
mean      206.521286
std       141.676361
min       -73.975266
25%       98.073288
50%      175.937088
75%      291.346222
max       771.201050
Name: count, dtype: float64

```

Set them to zero

```

for a,b in enumerate(predictions_hp0):
    if b < 0:
        predictions_hp0[a] = 0

```

<https://colab.research.google.com/#fileId=https%3A//storage.googleapis.com/kaggle-colab-exported-notebooks/trishalakarmacharya/predict-bike-sh...> 11/26

```

('int', ['datetime_as_int']): 5 | ['datetime', 'datetime.year', 'datetime.month', 'datetime.day', 'datetime.dayofweek']
0.2s = Fit runtime
9 features in original data used to generate 13 features in processed data.
Train Data (Processed) Memory Usage: 0.98 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.27s ...
AutoGluon will gauge predictive performance using evaluation metric: 'root_mean_squared_error'
This metric's sign has been flipped to adhere to being higher_is_better. The metric score can be multiplied by -1 to get the m
To change this, specify the eval_metric parameter of Predictor()
AutoGluon will fit 2 stack levels (L1 to L2) ...
Fitting 1 L1 models ...
Fitting model: LightGBM_BAG_L1 ... Training model for up to 199.77s of the 299.73s of remaining time.
Fitting 8 child models (S1F1 - S1F8) | Fitting with ParallelLocalFoldFittingStrategy
-130.9133 = Validation score (-root_mean_squared_error)
50.04s = Training runtime
3.34s = Validation runtime
Repeating k-fold bagging: 2/20

```

```
predictor_hp1.fit_summary()
```

```

*** Summary of fit() ***
Estimated performance of each model:

```

	model	score_val	pred_time_val	fit_time	pred_time_val_marginal	fit_time_marginal	stack_level	can_infer	fit_
0	LightGBM_BAG_L2	-129.461423	8.229146	177.717477	2.190549	78.716491	2	True	
1	WeightedEnsemble_L3	-129.461423	8.229950	177.724318	0.00804	0.006842	3	True	
2	LightGBM_BAG_L1	-129.587247	6.038597	99.000985	6.038597	99.000985	1	True	
3	WeightedEnsemble_L2	-129.587247	6.039573	99.007684	0.000976	0.006698	2	True	

```

Number of models trained: 4
Types of models trained:
{'StackerEnsembleModel_LGB', 'WeightedEnsembleModel'}
Bagging used: True (with 8 folds)
Multi-layer stack-ensembling used: True (with 3 levels)
Feature Metadata (Processed):
(raw dtype, special dtypes):
('float', []) : 3 | ['temp', 'atemp', 'windspeed']
('int', []) : 3 | ['season', 'weather', 'humidity']
('int', ['bool']) : 2 | ['holiday', 'workingday']
('int', ['datetime_as_int']): 5 | ['datetime', 'datetime.year', 'datetime.month', 'datetime.day', 'datetime.dayofweek']
*** End of fit() summary ***
{'model_types': {'LightGBM_BAG_L1': 'StackerEnsembleModel_LGB',
'WeightedEnsemble_L2': 'WeightedEnsembleModel',
'LightGBM_BAG_L2': 'StackerEnsembleModel_LGB',
'WeightedEnsemble_L3': 'WeightedEnsembleModel'},
'model_performance': {'LightGBM_BAG_L1': -129.58724666204176,
'WeightedEnsemble_L2': -129.58724666204176,
'LightGBM_BAG_L2': -129.46142312501328,
'WeightedEnsemble_L3': -129.46142312501328},
'model_best': 'WeightedEnsemble_L3',
'model_paths': {'LightGBM_BAG_L1': 'AutogluonModels/ag-20250616_161631/models/LightGBM_BAG_L1/',
'WeightedEnsemble_L2': 'AutogluonModels/ag-20250616_161631/models/WeightedEnsemble_L2/',
'LightGBM_BAG_L2': 'AutogluonModels/ag-20250616_161631/models/LightGBM_BAG_L2/',
'WeightedEnsemble_L3': 'AutogluonModels/ag-20250616_161631/models/WeightedEnsemble_L3/'},
'model_fit_times': {'LightGBM_BAG_L1': 99.00098514556885,
'WeightedEnsemble_L2': 0.0066983699798583984,
'LightGBM_BAG_L2': 78.71649146080017,
'WeightedEnsemble_L3': 0.0068416595458984375},
'model_pred_times': {'LightGBM_BAG_L1': 6.038597345352173,
'WeightedEnsemble_L2': 0.0009756088256835938,
'LightGBM_BAG_L2': 2.1905486583709717,
'WeightedEnsemble_L3': 0.008041858673095703},
'num_bag_folds': 8,
'max_stack_level': 3,
'model_hyperparams': {'LightGBM_BAG_L1': {'use_orig_features': True,
'max_base_models': 25,
'max_base_models_per_type': 5,
'save_bag_folds': True},
'WeightedEnsemble_L2': {'use_orig_features': False,
'max_base_models': 25,
'max_base_models_per_type': 5,
'save_bag_folds': True},
'LightGBM_BAG_L2': {'use_orig_features': True,
'max_base_models': 25,
'max_base_models_per_type': 5,
'save_bag_folds': True},
'WeightedEnsemble_L3': {'use_orig_features': False,
'max_base_models': 25,
'max_base_models_per_type': 5,
'save_bag_folds': True}}

```

```
#Displaying models which perform best.
```

```
predictor_hp1.leaderboard(silent = True).plot(kind = 'bar', x = 'model', y = 'score_val');
```


Initial score 1.56074

Step 4: Exploratory Data Analysis and Creating an additional feature

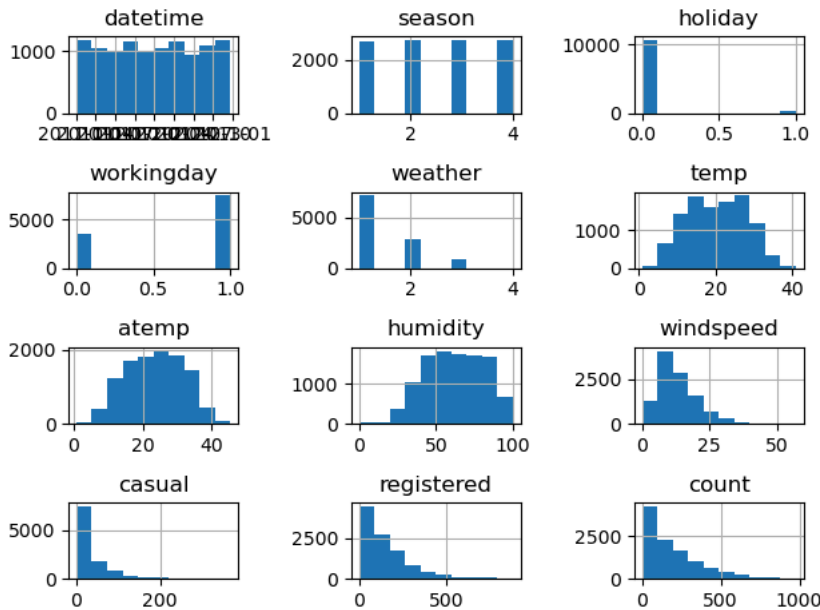
- Any additional feature will do, but a great suggestion would be to separate out the datetime into hour, day, or month parts.

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Create a histogram of all features to show the distribution of each one relative to the data. This is part of the exploratory data analysis
print("\nGenerating feature histograms for EDA...")
plt.figure(figsize=(15, 12))
train.hist()
plt.tight_layout()
plt.show()
```

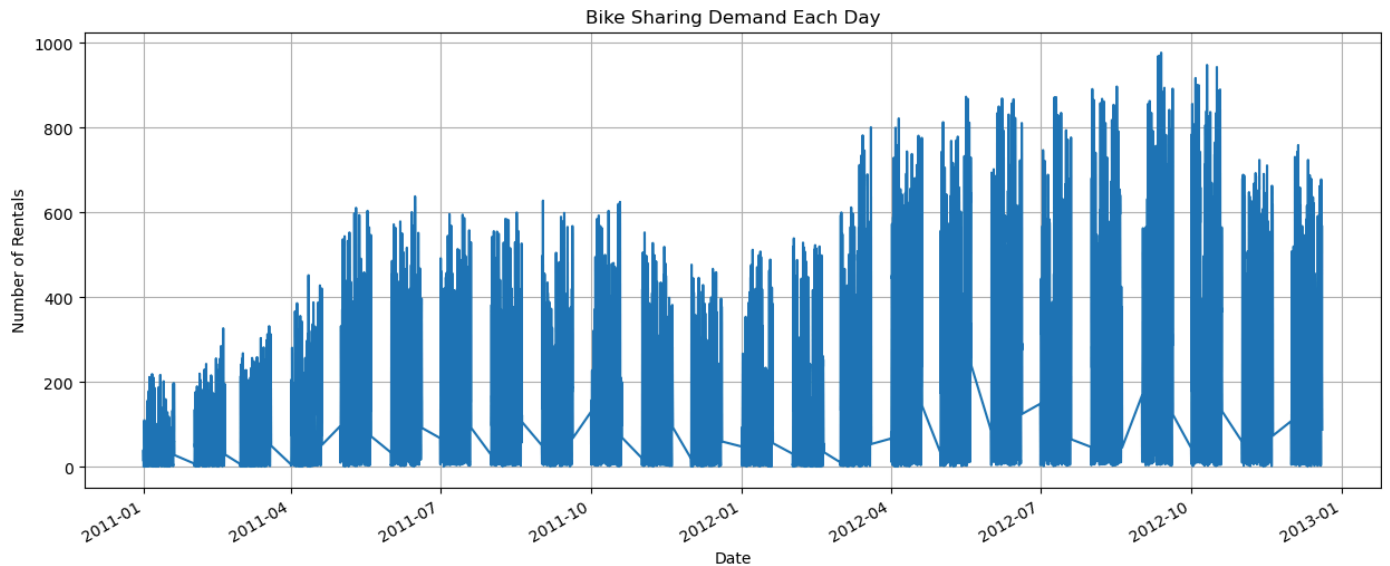


Generating feature histograms for EDA...
<Figure size 1500x1200 with 0 Axes>



NEW FEATURES

```
# Number of rentals per day
plt.figure(figsize=(15, 6))
train.set_index('datetime')['count'].plot()
plt.title('Bike Sharing Demand Each Day')
plt.xlabel('Date')
plt.ylabel('Number of Rentals')
plt.grid(True)
plt.show()
```



```
import pandas as pd

train = pd.read_csv('/kaggle/input/bike-sharing-demand/train.csv')
test = pd.read_csv('/kaggle/input/bike-sharing-demand/test.csv')

# Convert datetime column
train['datetime'] = pd.to_datetime(train['datetime'])
test['datetime'] = pd.to_datetime(test['datetime'])

#Hour of Day vs Day of Week
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

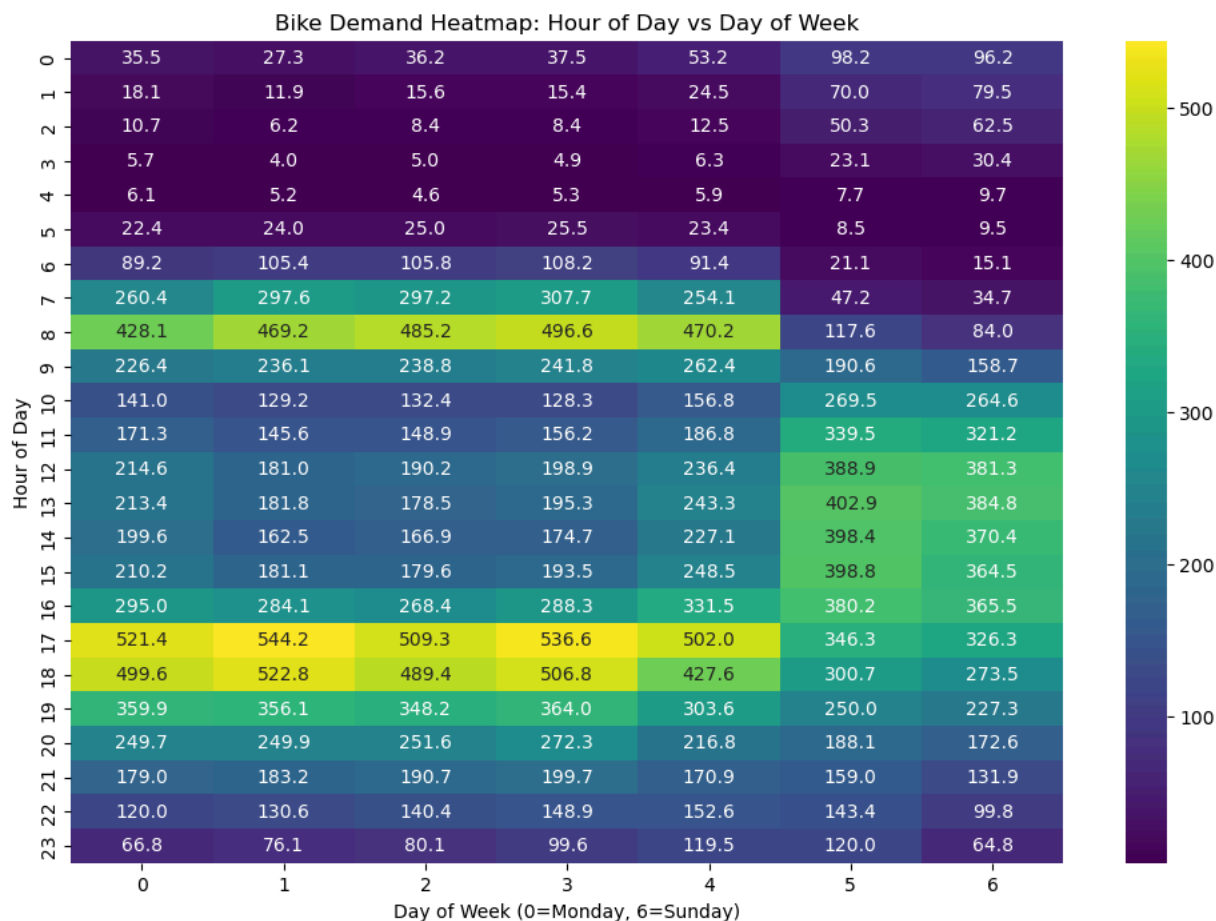
# Load the dataset
train = pd.read_csv('/kaggle/input/bike-sharing-demand/train.csv')
# Adjust the path as necessary

# Convert 'datetime' column to datetime format
train['datetime'] = pd.to_datetime(train['datetime'])

# Extract hour and day of week
train['hour'] = train['datetime'].dt.hour
train['dayofweek'] = train['datetime'].dt.dayofweek

# Create a pivot table for the heatmap
hour_day_heatmap = train.pivot_table(
    index='hour',
    columns='dayofweek',
    values='count', # Replace with the actual target column name
    aggfunc='mean'
)

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(hour_day_heatmap, cmap='viridis', annot=True, fmt='.1f')
plt.title('Bike Demand Heatmap: Hour of Day vs Day of Week')
plt.xlabel('Day of Week (0=Monday, 6=Sunday)')
plt.ylabel('Hour of Day')
plt.show()
```



```
#Average Bike Rentals by Hour of Day
# Create figure and axis
fig, ax2 = plt.subplots(figsize=(10, 6))

# Average demand by hour
hourly_avg = train.groupby(train['datetime'].dt.hour)['count'].mean()
hourly_avg.plot(kind='bar', ax=ax2, color='teal')

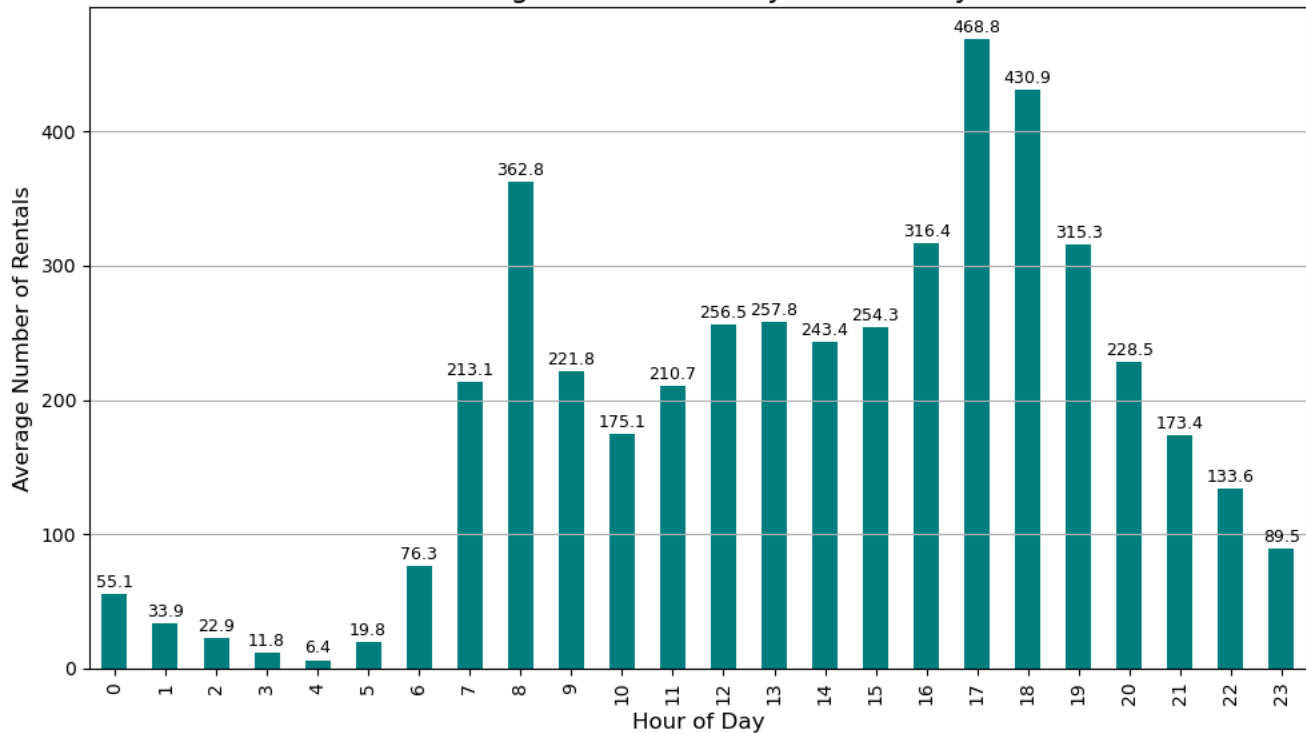
# Set labels and title
ax2.set_title('Average Bike Rentals by Hour of Day', fontsize=16)
ax2.set_xlabel('Hour of Day', fontsize=12)
ax2.set_ylabel('Average Number of Rentals', fontsize=12)
ax2.grid(True, axis='y')

# Add value labels above bars
for i, v in enumerate(hourly_avg):
    ax2.text(i, v + 5, f'{v:.1f}', ha='center', fontsize=9)

plt.tight_layout()
plt.show()
```




Average Bike Rentals by Hour of Day



✓ Make category types for these so models know they are not just numbers

- AutoGluon originally sees these as ints, but in reality they are int representations of a category.
- Setting the dtype to category will classify these as categories in AutoGluon.

```
# Create new datetime-based features
print("\nExtracting datetime features...")
# Extract hour from datetime - this is likely an important predictor for bike demand
train['hour'] = train['datetime'].dt.hour
test['hour'] = test['datetime'].dt.hour
```

```
# Extract additional potentially useful datetime features
train['day'] = train['datetime'].dt.day
train['month'] = train['datetime'].dt.month
train['dayofweek'] = train['datetime'].dt.dayofweek
train['year'] = train['datetime'].dt.year
```

```
test['day'] = test['datetime'].dt.day
test['month'] = test['datetime'].dt.month
test['dayofweek'] = test['datetime'].dt.dayofweek
test['year'] = test['datetime'].dt.year
```



Extracting datetime features...

```
# Set categorical features to the correct dtype
# This helps AutoGluon identify these as categorical variables rather than continuous
print("\nConverting categorical features to proper data types...")
train["season"] = train["season"].astype('category')
train["weather"] = train["weather"].astype('category')
train["hour"] = train["hour"].astype('category')
train["month"] = train["month"].astype('category')
train["dayofweek"] = train["dayofweek"].astype('category')
```

```
test["season"] = test["season"].astype('category')
test["weather"] = test["weather"].astype('category')
test["hour"] = test["hour"].astype('category')
test["month"] = test["month"].astype('category')
test["dayofweek"] = test["dayofweek"].astype('category')
```



Converting categorical features to proper data types...

```
# View the updated dataset
print("\nUpdated training data with new features:")
train.head()
```



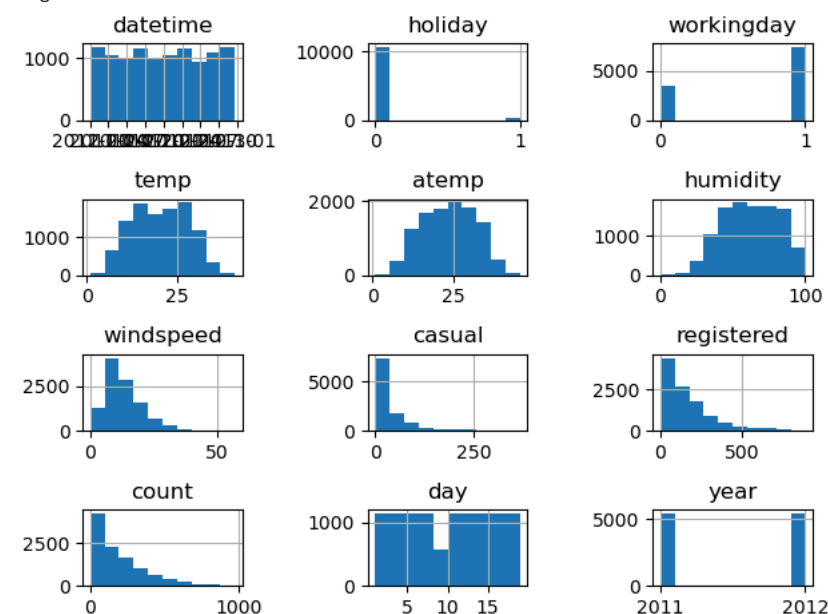
Updated training data with new features:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	hour	dayofweek	day	mon
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16	0	5	1	
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32	40	1	5	1	
	2011-01-															

```
# Generate histograms with new features to see their distributions
print("\nGenerating updated feature histograms...")
plt.figure(figsize=(15, 12))
train.hist()
plt.tight_layout()
plt.show()
```



Generating updated feature histograms...
<Figure size 1500x1200 with 0 Axes>



Below from Template

```
train["season"] = train["season"].astype('category')
train["weather"] = train["weather"].astype('category')
test["season"] = test["season"].astype('category')
test["weather"] = test["weather"].astype('category')
```


```
train.dtypes
```




```
datetime    datetime64[ns]
season      category
holiday     int64
workingday  int64
weather     category
temp        float64
atemp       float64
humidity    int64
windspeed  float64
casual      int64
```

```
registered      int64
count           int64
hour            category
dayofweek       category
day            int64
month           category
year           int64
dtype: object
```

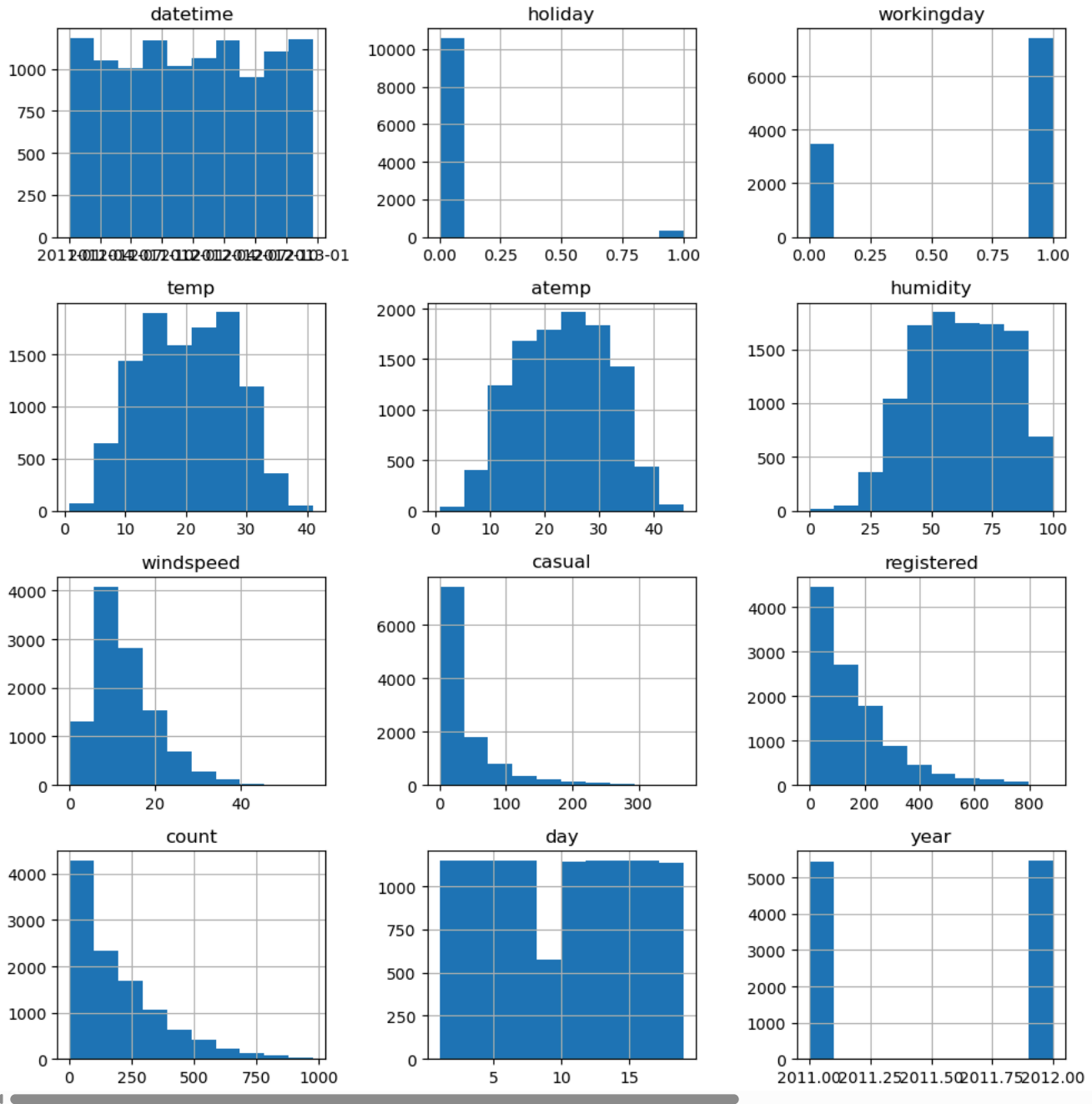
```
# View are new feature
train.head()
```



	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	hour	dayofweek	day	mon
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16	0	5	1	
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32	40	1	5	1	
	2011-01-															



```
train.hist(figsize = [10,10])
plt.tight_layout()
plt.show()
```



▼ Step 5: Rerun the model with the same settings as before, just with more features

```
# Define columns to exclude from training - same as before
exclude_columns_enhanced = ['casual', 'registered', 'datetime']
```

```
!pip install autogluon
```

```
from autogluon.tabular import TabularPredictor
```

```
# Train a new model with the enhanced feature set
print("\nTraining model with enhanced features...")
predictor_new_features = TabularPredictor(
    label='count',
    eval_metric='root_mean_squared_error',
    path='models/ag_models_enhanced'
).fit(
    train_data=train.drop(exclude_columns_enhanced, axis=1),
    time_limit=600,
```

```

presets='best_quality'
)

Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8, num_bag_sets=20
Beginning AutoGluon training ... Time limit = 600s
AutoGluon will save models to "models/ag_models_enhanced/"
AutoGluon Version: 0.6.2
Python Version: 3.7.12
Operating System: Linux
Platform Machine: x86_64
Platform Version: #1 SMP PREEMPT_DYNAMIC Sun Nov 10 10:07:59 UTC 2024
Train Data Rows: 10886
Train Data Columns: 13
Label Column: count
Preprocessing data ...
AutoGluon infers your prediction problem is: 'regression' (because dtype of label-column == int and many unique label-values observed)
Label info (max, min, mean, stddev): (977, 1, 191.57413, 181.14445)
If 'regression' is not the correct problem_type, please manually specify the problem_type parameter during predictor init (You
Using Feature Generators to preprocess the data ...
Fitting AutoMLPipelineFeatureGenerator...
Available Memory: 31527.03 MB
Train Data (Original) Memory Usage: 0.75 MB (0.0% of available memory)
Inferring data type of each feature based on column values. Set feature_metadata_in to manually specify special dtypes of the
Stage 1 Generators:
Fitting AsTypeFeatureGenerator...
Note: Converting 3 features to boolean dtype as they only contain 2 unique values.
Stage 2 Generators:
Fitting FillNaFeatureGenerator...
Stage 3 Generators:
Fitting IdentityFeatureGenerator...
Fitting CategoryFeatureGenerator...
Fitting CategoryMemoryMinimizeFeatureGenerator...
Stage 4 Generators:
Fitting DropUniqueFeatureGenerator...
Types of features in original data (raw dtype, special dtypes):
('category', []) : 5 | ['season', 'weather', 'hour', 'dayofweek', 'month']
('float', []) : 3 | ['temp', 'atemp', 'windspeed']
('int', []) : 5 | ['holiday', 'workingday', 'humidity', 'day', 'year']
Types of features in processed data (raw dtype, special dtypes):
('category', []) : 5 | ['season', 'weather', 'hour', 'dayofweek', 'month']
('float', []) : 3 | ['temp', 'atemp', 'windspeed']
('int', []) : 2 | ['humidity', 'day']
('int', ['bool']) : 3 | ['holiday', 'workingday', 'year']
0.1s = Fit runtime

Training model with enhanced features...
13 features in original data used to generate 13 features in processed data.
Train Data (Processed) Memory Usage: 0.53 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.18s ...
AutoGluon will gauge predictive performance using evaluation metric: 'root_mean_squared_error'
This metric's sign has been flipped to adhere to being higher_is_better. The metric score can be multiplied by -1 to get the m
To change this, specify the eval_metric parameter of Predictor()
AutoGluon will fit 2 stack levels (L1 to L2) ...
Fitting 11 L1 models ...
Fitting model: KNeighborsUnif_BAG_L1 ... Training model for up to 399.78s of the 599.81s of remaining time.
-158.9155 = Validation score (-root_mean_squared_error)
0.03s = Training runtime
0.07s = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 ... Training model for up to 399.64s of the 599.68s of remaining time.
-162.73768 = Validation score (-root_mean_squared_error)
0.03s = Training runtime
0.07s = Validation runtime

# Review the model training summary
print("\nEnhanced model training summary:")
predictor_new_features.fit_summary()

```

```

Enhanced model training summary:
*** Summary of fit() ***
Estimated performance of each model:

```

	model	score_val	pred_time_val	fit_time	pred_time_val_marginal	fit_time_marginal	stack_level	can_infer
0	WeightedEnsemble_L2	-34.048647	52.666773	195.641226	0.001009	0.436509	2	True
1	WeightedEnsemble_L3	-34.427321	61.448808	513.771962	0.000978	0.365591	3	True
2	LightGBM_BAG_L2	-34.647904	57.760886	386.473448	3.723547	41.757662	2	True
3	LightGBMX_BAG_L1	-34.770129	30.780114	101.422489	30.780114	101.422489	1	True
4	RandomForestMSE_BAG_L2	-35.216391	54.770710	387.799978	0.733371	43.084192	2	True
5	LightGBMX_BAG_L2	-35.471603	55.874546	392.175398	1.837207	47.459613	2	True
6	LightGBM_BAG_L1	-35.972101	21.190388	75.723888	21.190388	75.723888	1	True
7	CatBoost_BAG_L2	-37.132203	55.153704	381.104903	1.116365	36.389118	2	True
8	RandomForestMSE_BAG_L1	-38.921713	0.695261	18.058340	0.695261	18.058340	1	True
9	CatBoost_BAG_L1	-42.154194	1.225627	149.455994	1.225627	149.455994	1	True
10	KNeighborsUnif_BAG_L1	-158.915522	0.071259	0.025207	0.071259	0.025207	1	True
11	KNeighborsDist_BAG_L1	-162.737768	0.074689	0.029868	0.074689	0.029868	1	True

```

Number of models trained: 12
Types of models trained:
{'StackerEnsembleModel_LGB', 'StackerEnsembleModel_CatBoost', 'StackerEnsembleModel_RF', 'WeightedEnsembleModel', 'StackerEnsembleModel_LGB'}
Bagging used: True (with 8 folds)
Multi-layer stack-ensembling used: True (with 3 levels)
Feature Metadata (Processed):
(raw dtype, special dtypes):
('category', []) : 5 | ['season', 'weather', 'hour', 'dayofweek', 'month']
('float', []) : 3 | ['temp', 'atemp', 'windspeed']
('int', []) : 2 | ['humidity', 'day']
('int', ['bool']) : 3 | ['holiday', 'workingday', 'year']
*** End of fit() summary ***
{'model_types': {'KNeighborsUnif_BAG_L1': 'StackerEnsembleModel_KNN',
'KNeighborsDist_BAG_L1': 'StackerEnsembleModel_KNN',
'LightGBMXT_BAG_L1': 'StackerEnsembleModel_LGB',
'LightGBM_BAG_L1': 'StackerEnsembleModel_LGB',
'RandomForestMSE_BAG_L1': 'StackerEnsembleModel_RF',
'CatBoost_BAG_L1': 'StackerEnsembleModel_CatBoost',
'WeightedEnsemble_L2': 'WeightedEnsembleModel',
'LightGBMXT_BAG_L2': 'StackerEnsembleModel_LGB',
'LightGBM_BAG_L2': 'StackerEnsembleModel_LGB',
'RandomForestMSE_BAG_L2': 'StackerEnsembleModel_RF',
'CatBoost_BAG_L2': 'StackerEnsembleModel_CatBoost',
'WeightedEnsemble_L3': 'WeightedEnsembleModel'},
'model_performance': {'KNeighborsUnif_BAG_L1': -158.91552231156888,
'KNeighborsDist_BAG_L1': -162.737768284632,
'LightGBMXT_BAG_L1': -34.77012937123052,
'LightGBM_BAG_L1': -35.97210082374322,
'RandomForestMSE_BAG_L1': -38.921713427989935,
'CatBoost_BAG_L1': -42.15419365431957,
'WeightedEnsemble_L2': -34.04864668670487,
'LightGBMXT_BAG_L2': -35.471602781962936,
'LightGBM_BAG_L2': -34.64790441095406,
'RandomForestMSE_BAG_L2': -35.21639142199749,
'CatBoost_BAG_L2': -37.1322030518887,
'WeightedEnsemble_L3': -34.427320818702775},
'model_best': 'WeightedEnsemble_L2',
'model_paths': {'KNeighborsUnif_BAG_L1': 'models/ag_models_enhanced/models/KNeighborsUnif_BAG_L1/',
'KNeighborsDist_BAG_L1': 'models/ag_models_enhanced/models/KNeighborsDist_BAG_L1/',
'LightGBMXT_BAG_L1': 'models/ag_models_enhanced/models/LightGBMXT_BAG_L1/'
}

```

```

# Generate predictions on the test set
print("\nGenerating predictions with enhanced model...")
predictions_new_features = predictor_new_features.predict(test.drop(['datetime'], axis=1))
print("Preview of enhanced predictions:")
print(predictions_new_features.head())

```



```

Generating predictions with enhanced model...
Preview of enhanced predictions:
0    15.072573
1     3.991802
2     2.880972
3     3.136190
4     2.827018
Name: count, dtype: float32

```

```

# Handle negative predictions
negative_count_new = (predictions_new_features < 0).sum()
print(f"Number of negative predictions: {negative_count_new}")
predictions_new_features = predictions_new_features.clip(lower=0)
print("After clipping, minimum prediction value:", predictions_new_features.min())

```



```

Number of negative predictions: 112
After clipping, minimum prediction value: 0.0

```

```

import pandas as pd

submission = pd.read_csv('/kaggle/input/bike-sharing-demand/sampleSubmission.csv')

# Assuming predictor_new_features is your trained AutoGluon model and test is your test dataset
predictions = predictor_new_features.predict(test)

# Load submission file
submission = pd.read_csv('/kaggle/input/bike-sharing-demand/sampleSubmission.csv')

# Copy and assign predictions
submission_new_features = submission.copy()
submission_new_features["count"] = predictions

```

Warning: Looks like you're using an outdated API Version, please consider updating (server 1.7.4.2 / client 1.5.12)

fileName	date	description	status	publicScore	privateScore
submission_new_features.csv	2025-06-16 16:44:12	new features	error		
submission.csv	2025-06-16 16:21:14	first raw submission hp1	error		
submission.csv	2025-06-16 16:16:20	first raw submission hp0	complete	1.41005	1.41005

FROM TEMPLATE

```
!kaggle competitions submissions -c bike-sharing-demand
#| tail -n +1 | head -n 6
```

✓ New Score of 1.84672

```

predictor_new_features.leaderboard(silent = True).plot(kind = 'barh', x = 'model', y = 'score_val')

predictor_new_features.get_model_names()

predictor_new_features.get_model_best()

```

✓ Step 6: Hyper parameter optimization

- There are many options for hyper parameter optimization.
- Options are to change the AutoGluon higher level parameters or the individual model hyperparameters.
- The hyperparameters of the models themselves that are in AutoGluon. Those need the `hyperparameter` and `hyperparameter_tune_kwargs` arguments.

```

import warnings
warnings.filterwarnings('ignore')
predictor_new_hpo = TabularPredictor(label = 'count', eval_metric = 'accuracy',
                                     problem_type = 'multiclass',
                                     learner_kwargs = {"ignored_columns": ["casual", "registered"]}).fit(train_data = train,
                                                         time_limit = 320, presets = 'best_quality', hyperparameters = {'GBM': [
                                                                 hyperparameter_tune_kwargs = {
                                                                     'num_trials': 100,
                                                                     'search_strategy': 'random',
                                                                     'scheduler': 'local'})

```

```

➡ No path specified. Models will be saved in: "AutogluonModels/ag-20250616_164505/"
Presets specified: ['best_quality']
Warning: hyperparameter tuning is currently experimental and may cause the process to hang.
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8, num_bag_sets=20
Beginning AutoGluon training ... Time limit = 320s
AutoGluon will save models to "AutogluonModels/ag-20250616_164505/"
AutoGluon Version: 0.6.2
Python Version: 3.7.12
Operating System: Linux
Platform Machine: x86_64
Platform Version: #1 SMP PREEMPT_DYNAMIC Sun Nov 10 10:07:59 UTC 2024
Train Data Rows: 10886
Train Data Columns: 16
Label Column: count
Preprocessing data ...
Warning: Updated label_count_threshold from 10 to 2 to avoid cutting too many classes.
Warning: Some classes in the training set have fewer than 2 examples. AutoGluon will only keep 698 out of 822 classes for training and
Fraction of data from classes with at least 2 examples that will be kept for training models: 0.9886092228550432
Train Data Class Count: 698
Using Feature Generators to preprocess the data ...
Dropping user-specified ignored columns: ['casual', 'registered']
Fitting AutoMLPipelineFeatureGenerator...
Available Memory: 31020.8 MB
Train Data (Original) Memory Usage: 0.83 MB (0.0% of available memory)
Inferring data type of each feature based on column values. Set feature_metadata_in to manually specify special dtypes of the
Stage 1 Generators:
Fitting AsTypeFeatureGenerator...
Note: Converting 3 features to boolean dtype as they only contain 2 unique values.
Stage 2 Generators:
Fitting FillNaFeatureGenerator...
Stage 3 Generators:
Fitting IdentityFeatureGenerator...
Fitting CategoryFeatureGenerator...
Fitting CategoryMemoryMinimizeFeatureGenerator...
Fitting DatetimeFeatureGenerator...
Stage 4 Generators:
Fitting DropUniqueFeatureGenerator...
Types of features in original data (raw dtype, special dtypes):
('category', []) : 5 | ['season', 'weather', 'hour', 'dayofweek', 'month']
('datetime', []) : 1 | ['datetime']
('float', []) : 3 | ['temp', 'atemp', 'windspeed']
('int', []) : 5 | ['holiday', 'workingday', 'humidity', 'day', 'year']
Types of features in processed data (raw dtype, special dtypes):
('category', []) : 5 | ['season', 'weather', 'hour', 'dayofweek', 'month']
('float', []) : 3 | ['temp', 'atemp', 'windspeed']
('int', []) : 2 | ['humidity', 'day']

```



```

('int', ['bool']) : 3 | ['holiday', 'workingday', 'year']
('int', ['datetime_as_int']) : 5 | ['datetime', 'datetime.year', 'datetime.month', 'datetime.day', 'datetime.dayofweek']
0.3s = Fit runtime
14 features in original data used to generate 18 features in processed data.
Train Data (Processed) Memory Usage: 0.95 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.37s ...
AutoGluon will gauge predictive performance using evaluation metric: 'accuracy'
To change this, specify the eval_metric parameter of Predictor()
AutoGluon will fit 2 stack levels (L1 to L2) ...
Fitting 2 L1 models ...
Hyperparameter tuning model: LightGBMLarge_BAG_L1 ... Tuning model for up to 95.87s of the 319.63s of remaining time.

```

```

predictor_new_hpo.fit_summary()

```

```

*** Summary of fit() ***
Estimated performance of each model:

```

	model	score_val	pred_time_val	fit_time	pred_time_val_marginal	fit_time_marginal	stack_level	can_infer	fit
0	LightGBMLarge_BAG_L1	0.009199	17.811307	137.666097	17.811307	137.666097	1	True	
1	WeightedEnsemble_L2	0.009199	17.845022	138.013740	0.033715	0.347643	2	True	
2	LightGBMLarge_BAG_L2	0.007898	24.924868	1015.812776	7.113560	878.146679	2	True	
3	WeightedEnsemble_L3	0.007898	24.961848	1016.030067	0.036980	0.217290	3	True	

```

Number of models trained: 4
Types of models trained:
{'StackerEnsembleModel_LGB', 'WeightedEnsembleModel'}
Bagging used: True (with 8 folds)
Multi-layer stack-ensembling used: True (with 3 levels)
Feature Metadata (Processed):
(raw dtype, special dtypes):
('category', []) : 5 | ['season', 'weather', 'hour', 'dayofweek', 'month']
('float', []) : 3 | ['temp', 'atemp', 'windspeed']
('int', []) : 2 | ['humidity', 'day']
('int', ['bool']) : 3 | ['holiday', 'workingday', 'year']
('int', ['datetime_as_int']) : 5 | ['datetime', 'datetime.year', 'datetime.month', 'datetime.day', 'datetime.dayofweek']
*** End of fit() summary ***
{'model_types': {'LightGBMLarge_BAG_L1': 'StackerEnsembleModel_LGB',
'WeightedEnsemble_L2': 'WeightedEnsembleModel',
'LightGBMLarge_BAG_L2': 'StackerEnsembleModel_LGB',
'WeightedEnsemble_L3': 'WeightedEnsembleModel'},
'model_performance': {'LightGBMLarge_BAG_L1': 0.00919903363687047,
'WeightedEnsemble_L2': 0.00919903363687047,
'LightGBMLarge_BAG_L2': 0.007898160193272627,
'WeightedEnsemble_L3': 0.007898160193272627},
'model_best': 'WeightedEnsemble_L2',
'model_paths': {'LightGBMLarge_BAG_L1': 'AutogluonModels/ag-20250616_164505/models/LightGBMLarge_BAG_L1/',
'WeightedEnsemble_L2': 'AutogluonModels/ag-20250616_164505/models/WeightedEnsemble_L2/',
'LightGBMLarge_BAG_L2': 'AutogluonModels/ag-20250616_164505/models/LightGBMLarge_BAG_L2/',
'WeightedEnsemble_L3': 'AutogluonModels/ag-20250616_164505/models/WeightedEnsemble_L3/'},
'model_fit_times': {'LightGBMLarge_BAG_L1': 137.66609716415405,
'WeightedEnsemble_L2': 0.3476426601409912,
'LightGBMLarge_BAG_L2': 878.1466791629791,
'WeightedEnsemble_L3': 0.21729040145874023},
'model_pred_times': {'LightGBMLarge_BAG_L1': 17.811307191848755,
'WeightedEnsemble_L2': 0.033715248107910156,
'LightGBMLarge_BAG_L2': 7.113560438156128,
'WeightedEnsemble_L3': 0.036980390548706055},
'num_bag_folds': 8,
'max_stack_level': 3,
'num_classes': 698,
'model_hyperparams': {'LightGBMLarge_BAG_L1': {'use_orig_features': True,
'max_base_models': 25,
'max_base_models_per_type': 5,
'save_bag_folds': True},
'WeightedEnsemble_L2': {'use_orig_features': False,
'max_base_models': 25,
'max_base_models_per_type': 5,
'save_bag_folds': True},
'LightGBMLarge_BAG_L2': {'use_orig_features': True,
'max_base_models': 25,
'max_base_models_per_type': 5,
'save_bag_folds': True},
'WeightedEnsemble_L3': {'use_orig_features': False,
'max_base_models': 25,
'max_base_models_per_type': 5,
'save_bag_folds': True}}

```

```

predictor_new_hpo.leaderboard(silent = True).plot(kind = 'barh', x = 'model', y = 'score_val')

```



model	score_val
WeightedEnsemble_L3	0.88
LightGBMLarge_BAG_L2	0.87
WeightedEnsemble_L2	0.92

```
count    6493.000000
mean      384.294163
std       191.006507
min        2.000000
25%       234.000000
50%       365.000000
75%       540.000000
max       884.000000
Name: count, dtype: float64
```

Warning: Looks like you're using an outdated API		Version, please consider updating (server 1.7.4.2 / client 1.5.12)				
fileName	date		description	status	publicScore	privateScore
submission_new_hpo.csv	2025-06-16 17:03:30		new features with hyperparameters	complete	1.94330	1.94330
submission_new_features.csv	2025-06-16 16:44:12		new features	error		
submission.csv	2025-06-16 16:21:14		first raw submission hp1	error		
submission.csv	2025-06-16 16:16:20		first raw submission hp0	complete	1.41005	1.41005
submission.csv	2025-06-16 16:11:17		first raw submission	complete	2.06498	2.06498
submission_new_features.csv	2025-06-13 18:32:32		new features	error		
submission_new_hpo.csv	2025-06-12 15:46:55		new features with hyperparameters	complete	2.06084	2.06084
submission_new_features.csv	2025-06-12 15:40:53		new features	complete	1.84672	1.84672
submission.csv	2025-06-12 15:32:14		first raw submission hp1	complete	1.41005	1.41005
submission.csv	2025-06-12 15:24:00		first raw submission hp0	complete	1.41005	1.41005
submission.csv	2025-06-12 15:14:22		first raw submission	complete	2.03256	2.03256

<https://colab.research.google.com/#fileId=https%3A//storage.googleapis.com/kaggle-colab-exported-notebooks/trishalakarmacharya/predict-bike-sh...> 26/26