Project 2

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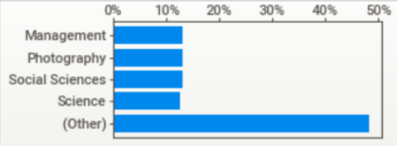
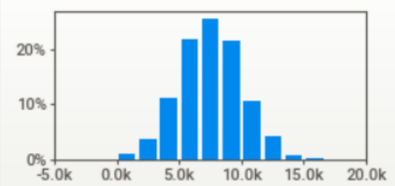
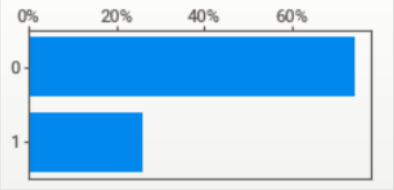
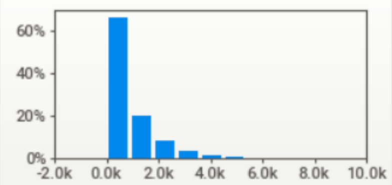
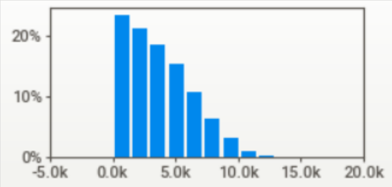
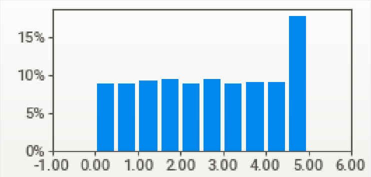
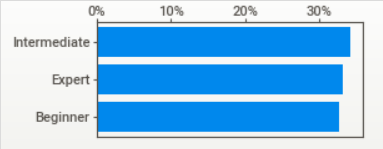
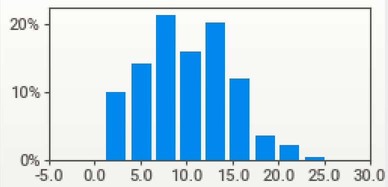
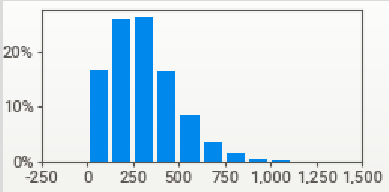
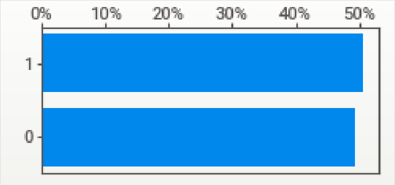
About Data

The data created is about online courses. 10000 online courses are generated with 11 features, which are subject, subscribers, free, fee, reviews, avg. reviews, level, lectures, duration, published date and subtitles. The features' definition and the way to generate them is listed in the table below:

Features	Definition	Way to generate	Graph
subject	The course's involved area, expected only 1 value	Random choose among {Management, Photography, Social Sciences, Science, Personal Development, Design, Information Technology, Music}	
subscribers	The number of subscribers of the course.	Sampling from a normal distribution N(7500,2500), each sample must no less than 0	
free	If the course is a free course, set as 1.	Bernoulli Trial with p=0.25	
fee	The fee of the course.	0 if free, the others sample from exponential distribution (Exp(0.01)+10)*10	

reviews	The number of reviews.	Sampling from uniform distribution with max = subscribers	
avg. reviews	The average score from reviews.	Sampling from uniform distribution 0.5n, 0⩽ n ⩽10 and n is integer. (Note that the plot merges 4.5 and 5.0 into a bar, it is still a uniform distribution)	
level	The level of the course.	Random choose among {Beginner, Intermediate, Expert}	
lectures	The number of lectures provided.	Sampling integer > 0 from normal distribution N(10,5).	
duration	The total duration of the lectures in minutes	Sampling average duration > 0 from normal distribution N(30,10) and multiply with number of lectures	
published date	The published date of the course	Generate a random date between 2002.01.01 and 2021.12.31	
subtitles	If the course has subtitles, set as 1.	Bernoulli Trial with p=0.5	

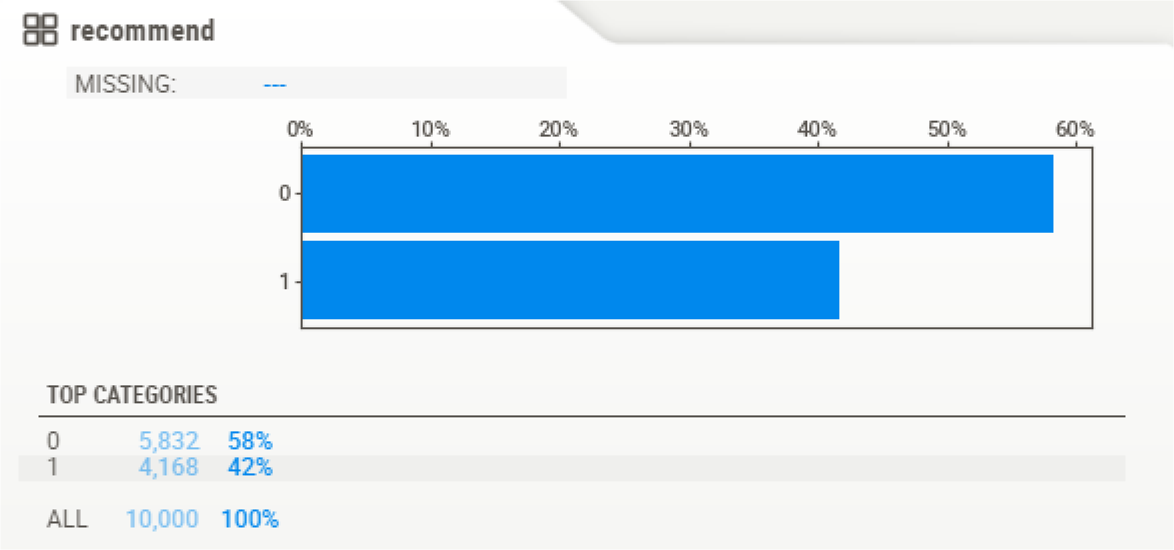
This data will like to recommend several courses according to these features. If a course will be recommended, at least 1 of the following rule should be satisfied:

1. subscriber > 12000
2. review >= 0.8*subscriber and avg. reviews >= 4.5

3. level = beginner and fee <= 100

4. level = intermediate and fee <= 250

5. level = expert and fee <= 500

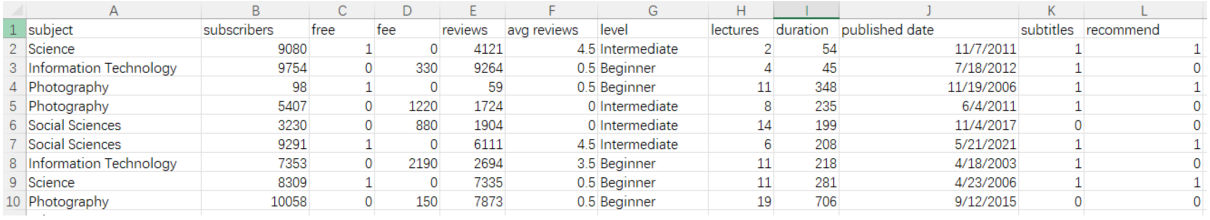


TOP CATEGORIES

0	5,832	58%
1	4,168	42%
ALL	10,000	100%

Figure 1: Distribution of the course

By these rules, the ratio of course that be recommended and not recommended is about 3:2. The plot below shows its distribution, 1 indicates the course is recommended.



	A	B	C	D	E	F	G	H	I	J	K	L
1	subject	subscribers	free	fee	reviews	avg reviews	level	lectures	duration	published date	subtitles	recommend
2	Science	9080	1	0	4121	4.5	Intermediate	2	54	11/7/2011	1	1
3	Information Technology	9754	0	330	9264	0.5	Beginner	4	45	7/18/2012	1	0
4	Photography	98	1	0	59	0.5	Beginner	11	348	11/19/2006	1	1
5	Photography	5407	0	1220	1724	0	Intermediate	8	235	6/4/2011	1	0
6	Social Sciences	3230	0	880	1904	0	Intermediate	14	199	11/4/2017	0	0
7	Social Sciences	9291	1	0	6111	4.5	Intermediate	6	208	5/21/2021	1	1
8	Information Technology	7353	0	2190	2694	3.5	Beginner	11	218	4/18/2003	1	0
9	Science	8309	1	0	7335	0.5	Beginner	11	281	4/23/2006	1	1
10	Photography	10058	0	150	7873	0.5	Beginner	19	706	9/12/2015	0	0

Figure 2: Example data generated

The details of the data can be viewed in EDA.html. The data is split into 4:1, i.e., 8000 for training and 2000 for testing.

Data Pre-processing

Several data pre-processes are done on the dataset.

Label Encoding

Label encoding on the categorical features, which are subject and level.

Conversion

Convert the published date into timestamp so that classification can be run on it. Reviews also be converted into ratio but not integer. The reason to do this conversion will be discussed in the session discussing decision tree.

Normalization

Normalization is done on numerical features, even though it doesn't affect decision tree, it will improve the result of KNN and Naïve Bayes classifier.

Result

Decision tree, KNN, and Naïve Bayes classifiers are tried to classify these courses. Discussion for each classifier will be made at each session and comparison will be made at the end of each session.

Decision Tree

The below is the tree generated by decision tree classifiers with the result. But because the tree is too large, for details please refer to *decision_tree_no_conversion.svg.*

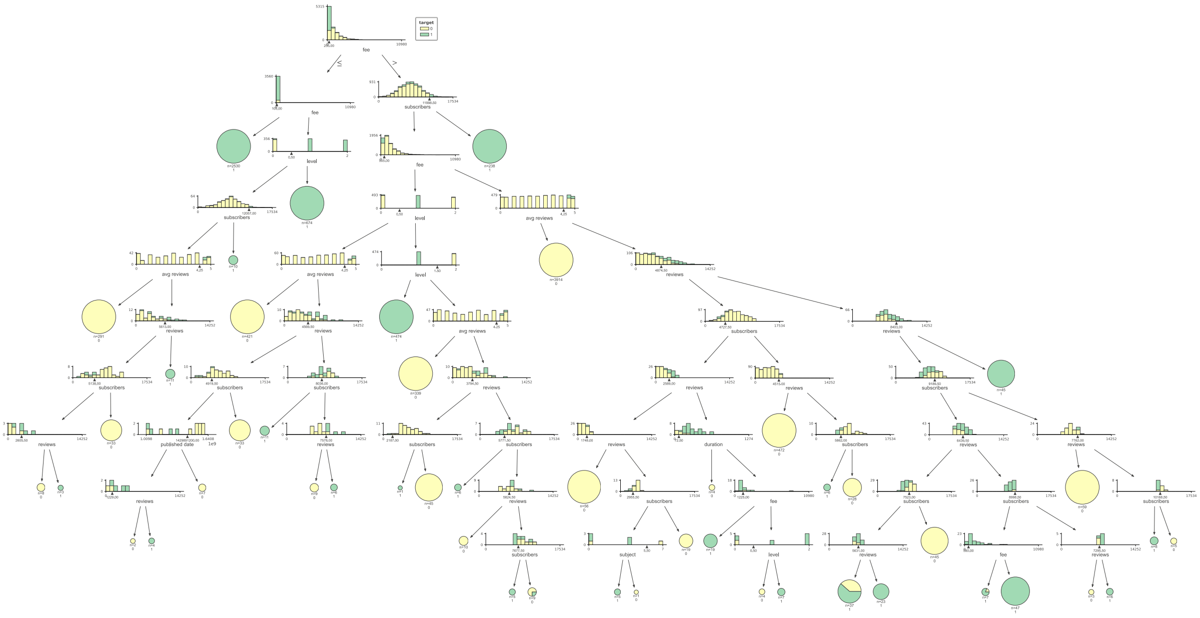


Figure 3: Decision Tree generated without conversion of reviews

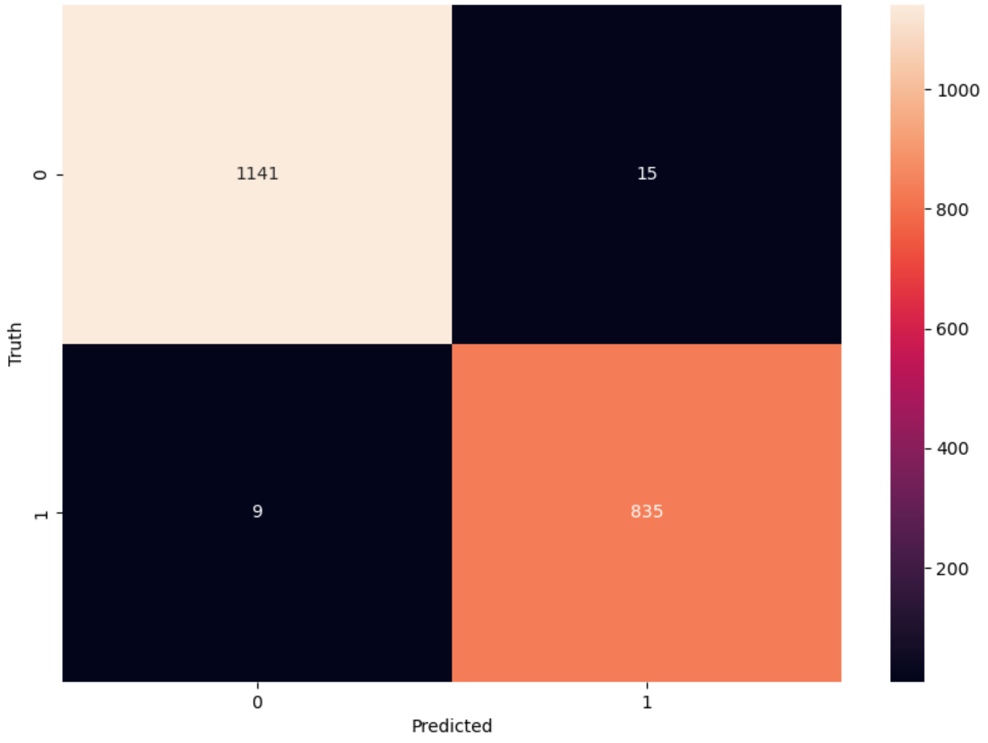


Figure 4: Confusion matrix of decision tree without conversion of reviews

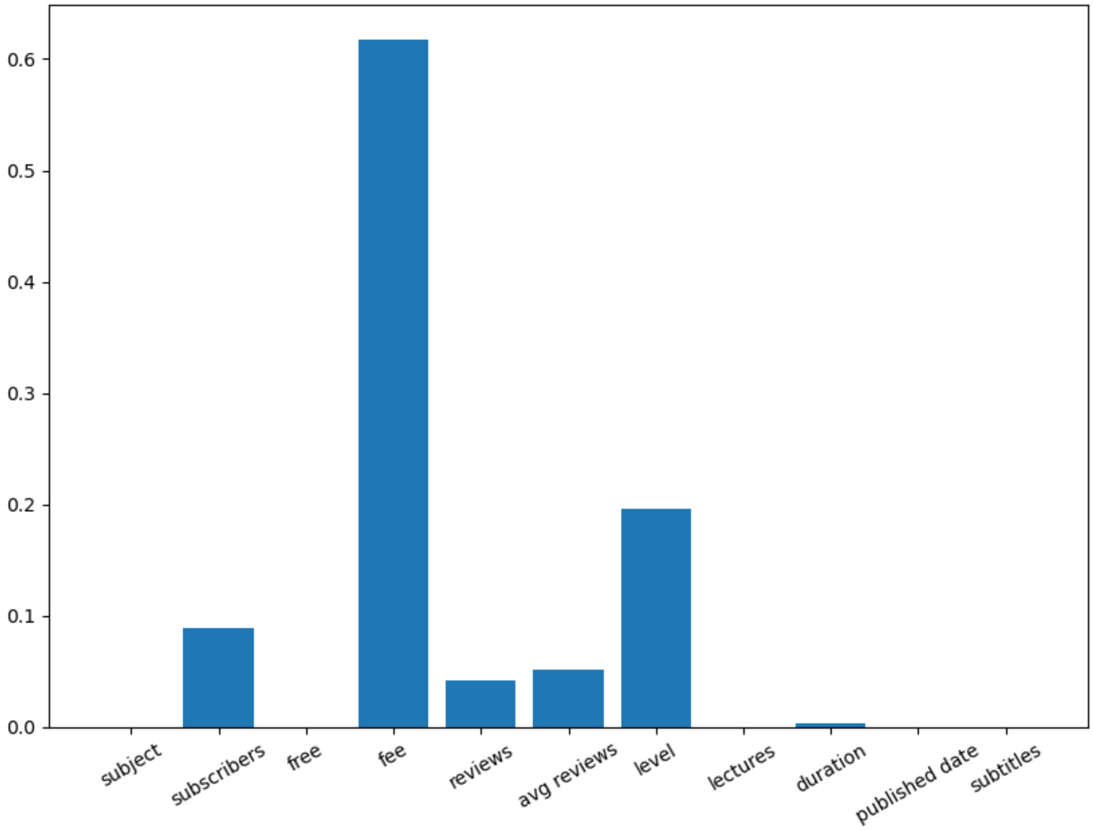


Figure 5: Feature importance of decision tree without conversion of reviews

	precision	recall	f1-score	support
0	0.99	0.99	0.99	1156
1	0.98	0.99	0.99	844
accuracy			0.99	2000
macro avg	0.99	0.99	0.99	2000
weighted avg	0.99	0.99	0.99	2000

Table 1: Classification Report of Decision Tree without conversion of reviews

Notice that the rule generated by this decision tree classifiers is too complex, thus it is not listed in this report. For details, please refers to *decision_tree_no_conversion.log*. By listing out the wrong cases, observed that 15 cases should not be recommended, and 9 cases are not recommended because the classifiers did not detect that the cases satisfied the rule 3 which is “review >= 0.8*subscriber and avg. reviews >= 4.5”. Thus, conversion is made on the reviews, and the rule 2 can also be treated as *review >= 0.8 and avg. reviews >= 4.5*.The result after this pre-processing is listed below:

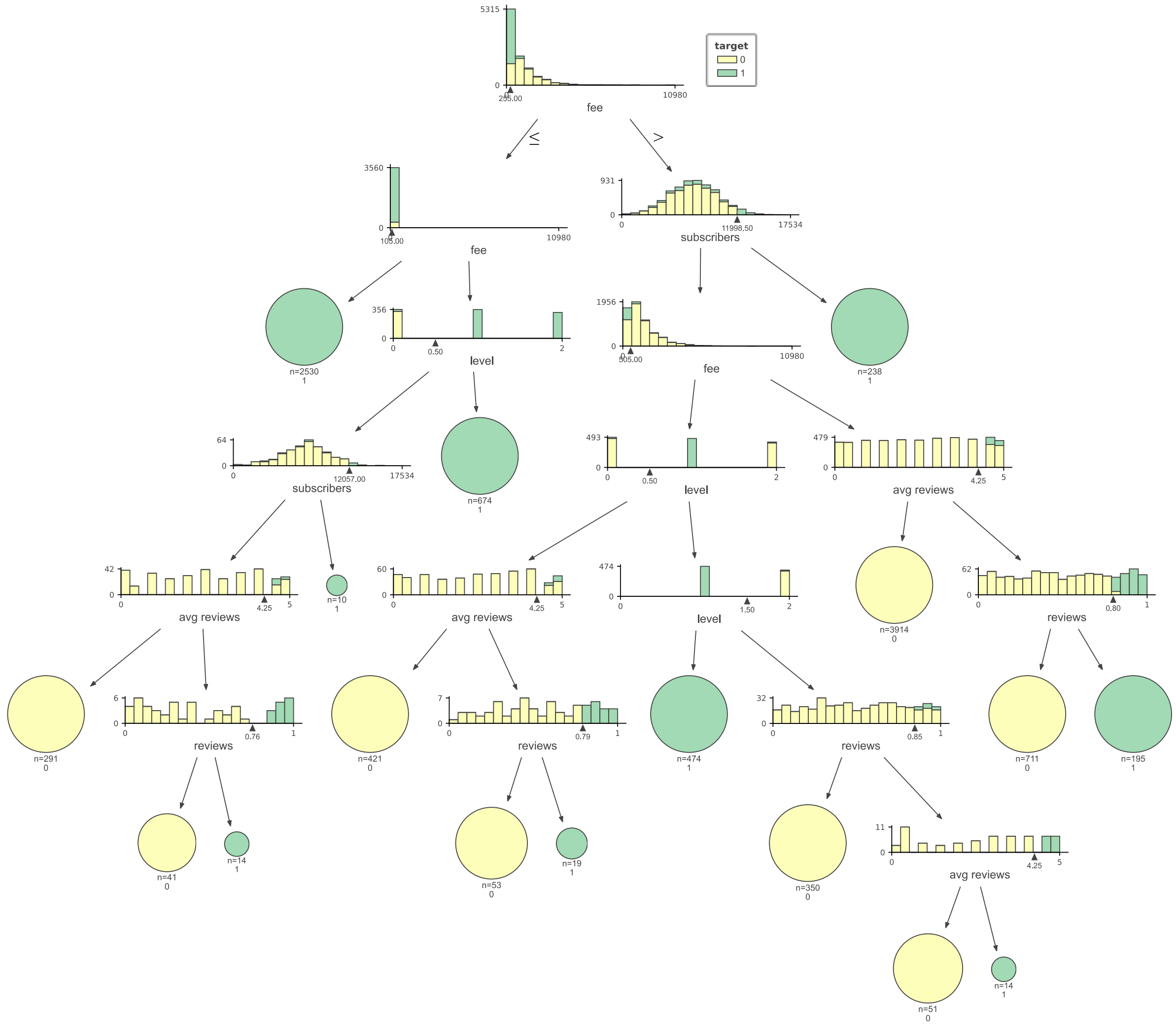


Figure 6: Decision Tree generated with conversion of reviews

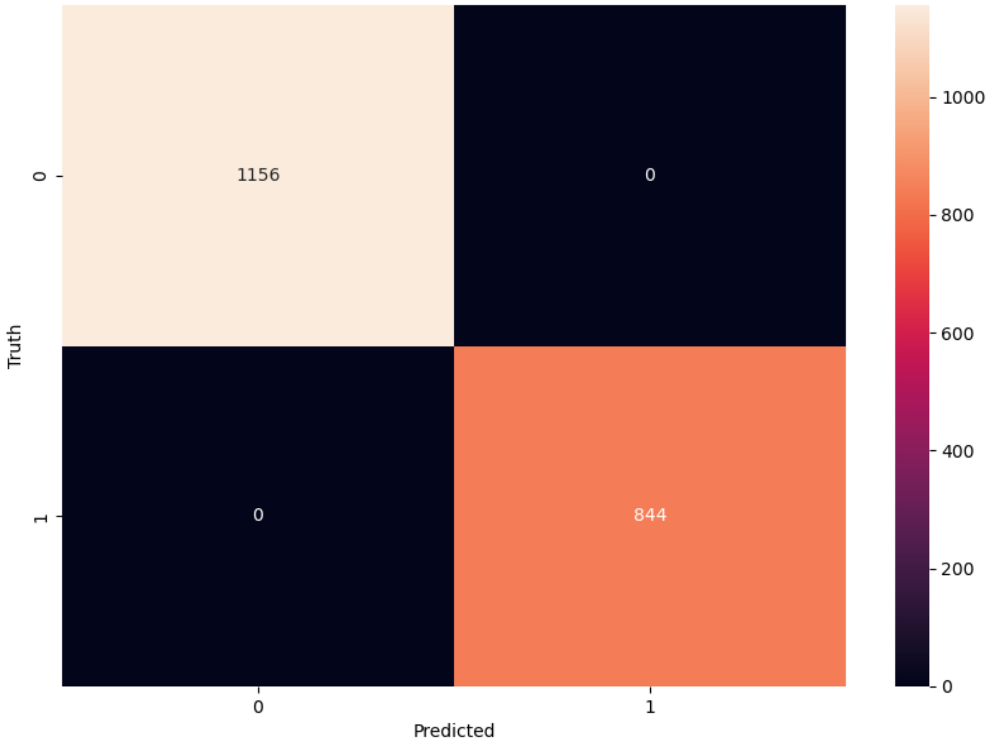


Figure 7: Confusion matrix of decision tree with conversion of reviews

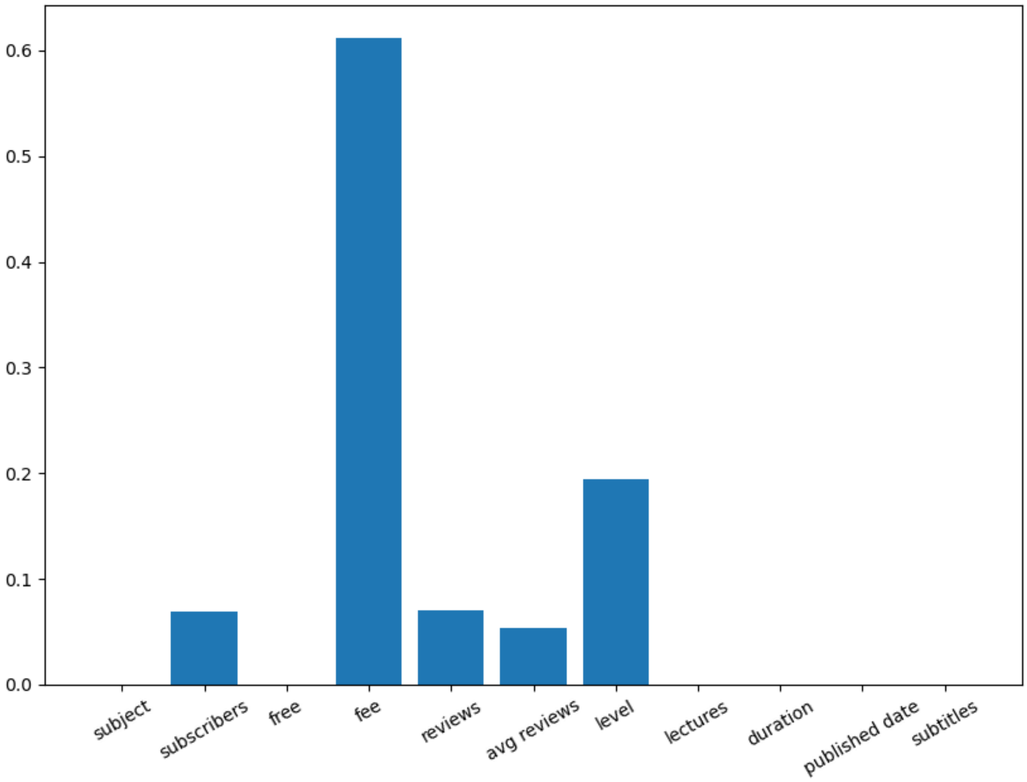


Figure 8: Feature importance of decision tree with conversion of reviews

	precision	recall	f1-score	support
0	1.00	1.00	1.00	1156
1	1.00	1.00	1.00	844
accuracy			1.00	2000
macro avg	1.00	1.00	1.00	2000
weighted avg	1.00	1.00	1.00	2000

Table 2: Classification Report of Decision Tree with conversion of reviews

According to figure 6, the rule generated by the classifiers are:

```
|--- fee <= 255.00
|   |--- fee <= 105.00
|   |   |--- class: 1
|   |--- fee >  105.00
|   |   |--- level <= 0.50
|   |   |   |--- subscribers <= 12057.00
|   |   |   |   |--- avg reviews <= 4.25
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- avg reviews >  4.25
|   |   |   |   |   |--- reviews <= 0.76
|   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- reviews >  0.76
|   |   |   |   |   |   |--- class: 1
|   |   |   |--- subscribers >  12057.00
|   |   |   |   |--- class: 1
|   |   |--- level >  0.50
|   |   |   |--- class: 1
|--- fee >  255.00
|   |--- subscribers <= 11998.50
|   |   |--- fee <= 505.00
|   |   |   |--- level <= 0.50
|   |   |   |   |--- avg reviews <= 4.25
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- avg reviews >  4.25
|   |   |   |   |   |--- reviews <= 0.79
|   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- reviews >  0.79
|   |   |   |   |   |   |--- class: 1
|   |   |   |--- level >  0.50
|   |   |   |   |--- level <= 1.50
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- level >  1.50
|   |   |   |   |   |--- reviews <= 0.85
|   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- reviews >  0.85
|   |   |   |   |   |   |--- avg reviews <= 4.25
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- avg reviews >  4.25
|   |   |   |   |   |   |   |--- class: 1
|   |   |--- fee >  505.00
|   |   |   |--- avg reviews <= 4.25
|   |   |   |   |--- class: 0
|   |   |   |--- avg reviews >  4.25
|   |   |   |   |--- reviews <= 0.80
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- reviews >  0.80
|   |   |   |   |   |--- class: 1
|   |--- subscribers >  11998.50
|   |   |--- class: 1
```

The rule is also log in *decision_tree_with_conversion.log*. After compressing the rule, and prune the unnecessary rule (or rewrite in a more simple way), it will become:

1. fee ⩽ 105 ⟶ recommend ⟹ **Correspond combination of rules 3,4,and 5**
2. avg. review > 4.25 ⟶ reviews >0.81 ⟶ recommend ⟹ **Correspond rule 2**
3. subscribers > 11998.50 ⟶ recommend ⟹ **Correspond rule 1**
4. 255 ⩾ fee > 105 ⟶ level = intermediate or expert ⟶ recommend ⟹ **Correspond combination of rules 4,and 5**
5. 505 ⩾ fee > 255.00 ⟶ level = expert ⟶ recommend ⟹ **Correspond rule 5**
6. Others not recommend

Generally, the rules generated by decision tree classifiers is similar to the absolutely-right rules designed. Besides, the feature importance plot also supports this inference as all the important features are all included in the absolutely-right rules designed. Thus, in decision tree classifiers, how the original rule designed will affect the performance, or in other words, how the features are pre-processed can affected the performance.

KNN

Now let's look at KNN. From the observation above, data with conversion is directly be used. Besides, normalization is done as it really affects the performance of KNN, because in KNN algorithms, the distance calculation involved.

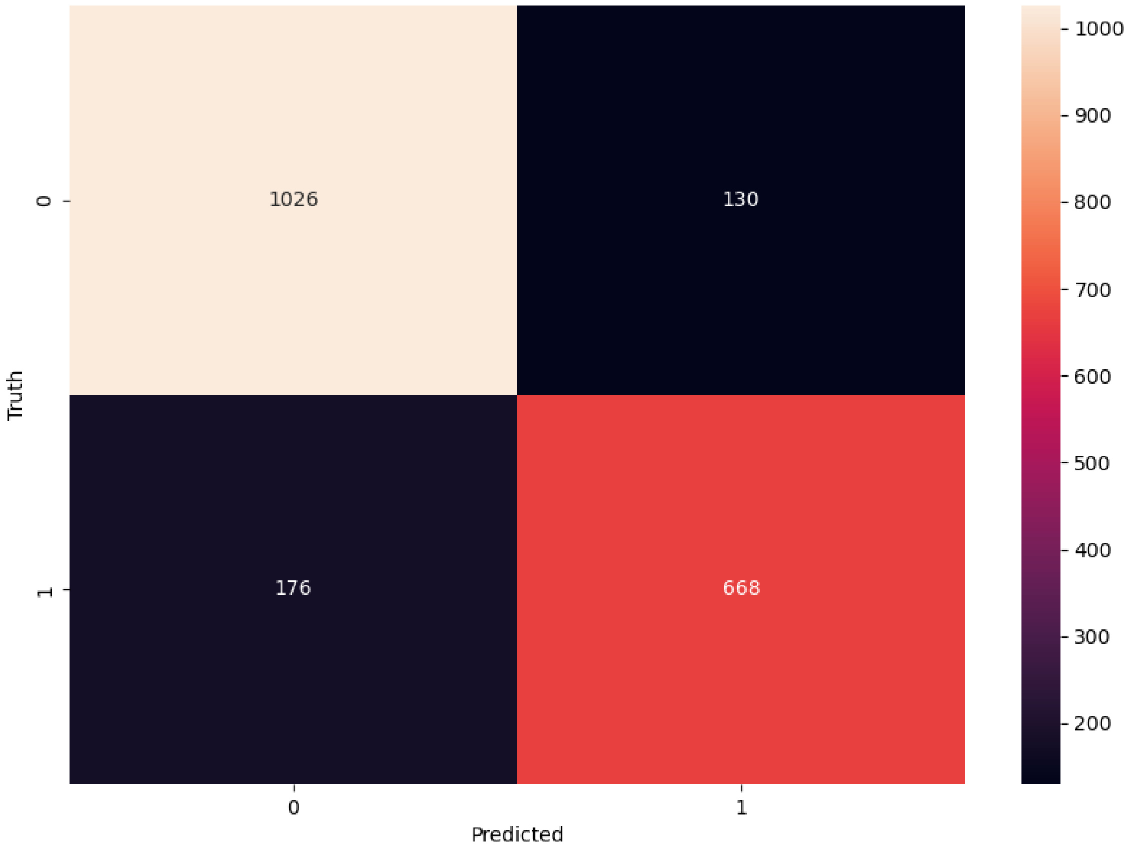


Figure 9: Confusion matrix of KNN(n_neighbors = 8) with conversion of reviews

	precision	recall	f1-score	support
0	0.85	0.89	0.87	1156
1	0.84	0.79	0.81	844
accuracy			0.85	2000
macro avg	0.85	0.84	0.84	2000
weighted avg	0.85	0.85	0.85	2000

Table 3: Classification Report of KNN(n_neighbors = 8) with conversion of reviews

The following is the number of each wrong cases:

1. 'Should not recommend': 130
2. 'Not recommend subscriber > 12000': 29
3. 'Not recommend review >= 0.8*subscriber && avg.reviews >= 4.5': 56
4. 'Not recommend level = beginner and fee <= 100': 2
5. 'Not recommend level = intermediate and fee <= 250': 9
6. 'Not recommend level = expert and fee <= 500': 80

This is the data when setting n_neighbors as 8. But when set n_neighbors=10

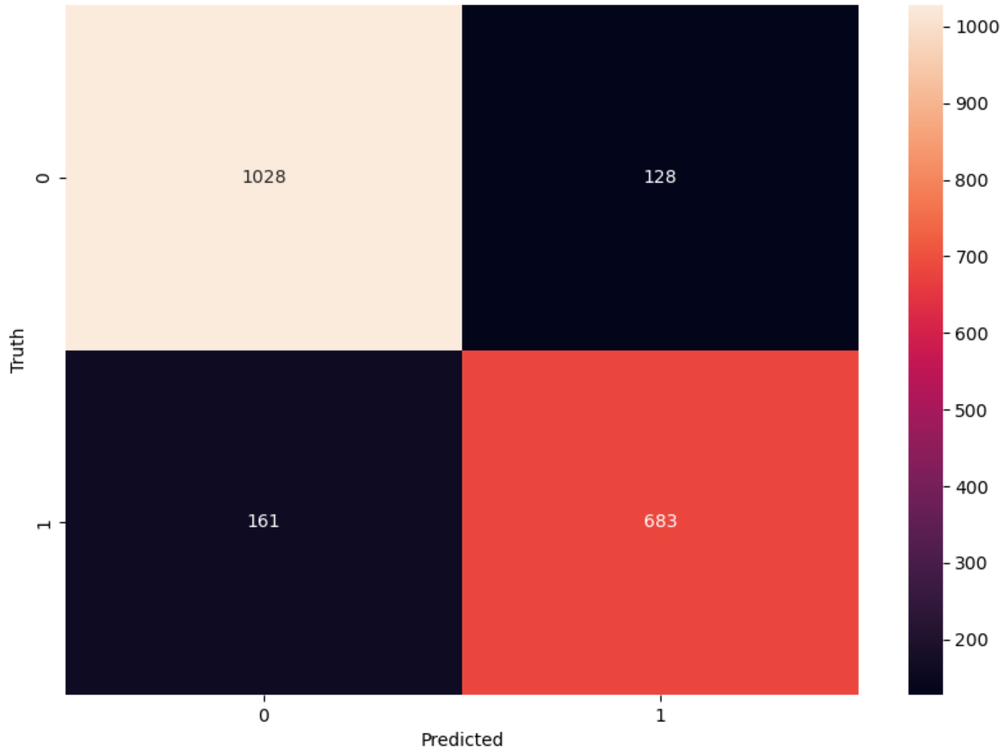


Figure 10: Confusion matrix of KNN(n_neighbors = 10) with conversion of reviews

	precision	recall	f1-score	support
0	0.86	0.89	0.88	1156
1	0.84	0.81	0.83	844
accuracy			0.86	2000
macro avg	0.85	0.85	0.85	2000
weighted avg	0.86	0.85	0.86	2000

Table 4: Classification Report of KNN(n_neighbors = 10) with conversion of reviews

The following is the number of each wrong cases:

1. 'Should not recommend': 128
2. 'Not recommend subscriber > 12000': 28
3. 'Not recommend review >= 0.8*subscriber && avg.reviews >= 4.5': 54
4. 'Not recommend level = intermediate and fee <= 250': 9
5. 'Not recommend level = expert and fee <= 500': 70

Obviously, increasing n_neighbors can improve the performance, but only slightly. It looks like it cannot reach the performance like decision tree, as the rules are designed for decision tree.

Naïve Bayes

Normalization is also be done as there it is better for discretize the range into bins.

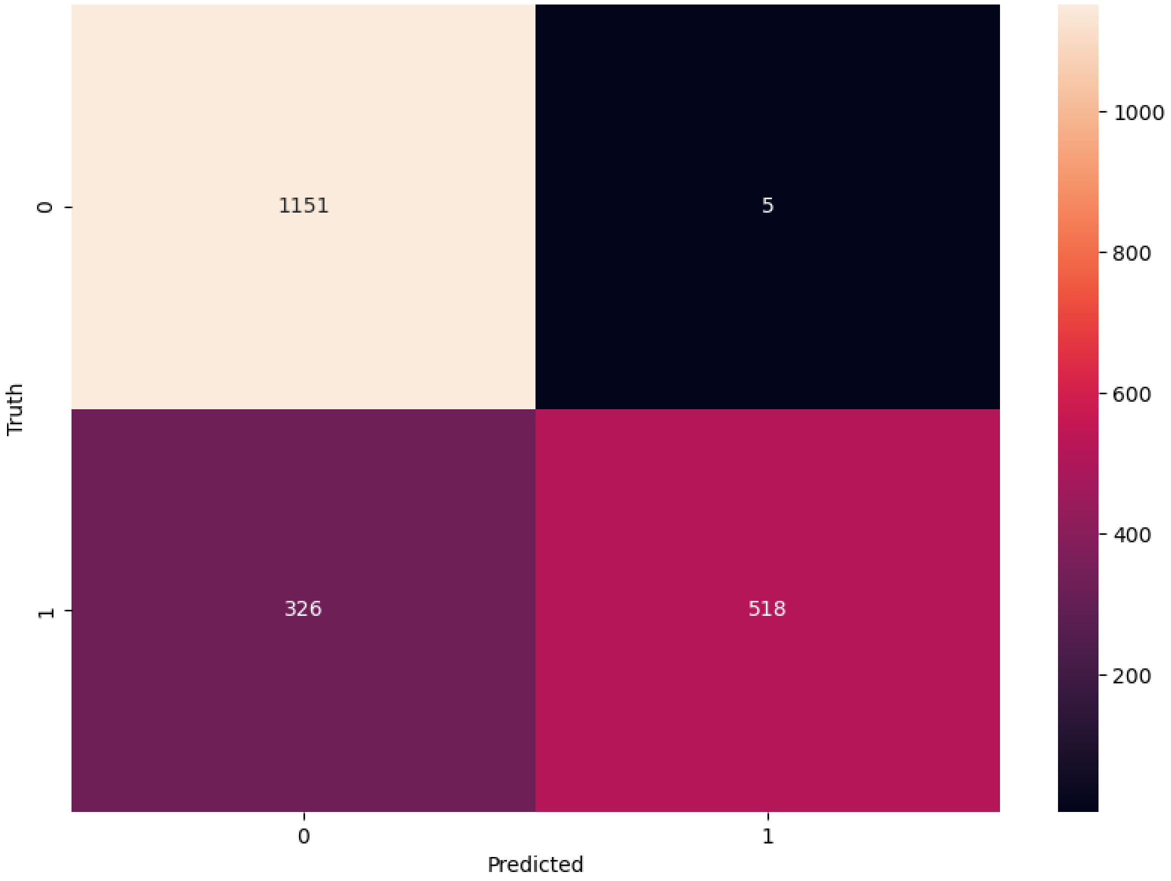


Figure 11: Confusion matrix of Naïve Bayes with conversion of reviews

	precision	recall	f1-score	support
0	0.78	1.00	0.87	1156
1	0.99	0.61	0.76	844
accuracy			0.83	2000
macro avg	0.88	0.80	0.82	2000
weighted avg	0.87	0.83	0.83	2000

Table 5: Classification Report of Naïve Bayes with conversion of reviews

The following is the number of each wrong cases:

1. 'Should not recommend': 5
2. 'Not recommend subscriber > 12000': 47
3. 'Not recommend review >= 0.8*subscriber && avg.reviews >= 4.5': 67
4. 'Not recommend level = beginner and fee <= 100': 2

5. 'Not recommend level = intermediate and fee <= 250': 49
6. 'Not recommend level = expert and fee <= 500': 161

By observation, Naïve Bayes has a good precision on recommend courses. Actually that is what a recommender system expected to have, i.e., recommend those good courses but don't recommend too many bad courses. Thus, even though the recall is low, Naïve Bayes classifiers can still be considered on this kind of task. Naïve Bayes doesn't reach the performance of decision tree because Naïve Bayes prefer dataset where each feature is independent with other, but this dataset isn't.