Data Science

Final Report

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Outline

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2. Data Source
3. Method Introduction
4. Model Processing
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Problem Background

How to manage bike and employee?

Data Source

datetime - hourly date + timestamp

season - 1 = spring, 2 = summer, 3 = fall, 4 = winter

holiday - whether the day is considered a holiday/ workingday - whether the day is neither a weekend nor holiday

weather - 1: Clear,Partly cloudy/ 2: Mist + Cloudy, Mist/ 3: Light Snow, Light Rain + Scattered clouds/ 4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog

temp - temperature in Celsius

atemp - "feels like" temperature in Celsius

humidity - relative humidity

windspeed - wind speed

count - number of total rentals (Dependent Varible)

Method Introduction

random forest :隨機森林其實就是進階版的決策樹，所謂的森林就是由很多棵決策樹所組成。隨機森林是使用 Bagging 加上隨機特徵採樣的方法所產生出來的整體學習演算法。

lasso: 迴歸的變形是引入正則化 regularization (i.e., shrinkage)的技巧，將迴歸的權重和給予限制，藉此「限制模型的複雜度」，解決 overfitting的問題。

Xgboost: Gradient Boosting Decision Tree的改良版。其中Gradient Boosting Machine是以Tree-based 為主，將數百個弱決策樹(CART)，跟梯度下降法和 Boosting 結合在一起。

Model Processing

First step

Null Model: Predict all testing data by the mean of training data.

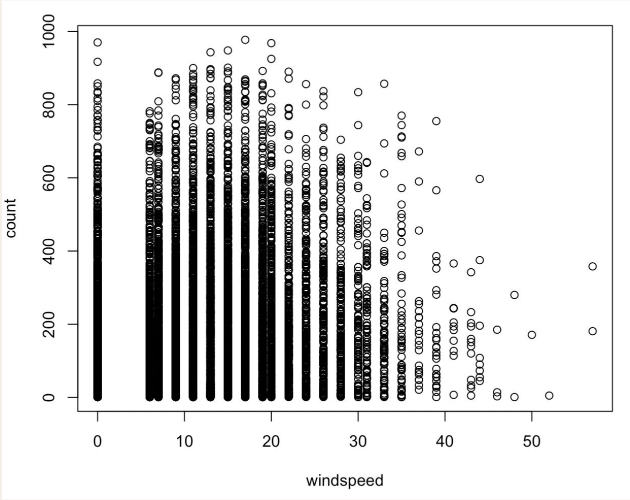
Way 1 (Spilt time):

Deal with the “date” variable by separating it to three variables, month, weekday and hour. Also, we use 3 times standard deviation to recongnize outliner and delete them.

Model Processing

Way 2 (Outliner):

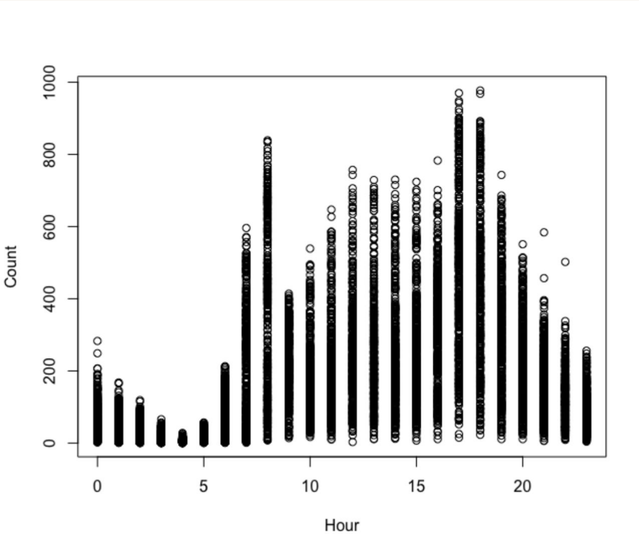
By EDA finding, we find there some strange value in windspeed variable. Since, windspeed is impossible to be equal to 0, we decided to train a model by “windspeed >0” and replace “windspeed=0” by model’s prediction.



Model Processing

Way 3 (Count hourly rank):

By EDA finding, we find there are obvious changes between different hours. There we decided to group hour by their rank of average count.



Conclusion-RMSE Table

RMSE Table

	dataset1	dataset2	dataset3
Random Forest	0.65195	0.64199	0.53741
Xgboost	0.84648	0.77997	0.78114
Lasso	2.65298	1.22353	1.04907

dataset1= split-time
dataset2=split-time, outliner
dataset3=split-time, outliner, time-rank

Conclusion-Xgboost factor contribution

```
> xgb.importance(colnames(dtrain1), model = xgb.model1)
```

	Feature	Gain	Cover	Frequency
1:	hour	0.615860013	0.149390264	0.188677845
2:	temp	0.093897934	0.150789130	0.147944799
3:	workingday	0.083391603	0.011555129	0.034055498
4:	atemp	0.051783455	0.123972105	0.075233714
5:	humidity	0.044005438	0.227609021	0.170425879
6:	season	0.032044820	0.027754237	0.042736311
7:	month	0.022320642	0.087474437	0.072043330
8:	weather	0.020773696	0.028921204	0.037542662
9:	wday	0.020122691	0.070243483	0.095934115
10:	windspeed	0.012818493	0.113148505	0.125612109
11:	holiday	0.002981215	0.009142486	0.009793738

Model1

```
xgb.importance(colnames(dtrain2), model = xgb.model2)
```

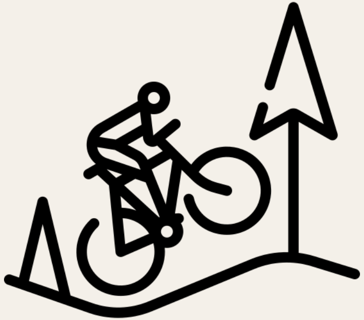
	Feature	Gain	Cover	Frequency
1:	hour	0.633683307	0.165721982	0.19702685
2:	temp	0.105467079	0.146540507	0.14414614
3:	workingday	0.068045635	0.013100942	0.03010132
4:	humidity	0.047603537	0.229691188	0.17151098
5:	season	0.036527228	0.027604354	0.04112122
6:	atemp	0.025890977	0.121720167	0.07669551
7:	weather	0.023774908	0.031590930	0.03875453
8:	wday	0.021046517	0.064937872	0.09525923
9:	month	0.019784188	0.084815188	0.06826418
10:	windspeed	0.015780387	0.104835675	0.12691369
11:	holiday	0.002396237	0.009441197	0.01020635

Model2

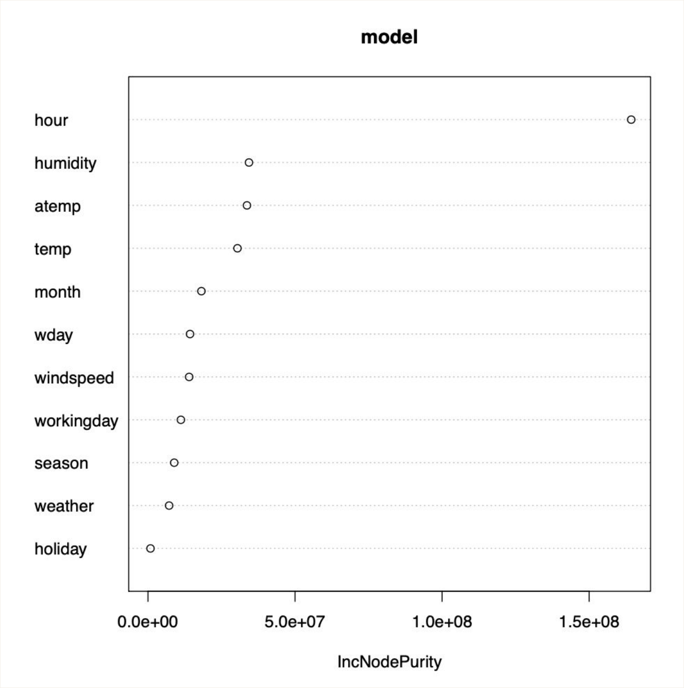
```
> xgb.importance(colnames(dtrain6), model = xgb.model6)
```

	Feature	Gain	Cover	Frequency
1:	hour	0.524250981	0.128843714	0.162998881
2:	hour_group	0.118397270	0.026742783	0.041700858
3:	temp	0.100193295	0.141316188	0.143304737
4:	workingday	0.051388542	0.016757564	0.032077583
5:	humidity	0.047925959	0.233204823	0.175680716
6:	atemp	0.033495270	0.132336048	0.072510257
7:	month	0.028836641	0.085533790	0.068183514
8:	weather	0.026542299	0.026539817	0.036031332
9:	season	0.025437447	0.029450226	0.039686684
10:	wday	0.022700827	0.063155580	0.088922044
11:	windspeed	0.017656024	0.108337428	0.129130921
12:	holiday	0.003175445	0.007782038	0.009772473

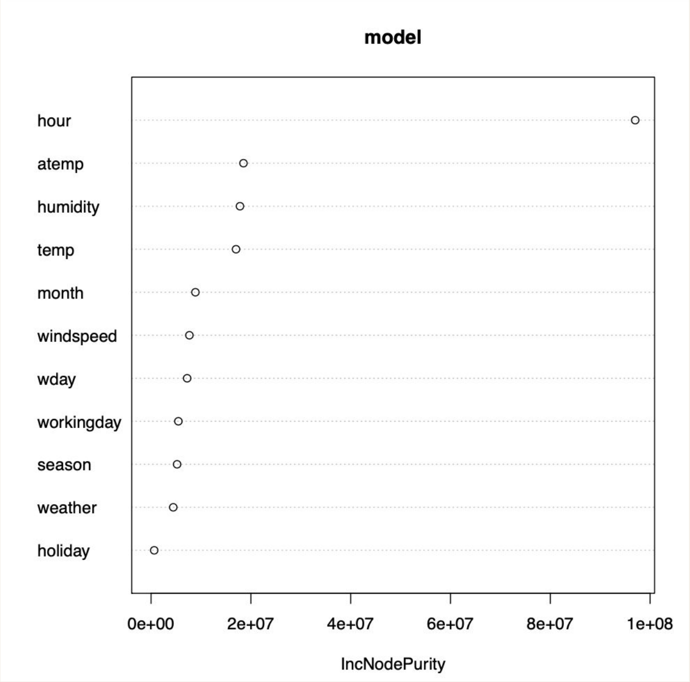
Model3



Conclusion-RF factor contribution

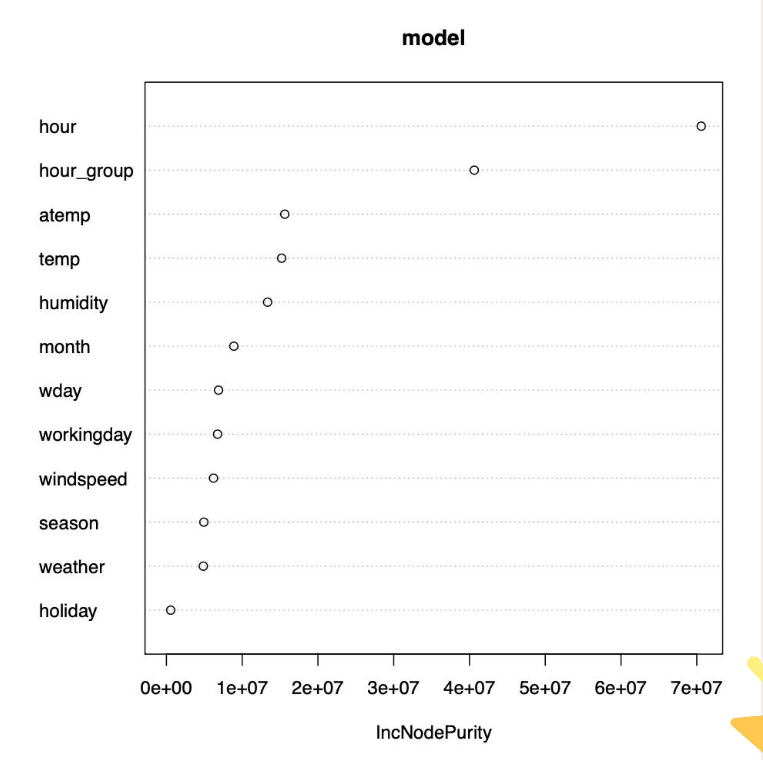


Model1



Model2

Conclusion-RF factor contribution



Model3

Conclusion-Lasso factor selection

```
12 x 1 sparse Matrix of class "dgCMatrix"
                    s1
(Intercept) 37.8935136
season       .
holiday      .
workingday   .
weather     -2.0794993
temp         2.3348893
atemp        4.3259506
humidity    -2.2496609
windspeed    0.3340296
month        7.2756514
wday         1.9244552
hour         7.5264667
```

Model1

```
12 x 1 sparse Matrix of class "dgCMatrix"
                    s1
(Intercept) 39.9144267
season       .
holiday      5.6974644
workingday  -8.4286541
weather     -0.9683099
temp         1.0460630
atemp        3.9875752
humidity    -1.7403809
windspeed    0.3194968
month        5.9027526
wday         1.4727930
hour         6.7564946
```

Model2

Conclusion-Lasso factor Selection

```
13 x 1 sparse Matrix of class "dgCMatrix"
                     s1
(Intercept) -17.1953294
season        .
holiday       5.9994683
workingday   -3.2767709
weather     -15.6479946
temp          0.9724485
atemp         3.4623013
humidity     -0.8280259
windspeed    -0.3570003
month         5.4669801
wday          1.8207767
hour          0.8868155
hour_group   75.5510028
```

Model3

Thank for Your Listening