

Test Assignment - Imanul jihad

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1 Problem statement

give personalized recommendations to student what to study next and what video to watch each time student completing a test.

given historical data of student performances on test and you're asked to predict probability of correct answer for the next question.

1.1 Task

1. Create an Exploratory data analysis (EDA) and create a model to predict probability of `is_correct` in `test.csv` file given the training data.
2. Briefly Explain your thought process and approach

2 Business Problem

from task above we can conclude that we want to predict probability of correct answer for the next question. From business case and from dataset we can create a supervised learning with classification method.

in supervised learning we can create several methods and find the best method that gives the best success matrix. after that we can train that model with hypermeter tuning to get best hyperparameter set so we can improve our model.

success criteria that request from this task is area under the ROC curve between the predicted probability and the observed target.

the expected output is a `submission.csv` file with the same format as `submission_example.csv` file.

the dataset come from the task so we can assume that the data was clean and easy to access.

3 Library

```
[28]: import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
```

```
[29]: %load_ext autoreload
      %autoreload 2

      import sys
      sys.path.append(f'E:\\gitlab\\custom-script\\script')
      from ursar import describe,visual,tunning,fe, model, scoring, feature_importance

      %reload_ext autoreload
```

The autoreload extension is already loaded. To reload it, use:

```
%reload_ext autoreload
```

4 Dataset

4.1 Files

```
[173]: train = pd.read_csv('train.csv')
      train.head()
```

```
[173]:
```

	user_id	session_id	session_no	topic	sub_topic	learning_node	\
0	2348875	5473538500	1.0	1064573894	6164056362	1683819444	
1	2348875	5473538500	1.0	1064573894	6164056362	1683819444	
2	2348875	3206055652	2.0	1064573894	6164056362	1683819444	
3	2766044	9605991415	1.0	4794286044	6471306273	3791168789	
4	2766044	7255460452	2.0	4794286044	2158335016	7856645946	

	question_id	question_type	session_question_no	learning_node_question_no	\
0	2226271822	Single choice	1	1	
1	2226271822	Single choice	2	2	
2	5592568637	Single choice	1	1	
3	1243898418	Single choice	1	1	
4	4732798598	Single choice	1	1	

	question_difficulty	question_number_of_choice	\
0	medium	4	
1	medium	4	
2	medium	4	
3	medium	4	
4	medium	4	

	question_number_of_correct_choice	question_number_of_correct_selected	\
0	1	0	
1	1	0	
2	1	1	
3	1	1	
4	1	1	

	question_number_of_wrong_selected	ms_first_response	is_correct	row_id
0	1	18.0	0.0	0
1	1	12.0	0.0	1
2	0	11.0	1.0	2
3	0	47.0	1.0	3
4	0	7.0	1.0	4

```
[174]: test = pd.read_csv('test.csv')
test.head()
```

```
[174]: user_id session_id session_no topic sub_topic learning_node \
0 2348875 3206055652 2.0 1064573894 6164056362 1683819444
1 2766044 2972889287 11.0 1737274108 6197171301 8772005155
2 3604867 8630265714 4.0 2624511878 5665086549 1064446677
3 4061807 7315912009 10.0 147927464 5665086549 7469873307
4 5713467 7344767708 3.0 253258722 2774427363 3261917054
```

	question_id	question_type	session_question_no	learning_node_question_no	\
0	2226271822	Single choice	2		2
1	8350981375	Single choice	6		2
2	7911407965	Single choice	8		2
3	2368078655	Single choice	7		1
4	6616709393	Single choice	9		3

	question_difficulty	question_number_of_choice	\
0	medium	4	
1	medium	4	
2	NaN	4	
3	NaN	4	
4	medium	4	

	question_number_of_correct_choice	row_id
0	1	0
1	1	1
2	1	2
3	1	3
4	1	4

5 Data understanding

5.1 Dataset info

```
[6]: describe.describe_data(train)
```

```
'table size 286886 x 18'
```

```
Dataframe has 18 columns.
```

```
There are 1 columns that have missing values.
```

```
[6]:
```

	column_names	Data Type	Missing Values	% missing	\
0	user_id	int64	0	0.00	
1	session_id	int64	0	0.00	
2	session_no	float64	0	0.00	
3	topic	int64	0	0.00	
4	sub_topic	int64	0	0.00	
5	learning_node	int64	0	0.00	
6	question_id	int64	0	0.00	
7	question_type	object	0	0.00	
8	session_question_no	int64	0	0.00	
9	learning_node_question_no	int64	0	0.00	
10	question_difficulty	object	166513	58.04	
11	question_number_of_choice	int64	0	0.00	
12	question_number_of_correct_choice	int64	0	0.00	
13	question_number_of_correct_selected	int64	0	0.00	
14	question_number_of_wrong_selected	int64	0	0.00	
15	ms_first_response	float64	0	0.00	
16	is_correct	float64	0	0.00	
17	row_id	int64	0	0.00	

	low Value	Hi Value	stddev Value	unique
0	2348875	9997990646	2875513775	7000.0
1	424084	9999846794	2878680609	47222.0
2	1	1311	164	1311.0
3	1952256	9999385357	3013026089	1639.0
4	1314703	9993728634	1932006810	2265.0
5	4985900	9999782161	2889600192	12093.0
6	179554	9999972554	2921249861	30653.0
7	0	0	0	3.0
8	1	44	4	44.0
9	1	32	1	32.0
10	0	0	0	4.0
11	2	6	1	5.0
12	1	1	0	1.0
13	0	1	0	2.0
14	0	3	0	4.0
15	1	2171996	11812	8806.0
16	0	1	0	2.0
17	0	286885	82817	286886.0

```
[7]: describe.describe_data(test)
```

```
'table size 7000 x 14'
```

```
Dataframe has 14 columns.
```

```
There are 1 columns that have missing values.
```

```
[7]:
```

	column_names	Data Type	Missing Values	% missing	\
0	user_id	int64	0	0.0	
1	session_id	int64	0	0.0	
2	session_no	float64	0	0.0	
3	topic	int64	0	0.0	
4	sub_topic	int64	0	0.0	
5	learning_node	int64	0	0.0	
6	question_id	int64	0	0.0	
7	question_type	object	0	0.0	
8	session_question_no	int64	0	0.0	
9	learning_node_question_no	int64	0	0.0	
10	question_difficulty	object	2877	41.1	
11	question_number_of_choice	int64	0	0.0	
12	question_number_of_correct_choice	int64	0	0.0	
13	row_id	int64	0	0.0	

	low Value	Hi Value	stddev Value	unique
0	2348875	9997990646	2880925984	7000.0
1	1104080	9999097475	2878866406	7000.0
2	1	1311	30	116.0
3	1952256	9999385357	3101228743	1132.0
4	10204249	9974498793	2262454745	1229.0
5	9253933	9998905485	2926192694	3591.0
6	338236	9999972554	2950053992	4829.0
7	0	0	0	2.0
8	1	45	5	27.0
9	1	33	1	9.0
10	0	0	0	4.0
11	2	5	1	4.0
12	1	1	0	1.0
13	0	6999	2021	7000.0

5.2 Define data

from the examples above we can conclude:

1. unit analysis is user ID
2. features that we want to analyse and have high probability to become input for our model later are:
 - a. session_no
 - b. topic
 - c. sub_topic
 - d. learning_node
 - e. question_id
 - f. question_type

- g. session_question_no
 - h. learning_node_question_no
 - i. question_difficulty
 - j. question_number_of_choice
3. these are features that just a unique ID, haven't impact to our data or only have single value for entire dataset, there are:
 - a. session_id
 - b. row_id
 - c. question_number_of_correct_choice
 4. These are features just exist at training data and didn't exist at testing data so these features can't be include in train data
 - a. ms_first_response
 - b. question_number_of_wrong_selected
 - c. question_number_of_correct_selected
 5. The label data is **is_correct** with binary unique value, so we want to create model of binary classification supervised learning. **1 if correct and 0 otherwise**

from selected features we can separate them to numerical and categorical data so we can easy to planning next step:

from dataset info previously we got all numerical data from training dataset for all features with numeric value and just single categorical data. But if we look deeper for every feature we can conclude some features are better to be categorical rather than numerical such as:

- a. topic
- b. sub_topic
- c. learning_node
- d. question_id

because at these features number just a separating value from each other number and have not a meaningful order. so we plan to change these features data type to categorical.

There is a note here, because the range of these features is too high for academic purpose (i.e. 1132 topics in academic is huge number of topic) so we can assume these features are random value.

however, if these features will become categorical, we found out that in test dataset there are rows that have unlist value in these 4 features at training dataset (you can see detail at **unlist value from test dataset compare to train dataset**). This condition is kinda bad because these 4 features are quite related to business case that we want to solve (i.e. some topics / sub topics are difficult for some students and will give enough weight for some students to give a correct answer).

because of that, we will propose to give a weight of evidence encoding for these features. this kind of encoding will measure the "strength" of a grouping technique to separate true and false (from label data) and also this method create binning process to create a few categories. binning process

is good for these features because although these features have not a meaningful order, but in some cases (i.e. topic about something) the similar topic always close for each other, so we can assume binning process is fine for the dataset. another argument is all the unlist data still in the range of these features at training data look at comparing unlist value from training data to test data, did the unlist data still in the range of training data? so binning process can work fine with our dataset.

one of the features has high missing value, this feature `question_difficulty` has 58% missing value from training dataset and 41% from test dataset. there are many ways to handle this feature:

1. we can remove it from all dataset
2. we can filling it with random value from known range value (but this method will lead to huge variance because we lost almost 50% confident for this feature and because this feature is categorical, random filling will lead to miss interpretation)
3. create new value for missing value (this method may be the best solution expecially for categorical, and we can create OHE for this feature and create 1 column to give value where missing value occur)

5.3 Unlist value from test dataset compare to train dataset

```
[8]: test[~test['topic'].isin(train['topic'])]
```

```
[8]:
```

	user_id	session_id	session_no	topic	sub_topic	\
2251	3172304218	6089320365	10.0	7965792980	6028671853	
3793	5379331392	1595179603	7.0	4231385167	5665086549	
5383	7634315972	8227487092	2.0	1154474360	3007338813	
5967	8475903903	8888589494	3.0	6137286633	2855158986	
6113	8697871451	1963868665	2.0	9379519776	1698816542	

	learning_node	question_id	question_type	session_question_no	\
2251	4690301528	3405472432	Single choice	1	
3793	6395264132	5278745365	Single choice	1	
5383	8081729241	8569812195	Single choice	1	
5967	9131938417	5549837575	Single choice	1	
6113	4449847444	5959431743	Single choice	1	

	learning_node_question_no	question_difficulty	\
2251	1	medium	
3793	1	NaN	
5383	1	medium	
5967	1	medium	
6113	1	medium	

	question_number_of_choice	question_number_of_correct_choice	row_id
2251	4	1	2251
3793	5	1	3793
5383	5	1	5383

5967	4	1	5967
6113	4	1	6113

```
[9]: test[~test['sub_topic'].isin(train['sub_topic'])]
```

```
[9]:
```

	user_id	session_id	session_no	topic	sub_topic	\
16	31096286	4935449409	21.0	7698081065	8494431232	
651	949706212	5097570453	1.0	4444322909	221225755	
1224	1712017337	1977901645	1.0	1957384178	2877607674	
4918	6993987802	9158250163	1.0	2904461013	2195376043	

	learning_node	question_id	question_type	session_question_no	\
16	7531642834	7395238231	Single choice		1
651	8375959185	930873949	Single choice		5
1224	5379146646	9944632419	Single choice		5
4918	3757499870	1898943844	Single choice		5

	learning_node_question_no	question_difficulty	\
16	1	medium	
651	1	medium	
1224	1	medium	
4918	1	medium	

	question_number_of_choice	question_number_of_correct_choice	row_id
16	5		1 16
651	5		1 651
1224	5		1 1224
4918	5		1 4918

```
[10]: test[~test['learning_node'].isin(train['learning_node'])]
```

```
[10]:
```

	user_id	session_id	session_no	topic	sub_topic	\
124	175768950	6068179256	1.0	7782355726	5665086549	
141	199796999	4003506723	2.0	2373689175	1808541640	
195	275884425	9299936660	1.0	9571703988	4248113749	
299	433567593	894883782	1.0	7355707374	5665086549	
375	528873677	6458146634	21.0	9813543922	3845158305	
...	
6538	9336481191	3982168154	1.0	7368974261	7539953578	
6801	9704168779	4764572647	16.0	9072251744	6028671853	
6837	9771177228	8802502204	2.0	701160701	9662448319	
6899	9860654599	2290296405	1.0	227751039	7244770119	
6992	9985081626	1960503530	1.0	5970464404	8363968718	

	learning_node	question_id	question_type	session_question_no	\
124	9456016016	6326974992	Single choice		6
141	4271422668	1366995099	Single choice		7

195	8071390837	6946342972	Single choice	9
299	6788581348	1667422462	Single choice	2
375	9354664726	3678458087	Single choice	8
...
6538	9403995534	3324709555	Single choice	5
6801	9137050916	700270568	Single choice	8
6837	1654827980	7702943795	Single choice	6
6899	6109881556	3963782537	Single choice	13
6992	7359359464	5953566422	Single choice	4

	learning_node_question_no	question_difficulty	\
124	1	NaN	
141	1	medium	
195	1	medium	
299	1	NaN	
375	1	medium	
...	
6538	1	medium	
6801	1	medium	
6837	1	medium	
6899	1	medium	
6992	1	medium	

	question_number_of_choice	question_number_of_correct_choice	row_id
124	5	1	124
141	5	1	141
195	5	1	195
299	5	1	299
375	5	1	375
...
6538	5	1	6538
6801	4	1	6801
6837	5	1	6837
6899	5	1	6899
6992	5	1	6992

[76 rows x 14 columns]

```
[11]: test[~test['question_id'].isin(train['question_id'])]
```

	user_id	session_id	session_no	topic	sub_topic	\
34	53501860	9789010669	1.0	3070768229	9710050288	
40	65410125	6941023428	9.0	5481091354	2230285223	
48	79246003	1522584804	1.0	4524197618	1906871219	
70	102548374	3919301125	1.0	7207679382	6521270055	
85	122624186	4641634284	1.0	144815081	3763689638	
...	

6981	9973419602	9466302379	1.0	9972533064	8607737295
6986	9979680855	6747643499	2.0	8640910518	4444442673
6988	9981754407	5128024958	1.0	1676475660	1345997982
6992	9985081626	1960503530	1.0	5970464404	8363968718
6997	9989505176	6679766557	6.0	1937708227	2177007574

	learning_node	question_id	question_type	session_question_no	\
34	6965979883	4072300635	Single choice		6
40	2465188488	5933428626	Single choice		2
48	8260971862	3946876502	Single choice		14
70	7646070404	6452304698	Single choice		3
85	8419046807	9095763210	Single choice		2
...	
6981	7677200932	3837184927	Single choice		2
6986	5170944250	2336495034	Single choice		1
6988	7996123806	2100463006	Single choice		7
6992	7359359464	5953566422	Single choice		4
6997	3886489050	6675622814	Single choice		14

	learning_node_question_no	question_difficulty	\
34	3	medium	
40	2	medium	
48	2	medium	
70	3	medium	
85	2	medium	
...	
6981	2	medium	
6986	1	medium	
6988	1	medium	
6992	1	medium	
6997	2	medium	

	question_number_of_choice	question_number_of_correct_choice	row_id
34	4	1	34
40	4	1	40
48	5	1	48
70	5	1	70
85	5	1	85
...
6981	4	1	6981
6986	4	1	6986
6988	4	1	6988
6992	5	1	6992
6997	5	1	6997

[364 rows x 14 columns]

5.3.1 comparing unlist value from training data to test data, did the unlist data still in the range of training data?

```
[12]: test[test['topic'] > np.max(train['topic'])]
```

```
[12]: Empty DataFrame
Columns: [user_id, session_id, session_no, topic, sub_topic, learning_node,
question_id, question_type, session_question_no, learning_node_question_no,
question_difficulty, question_number_of_choice,
question_number_of_correct_choice, row_id]
Index: []
```

```
[13]: test[test['sub_topic'] > np.max(train['sub_topic'])]
```

```
[13]: Empty DataFrame
Columns: [user_id, session_id, session_no, topic, sub_topic, learning_node,
question_id, question_type, session_question_no, learning_node_question_no,
question_difficulty, question_number_of_choice,
question_number_of_correct_choice, row_id]
Index: []
```

```
[14]: test[test['learning_node'] > np.max(train['learning_node'])]
```

```
[14]: Empty DataFrame
Columns: [user_id, session_id, session_no, topic, sub_topic, learning_node,
question_id, question_type, session_question_no, learning_node_question_no,
question_difficulty, question_number_of_choice,
question_number_of_correct_choice, row_id]
Index: []
```

```
[15]: test[test['question_id'] > np.max(train['question_id'])]
```

```
[15]: Empty DataFrame
Columns: [user_id, session_id, session_no, topic, sub_topic, learning_node,
question_id, question_type, session_question_no, learning_node_question_no,
question_difficulty, question_number_of_choice,
question_number_of_correct_choice, row_id]
Index: []
```

6 EDA

```
[16]: train.columns
```

```
[16]: Index(['user_id', 'session_id', 'session_no', 'topic', 'sub_topic',
'learning_node', 'question_id', 'question_type', 'session_question_no',
'learning_node_question_no', 'question_difficulty',
'question_number_of_choice', 'question_number_of_correct_choice',
'question_number_of_correct_selected',
```

```

        'question_number_of_wrong_selected', 'ms_first_response', 'is_correct',
        'row_id'],
        dtype='object')

```

```

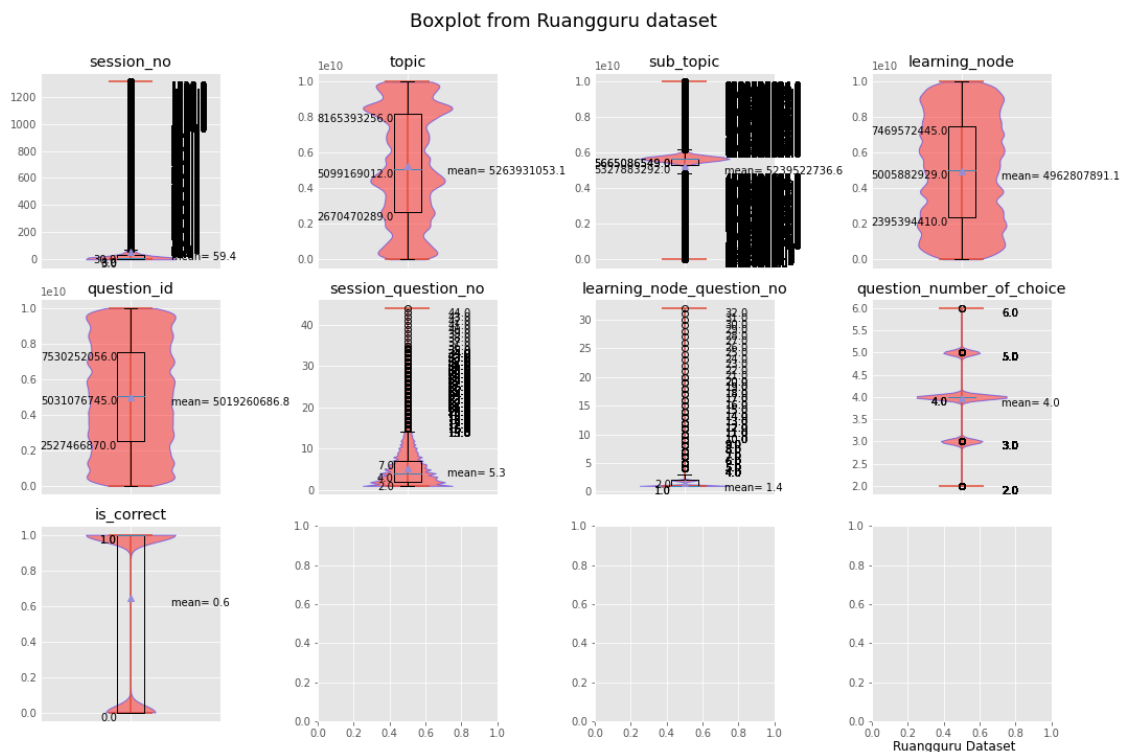
[52]: col = ['session_no', 'topic', 'sub_topic',
            'learning_node', 'question_id', 'question_type', 'session_question_no',
            'learning_node_question_no', 'question_difficulty',
            'question_number_of_choice',
            'is_correct']

```

```

[18]: visual.boxplot(train,col,row_col=(3,4)
                    ,title="Ruangguru",footnote='Ruangguru Dataset')

```



from boxplot we can conclude that:

1. we have high outlier for session_no, learning_node_question_no, session_question_no and one feature with outlier for both side at sub_topic
2. 3 features with good distribution (as the box plot shown) are topic, learning_node and question_id
3. question_number_of choice has categorical data type with high unique count at number 4

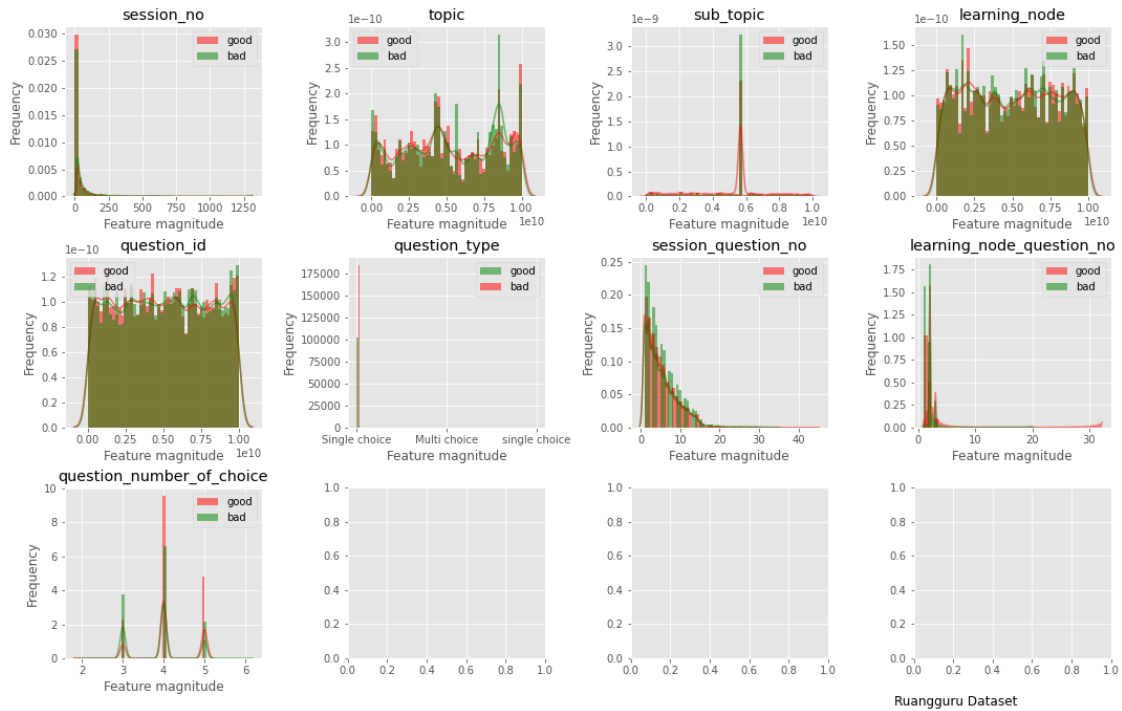
```

[25]: visual.histogram_columns(train[col], 'is_correct', label=["good", "bad"],
                               row_col=(3,4), bins=50, title="Ruangguru",

```

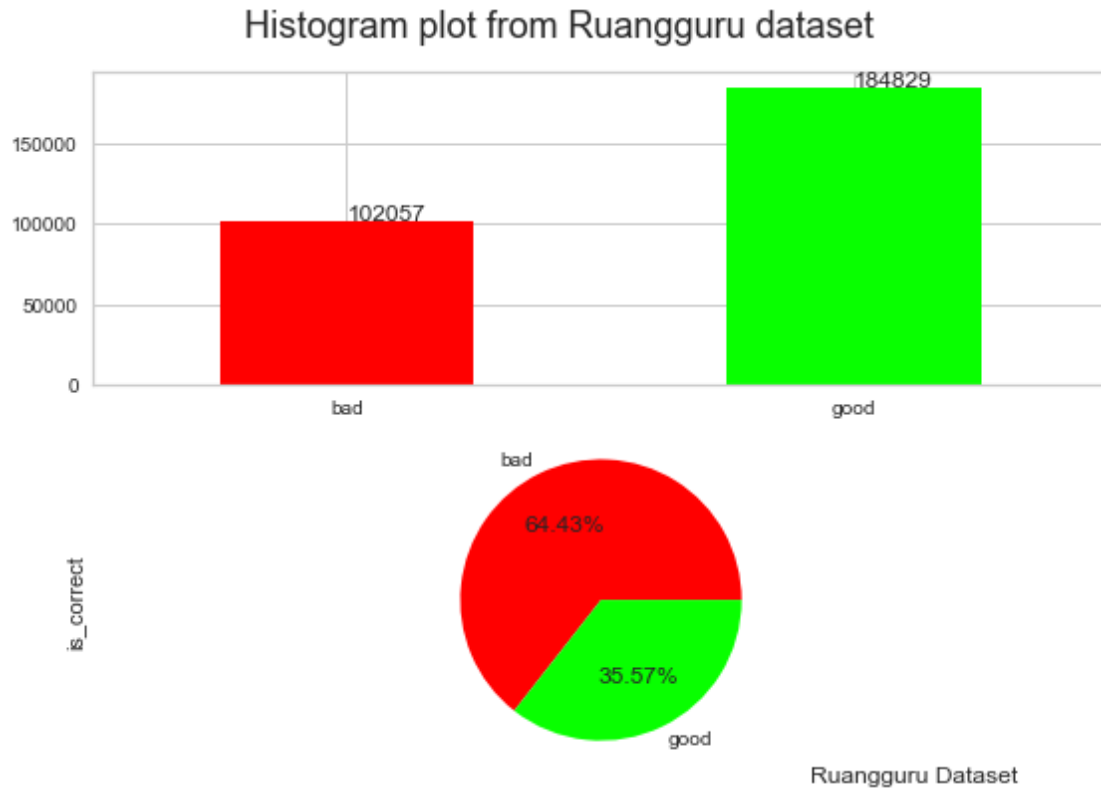
```
footnote='Ruangguru Dataset')
```

Histogram plot from Ruangguru dataset



from plot above we can find that sub_topic, question_number_of_choice and question_type have quite distance value for each classes at label.

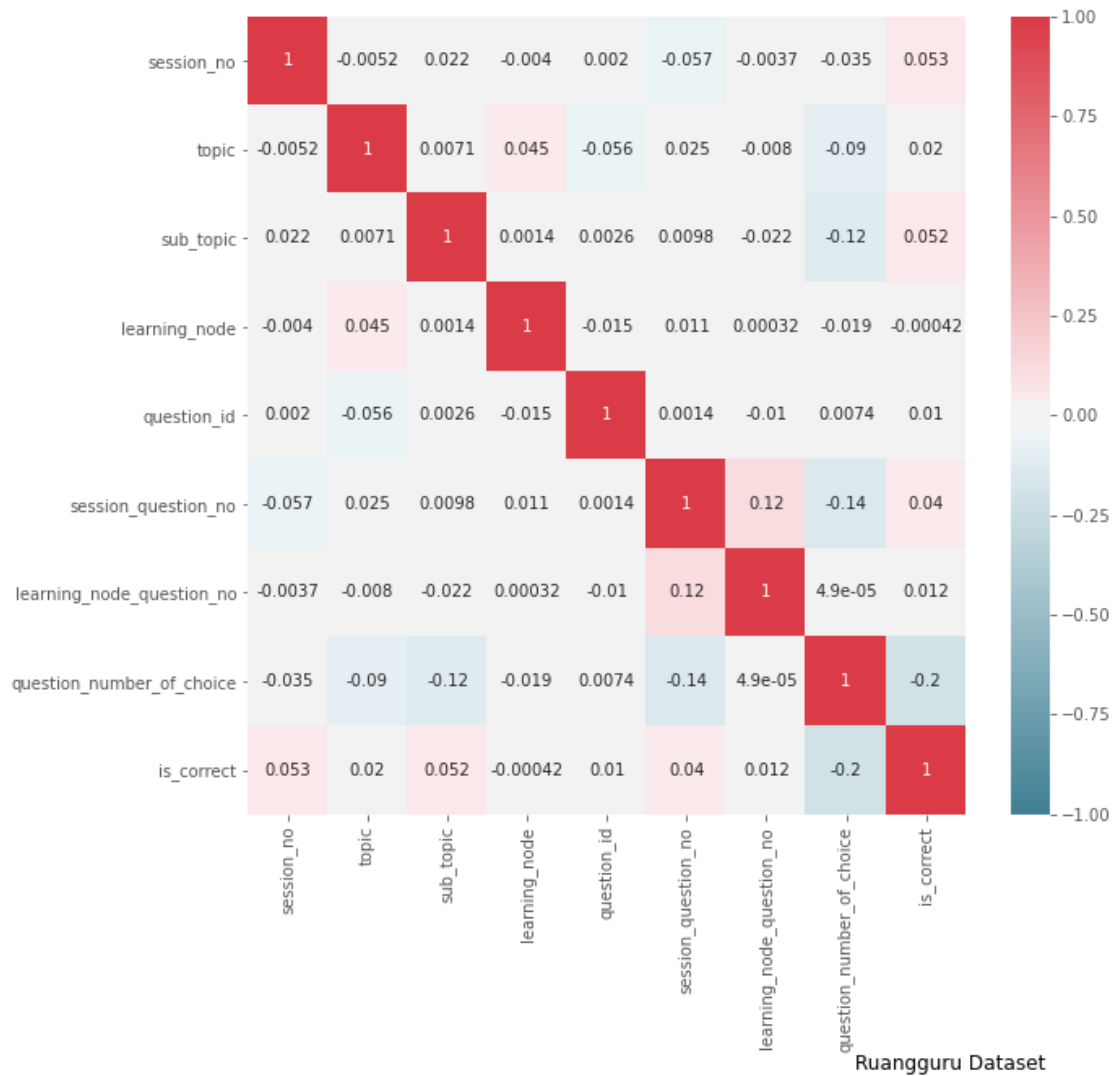
```
[56]: visual.bar_and_pie_plot(train, 'is_correct', label=["bad", "good"],
                                title="Ruangguru", footnote='Ruangguru Dataset')
```



from our dataset we found that we have imbalance dataset with bad(0):good(1) ratio about 64:36. so, we can perpose to add imbalance handleing process such as smote, Nearmiss, or under-sampling etc.

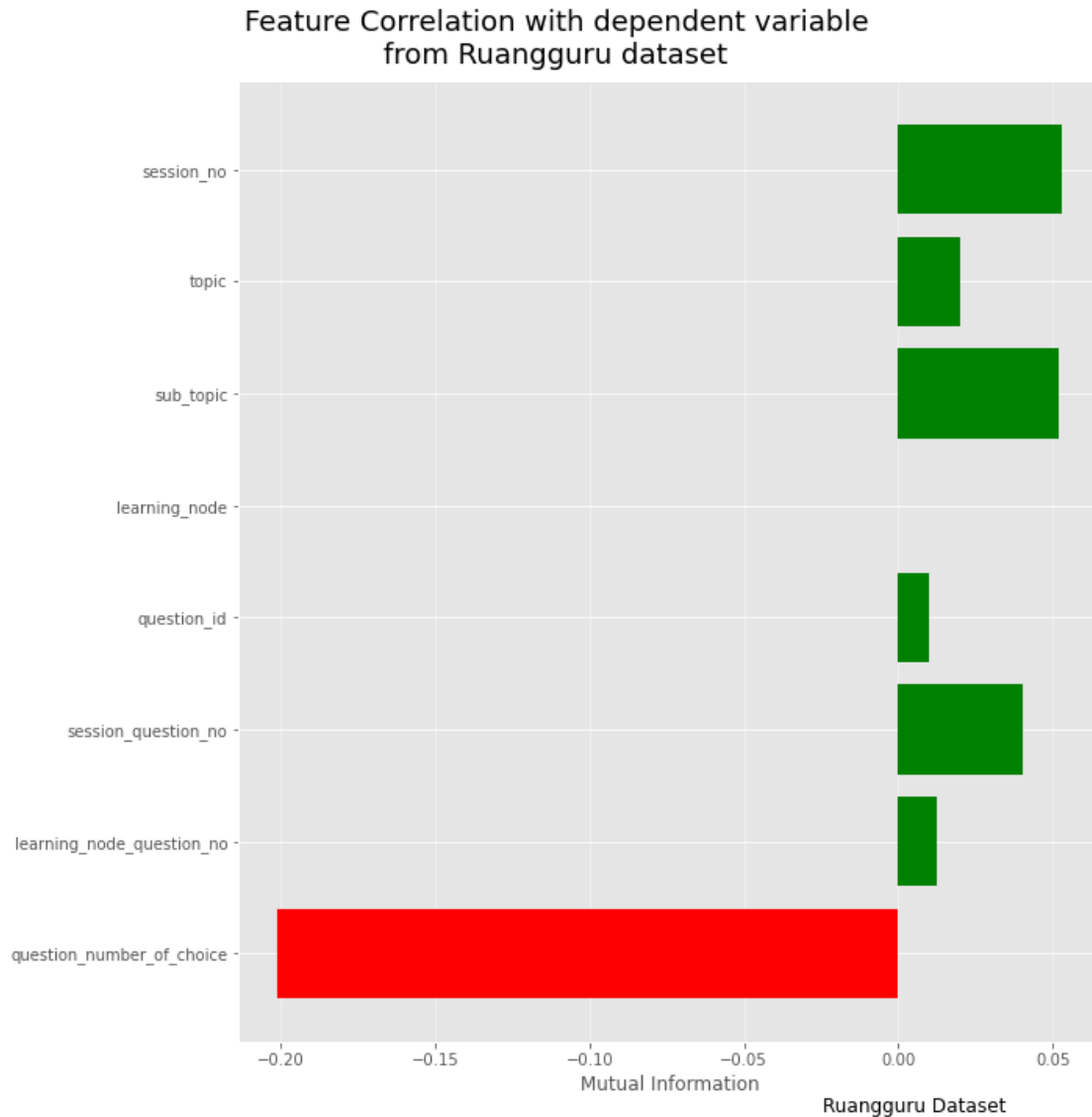
```
[39]: visual.heatmap_corr(train[col], "pearson",  
                           title="Ruangguru", footnote='Ruangguru Dataset')
```

heatmap plot from Ruangguru dataset



from plot above we found that there is no high corelation between features (more than 0.5). this is good start because be don't need to change those features except all the steps that we have plan before.

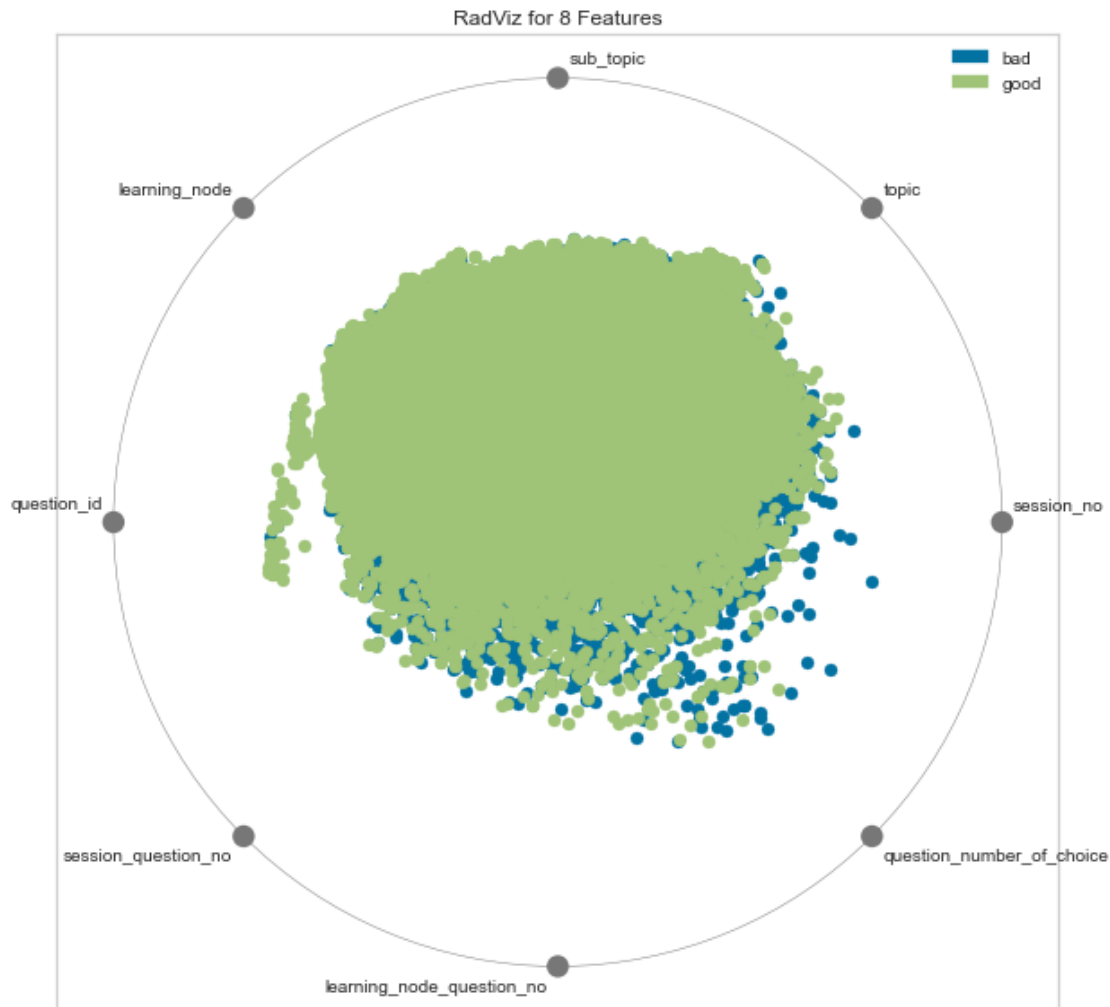
```
[41]: visual.label_corr(train[col], 'is_correct', type_coor="pearson",
                        title="Ruangguru", footnote='Ruangguru Dataset')
```



as we can see we got high correlation at `question_number_of_choice` to label data. we will see this plot again after we have doing some feature engineering to see changing value from this plot.

```
[57]: col = ['session_no', 'topic', 'sub_topic',
            'learning_node', 'question_id', 'session_question_no',
            'learning_node_question_no',
            'question_number_of_choice',
            'is_correct']
```

```
[58]: visual.radviz(train[col], 'is_correct', labels=["bad", "good"])
```

from this plot we can see that we create multivariate data visualization to see how well separability between classes compare with features. as we can see we almost can't to detect separability between classes and maybe it lead to low opportunity to learn from the feature set for prediction.

7 Feature Engineering

7.1 Selected Columns

```
[175]: col = ['session_no', 'topic', 'sub_topic',
              'learning_node', 'question_id', "question_type", 'session_question_no',
              'learning_node_question_no', 'question_difficulty',
              'question_number_of_choice', 'is_correct']
```

```
[176]: train = train[col]
```

```
[177]: describe.describe_data(train)
```

'table size 286886 x 11'

Dataframe has 11 columns.

There are 1 columns that have missing values.

```
[177]:
```

	column_names	Data Type	Missing Values	% missing	low Value	\
0	session_no	float64	0	0.00	1	
1	topic	int64	0	0.00	1952256	
2	sub_topic	int64	0	0.00	1314703	
3	learning_node	int64	0	0.00	4985900	
4	question_id	int64	0	0.00	179554	
5	question_type	object	0	0.00	0	
6	session_question_no	int64	0	0.00	1	
7	learning_node_question_no	int64	0	0.00	1	
8	question_difficulty	object	166513	58.04	0	
9	question_number_of_choice	int64	0	0.00	2	
10	is_correct	float64	0	0.00	0	

	Hi Value	stddev Value	unique
0	1311	164	1311.0
1	9999385357	3013026089	1639.0
2	9993728634	1932006810	2265.0
3	9999782161	2889600192	12093.0
4	9999972554	2921249861	30653.0
5	0	0	3.0
6	44	4	44.0
7	32	1	32.0
8	0	0	4.0
9	6	1	5.0
10	1	0	2.0

7.2 WoE Transform

```
[178]: train,topic_res = fe.encode(train,'topic','woe',  
                                   label_col='is_correct',label=['bad','good'])
```

```
[179]: train,sub_topic_res = fe.encode(train,'sub_topic','woe',  
                                       label_col='is_correct',label=['bad','good'])
```

```
[180]: train,learning_node_res = fe.encode(train,'learning_node','woe',  
                                           label_col='is_correct',label=['bad','good'])
```

```
[181]: train,question_id_res = fe.encode(train,'question_id','woe',  
                                         label_col='is_correct',label=['bad','good'])
```

```
[117]: train = train.drop(columns =  
    ↪ ["topic","sub_topic","learning_node","question_id"])
```

```
[118]: describe.describe_data(train)
```

```
'table size 286886 x 11'
```

```
Dataframe has 11 columns.
```

```
There are 1 columns that have missing values.
```

```
[118]:
```

	column_names	Data Type	Missing Values	% missing	low Value	\
0	session_no	float64	0	0.00	1	
1	question_type	object	0	0.00	0	
2	session_question_no	int64	0	0.00	1	
3	learning_node_question_no	int64	0	0.00	1	
4	question_difficulty	object	166513	58.04	0	
5	question_number_of_choice	int64	0	0.00	2	
6	is_correct	float64	0	0.00	0	
7	topic_WoE_Encode	float64	0	0.00	-9999	
8	sub_topic_WoE_Encode	float64	0	0.00	-9999	
9	learning_node_WoE_Encode	float64	0	0.00	-9999	
10	question_id_WoE_Encode	float64	0	0.00	-9999	

	Hi Value	stddev	Value	unique
0	1311	164	1311.0	
1	0	0	3.0	
2	44	4	44.0	
3	32	1	32.0	
4	0	0	4.0	
5	6	1	5.0	
6	1	0	2.0	
7	14	232	1019.0	
8	14	391	807.0	
9	14	1178	1369.0	
10	14	2145	1125.0	

7.3 Encode Transform

7.3.1 question_difficulty

```
[49]: train['question_difficulty'] = train['question_difficulty'].replace(np.nan,
↳ "None")
```

```
[50]: train['question_difficulty'].unique()
```

```
[50]: array(['medium', 'None', 'easy', 'hard', 'hots'], dtype=object)
```

```
[51]: train = fe.encode(train, ['question_difficulty'], "ohe")
```

```
[52]: train
```

[52]:

	session_no	question_type	session_question_no	\
0	1.0	Single choice	1	
1	1.0	Single choice	2	
2	2.0	Single choice	1	
3	1.0	Single choice	1	
4	2.0	Single choice	1	
...	
286881	56.0	Single choice	9	
286882	56.0	Single choice	10	
286883	57.0	Single choice	1	
286884	57.0	Single choice	2	
286885	57.0	Single choice	3	

	learning_node_question_no	question_number_of_choice	is_correct	\
0	1	4	0.0	
1	2	4	0.0	
2	1	4	1.0	
3	1	4	1.0	
4	1	4	1.0	
...	
286881	1	3	1.0	
286882	2	3	1.0	
286883	1	3	1.0	
286884	1	3	1.0	
286885	1	3	1.0	

	topic_WoE_Encode	sub_topic_WoE_Encode	learning_node_WoE_Encode	\
0	1.284016	1.351203	1.351203	
1	1.284016	1.351203	1.351203	
2	1.284016	1.351203	1.351203	
3	0.285275	0.583146	-0.154151	
4	0.285275	0.729961	0.887303	
...	
286881	1.969312	0.947891	1.951845	
286882	1.969312	0.947891	1.951845	
286883	1.809824	0.947891	4.718499	
286884	1.809824	0.947891	3.601868	
286885	1.809824	0.947891	1.598856	

	question_id_WoE_Encode	question_difficulty_None	\
0	1.306252	0	
1	1.306252	0	
2	1.386294	0	
3	0.405465	0	
4	13.815511	0	
...	
286881	2.622436	1	

286882	2.622436	1
286883	4.718499	1
286884	3.601868	1
286885	1.598856	1

	question_difficulty_easy	question_difficulty_hard \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
...
286881	0	0
286882	0	0
286883	0	0
286884	0	0
286885	0	0

	question_difficulty_hots	question_difficulty_medium
0	0	1
1	0	1
2	0	1
3	0	1
4	0	1
...
286881	0	0
286882	0	0
286883	0	0
286884	0	0
286885	0	0

[286886 rows x 15 columns]

7.3.2 question_type

```
[53]: train['question_type'].unique()

[53]: array(['Single choice', 'Multi choice', 'single choice'], dtype=object)

[54]: train['question_type'] = train['question_type'].replace("single choice", "Single choice")

[55]: train['question_type'].unique()

[55]: array(['Single choice', 'Multi choice'], dtype=object)

[56]: key = [{0.0:"Single choice", 1.0:'Multi choice'}]
```

```
[57]: train,dicts = fe.mapping(train,['question_type'], "def",key)
```

```
[58]: train
```

```
[58]:
```

	session_no	question_type	session_question_no	\
0	1.0	0.0	1	
1	1.0	0.0	2	
2	2.0	0.0	1	
3	1.0	0.0	1	
4	2.0	0.0	1	
...	
286881	56.0	0.0	9	
286882	56.0	0.0	10	
286883	57.0	0.0	1	
286884	57.0	0.0	2	
286885	57.0	0.0	3	

	learning_node_question_no	question_number_of_choice	is_correct	\
0	1	4	0.0	
1	2	4	0.0	
2	1	4	1.0	
3	1	4	1.0	
4	1	4	1.0	
...	
286881	1	3	1.0	
286882	2	3	1.0	
286883	1	3	1.0	
286884	1	3	1.0	
286885	1	3	1.0	

	topic_WoE_Encode	sub_topic_WoE_Encode	learning_node_WoE_Encode	\
0	1.284016	1.351203	1.351203	
1	1.284016	1.351203	1.351203	
2	1.284016	1.351203	1.351203	
3	0.285275	0.583146	-0.154151	
4	0.285275	0.729961	0.887303	
...	
286881	1.969312	0.947891	1.951845	
286882	1.969312	0.947891	1.951845	
286883	1.809824	0.947891	4.718499	
286884	1.809824	0.947891	3.601868	
286885	1.809824	0.947891	1.598856	

	question_id_WoE_Encode	question_difficulty_None	\
0	1.306252	0	
1	1.306252	0	
2	1.386294	0	

3	0.405465	0
4	13.815511	0
...
286881	2.622436	1
286882	2.622436	1
286883	4.718499	1
286884	3.601868	1
286885	1.598856	1

	question_difficulty_easy	question_difficulty_hard \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
...
286881	0	0
286882	0	0
286883	0	0
286884	0	0
286885	0	0

	question_difficulty_hots	question_difficulty_medium
0	0	1
1	0	1
2	0	1
3	0	1
4	0	1
...
286881	0	0
286882	0	0
286883	0	0
286884	0	0
286885	0	0

[286886 rows x 15 columns]

```
[59]: describe.describe_data(train)
```

'table size 286886 x 15'

Dataframe has 15 columns.

There are 0 columns that have missing values.

```
[59]:
```

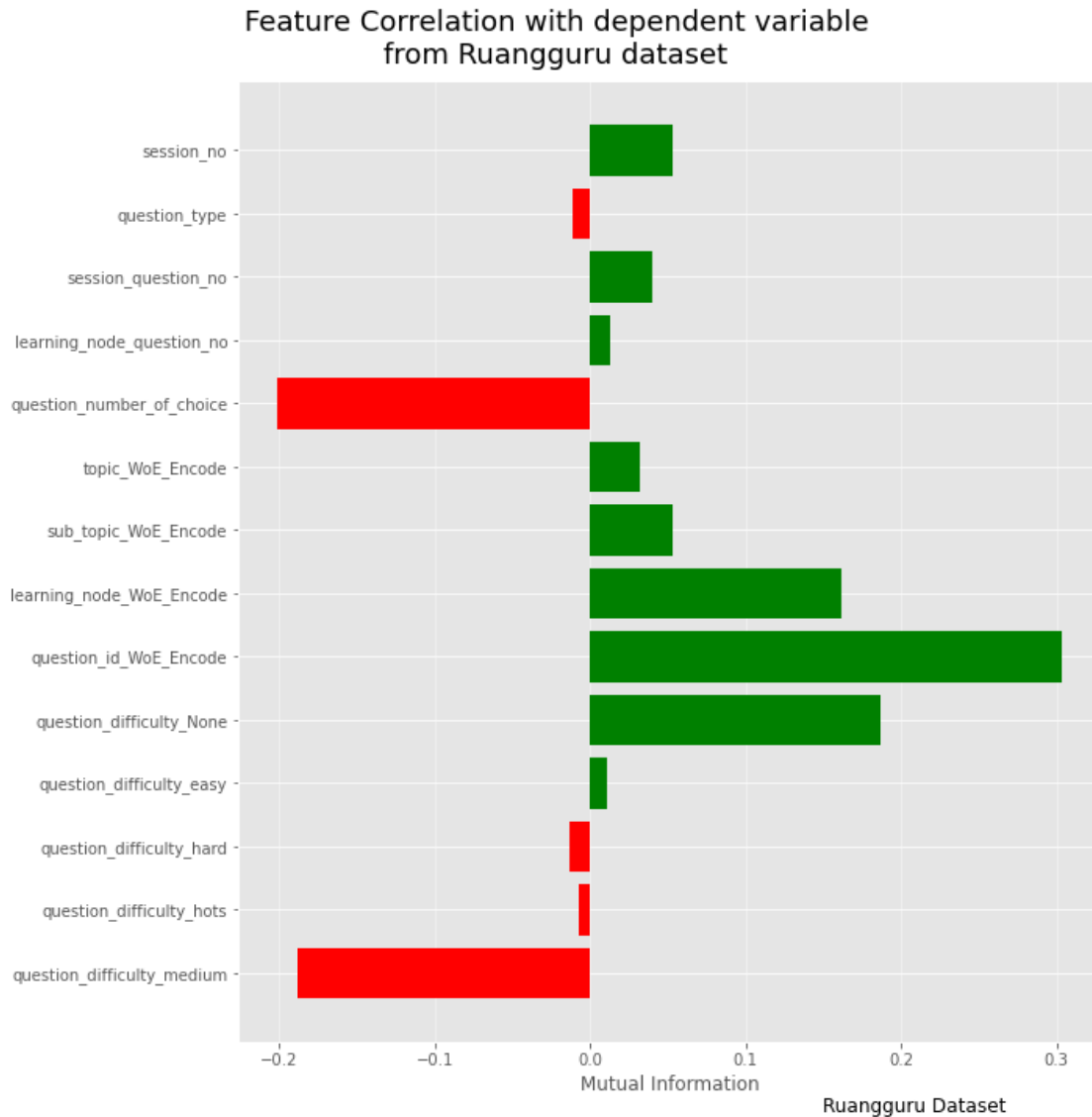
	column_names	Data Type	Missing Values	% missing	low Value \
0	session_no	float64	0	0.0	1
1	question_type	float64	0	0.0	0
2	session_question_no	int64	0	0.0	1

3	learning_node_question_no	int64	0	0.0	1
4	question_number_of_choice	int64	0	0.0	2
5	is_correct	float64	0	0.0	0
6	topic_WoE_Encode	float64	0	0.0	-9999
7	sub_topic_WoE_Encode	float64	0	0.0	-9999
8	learning_node_WoE_Encode	float64	0	0.0	-9999
9	question_id_WoE_Encode	float64	0	0.0	-9999
10	question_difficulty_None	uint8	0	0.0	0
11	question_difficulty_easy	uint8	0	0.0	0
12	question_difficulty_hard	uint8	0	0.0	0
13	question_difficulty_hots	uint8	0	0.0	0
14	question_difficulty_medium	uint8	0	0.0	0

	Hi	Value	stddev	Value	unique
0		1311		164	1311.0
1		1		0	2.0
2		44		4	44.0
3		32		1	32.0
4		6		1	5.0
5		1		0	2.0
6		14		232	1019.0
7		14		391	807.0
8		14		1178	1369.0
9		14		2145	1125.0
10		0		0	2.0
11		0		0	2.0
12		0		0	2.0
13		0		0	2.0
14		0		0	2.0

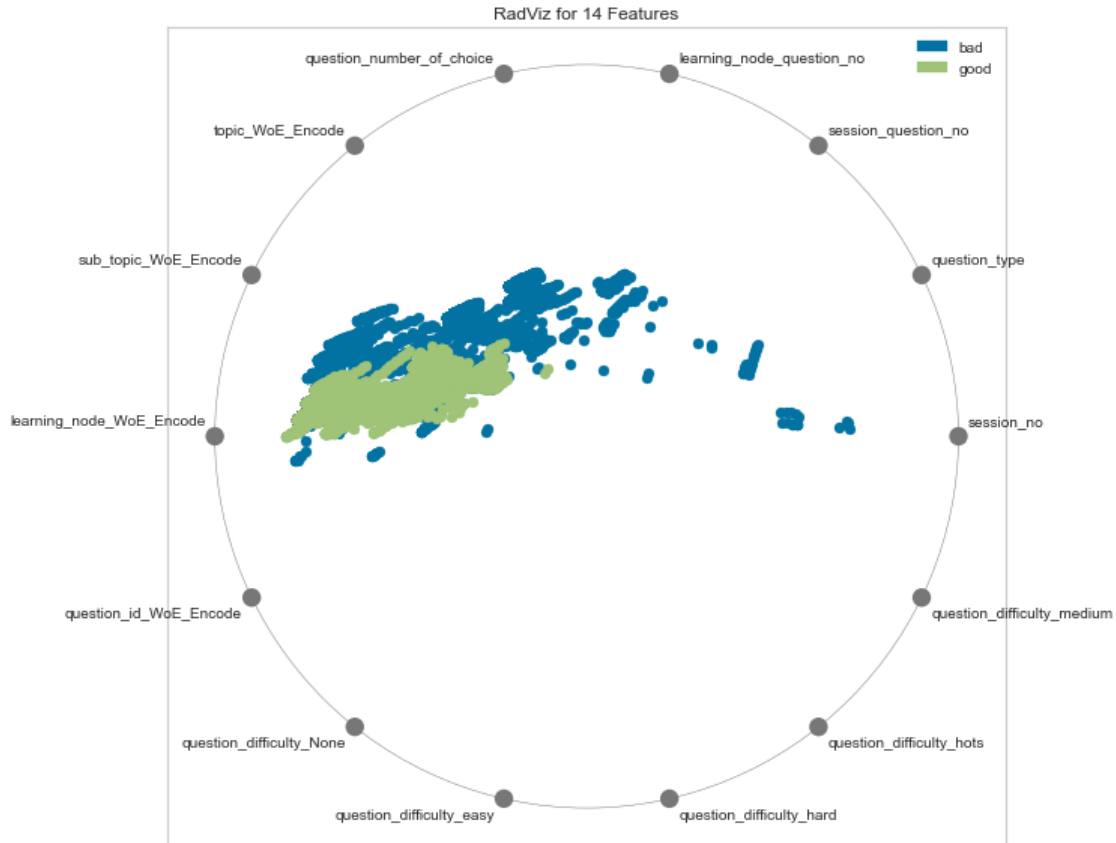
7.3.3 take a look to our relation of our dataset

```
[26]: visual.label_corr(train, 'is_correct', type_corr="pearson",
                        title="Ruangguru", footnote='Ruangguru Dataset')
```

as we can see, we got high positive corellation from `learning_node_WoE_Encode`, `question_id_WoE_Encode` and `question_difficulty_None` and high negative corellation from `question_number_of_choice` and `question_difficulty_medium`

```
[27]: visual.radviz(train, 'is_correct', labels=["bad", "good"])
```

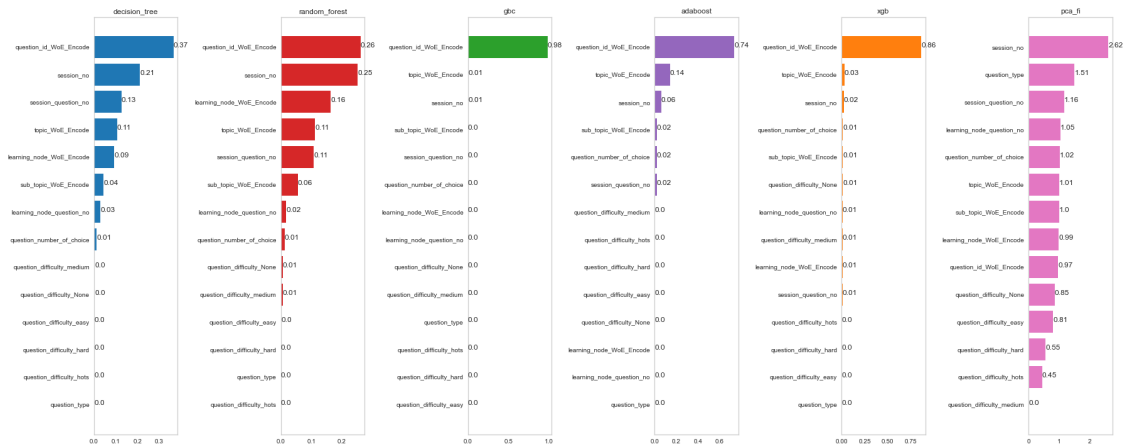


Firstly, from plot above we can see that our dataset has good separability between classes in label. secondly, from this plot we can conclude that we have opportunity to learn from our features set and chance our features just bunch of noise is low.

8 Feature Importance

```
[28]: rest = feature_importance(train, 'is_correct', 20).plot_FI(["all"])
```

```
ursar
feature_importance
```



[31]: rest

[31]:	features	decision_tree	random_forest	gbc	\
0	session_no	0.2116	0.2533	0.0065	
1	question_type	0.0002	0.0002	0.0000	
2	session_question_no	0.1261	0.1087	0.0007	
3	learning_node_question_no	0.0303	0.0178	0.0004	
4	question_number_of_choice	0.0123	0.0123	0.0007	
5	topic_WoE_Encode	0.1056	0.1125	0.0089	
6	sub_topic_WoE_Encode	0.0447	0.0555	0.0013	
7	learning_node_WoE_Encode	0.0936	0.1641	0.0005	
8	question_id_WoE_Encode	0.3662	0.2626	0.9808	
9	question_difficulty_None	0.0033	0.0059	0.0002	
10	question_difficulty_easy	0.0011	0.0007	0.0000	
11	question_difficulty_hard	0.0005	0.0004	0.0000	
12	question_difficulty_hots	0.0003	0.0002	0.0000	
13	question_difficulty_medium	0.0043	0.0059	0.0001	
	adaboost	xgb	pca_fi		
0	0.06	0.0248	2.6186		
1	0.00	0.0000	1.5114		
2	0.02	0.0093	1.1619		
3	0.00	0.0113	1.0511		
4	0.02	0.0134	1.0219		
5	0.14	0.0318	1.0073		
6	0.02	0.0119	1.0020		
7	0.00	0.0105	0.9865		
8	0.74	0.8646	0.9743		
9	0.00	0.0116	0.8550		
10	0.00	0.0000	0.8062		
11	0.00	0.0000	0.5540		

```
12      0.00  0.0000  0.4499
13      0.00  0.0110  0.0000
```

from feature importance above we found that `question_type` has low importance value and `question_id_WoE_Encode` has high importance value.

9 Model

9.1 Seperate feature and label set

```
[60]: X = train.drop(["is_correct"], axis=1)
      y = train["is_correct"]
```

9.2 Split data

this process we will split data to become train and validate before we apply our model to test dataset

```
[61]: X_train, X_test, y_train, y_test = train_test_split(X,y,
                                                         test_size = 0.2,
                                                         random_state=None)
```

```
[62]: print('X_train size shape= {0}'.format(X_train.shape))
      print('X_test size shape= {0}'.format(X_test.shape))
      print('y_train size shape= {0}'.format(y_train.shape))
      print('y_test size shape= {0}'.format(y_test.shape))
```

```
X_train size shape= (229508, 14)
X_test size shape= (57378, 14)
y_train size shape= (229508,)
y_test size shape= (57378,)
```

9.3 Train the dataset with 5 fold and hyperparameter default

```
[63]: result,proba = model.cv_model_train(X_train.to_numpy(), y_train.to_numpy(),
                                           ['random_forest',"adaboost","gb","xgb",'naive_bayes','lr'],5)
```

```
Finished training for model:
Random Forest
Ada Boosting
Gradient Boosting
Extra Gradient Boosting
Logistic Regression
Naive Bayes
```

```
[64]: result
```

```
[64]:
```

	Method	accuracy	accuracy_std	balanced_acc \
0	Gradient Boosting	0.7537	0.0028	0.7032

1	Extra Gradient Boosting	0.7536	0.0012	0.7027
2	Logistic Regression	0.7520	0.0017	0.7016
3	Ada Boosting	0.7519	0.0020	0.7016
4	Random Forest	0.7195	0.0012	0.6815
5	Naive Bayes	0.6905	0.0032	0.5664

	balanced_acc_std	F1	F1_std	AUC	AUC_std	AUC_ROC	AUC_ROC_std	\
0	0.0032	0.7440	0.0033	0.8906	0.0010	0.8191	0.0011	
1	0.0026	0.7437	0.0019	0.8905	0.0008	0.8189	0.0007	
2	0.0028	0.7423	0.0021	0.8898	0.0015	0.8178	0.0017	
3	0.0044	0.7422	0.0016	0.8895	0.0016	0.8173	0.0017	
4	0.0008	0.7154	0.0012	0.8608	0.0013	0.7778	0.0008	
5	0.0011	0.6040	0.0041	0.7305	0.0019	0.6300	0.0013	

	Recall	Recall_std	Precision	Precision_std	Fit Time	Pred Time
0	0.8785	0.0011	0.7711	0.0038	56.2884	0.2936
1	0.8791	0.0046	0.7707	0.0036	11.8784	0.2598
2	0.8762	0.0026	0.7704	0.0022	3.1922	0.1400
3	0.8759	0.0137	0.7705	0.0048	10.4964	0.6622
4	0.8133	0.0015	0.7659	0.0013	40.8637	4.5376
5	0.9964	0.0003	0.6763	0.0033	0.1732	0.1766

From the table above we got high AUC_ROC at Gradient Boosting model

9.4 Hyperparameter Tunning

```
[29]: param_grid = [
      {
          'max_depth': [3,5,10],
          'n_estimators': [60,80,100],
          'learning_rate': [0.1,1,10]
      }
    ]
```

```
[30]: res_gs = tuning.gridsearch(X_train, y_train,param_grid,['gb'],
                                scoring='roc_auc',cv=3)
```

Fitting 3 folds for each of 27 candidates, totalling 81 fits

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done 25 tasks      | elapsed: 4.4min
[Parallel(n_jobs=-1)]: Done 81 out of 81 | elapsed: 14.9min finished
```

Best parameter for gb =

```
learning_rate      :      0.1
max_depth          :      5
n_estimators        :     100
```

9.4.1 apply best param to model

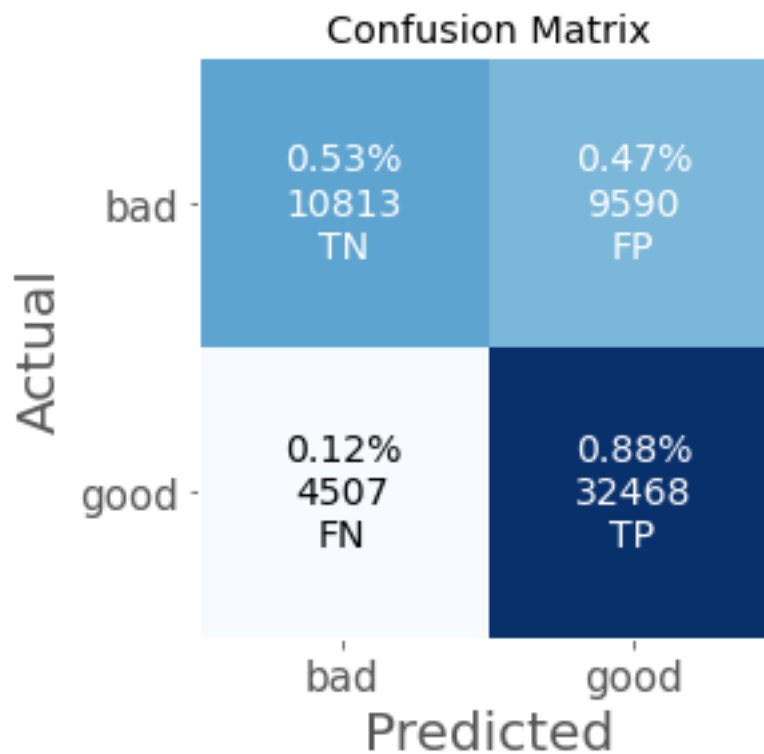
```
[209]: models, names_model, probs_model, probs_bool_model, pred_model, time_1, time_2 =   
        ↪ model.modeling(  
            X_train.to_numpy(), X_test.to_numpy(), y_train.to_numpy(), y_test.  
            ↪ to_numpy(), list_model=['gb'])
```

we have done with these models:

Gradient_boosting_Classifier

```
[210]: scoring.print_score(y_test.to_numpy(), pred_model[0], y_probs=probs_model[0],  
                           types='classification', labels=["bad", "good"],  
                           time1=time_1[0], time2=time_2[0],  
                           X_train=None, y_train=None, X_test=None)
```

```
confusion matrix =  
[[10813  9590]  
 [ 4507 32468]]
```



```
accuracy_score = 0.7543  
balanced_accuracy_score = 0.704
```

```
precision score = 0.772
```

average precision score = 0.7564
 recall score = 0.8781
 Brier score loss (the smaller the better) = 0.1609

 F1 score = 0.8216
 F2 score = 0.8546
 F3 score = 0.8662
 F_beta score (0.5) = 0.7911
 Matthews Correlation Coefficient score = 0.4416

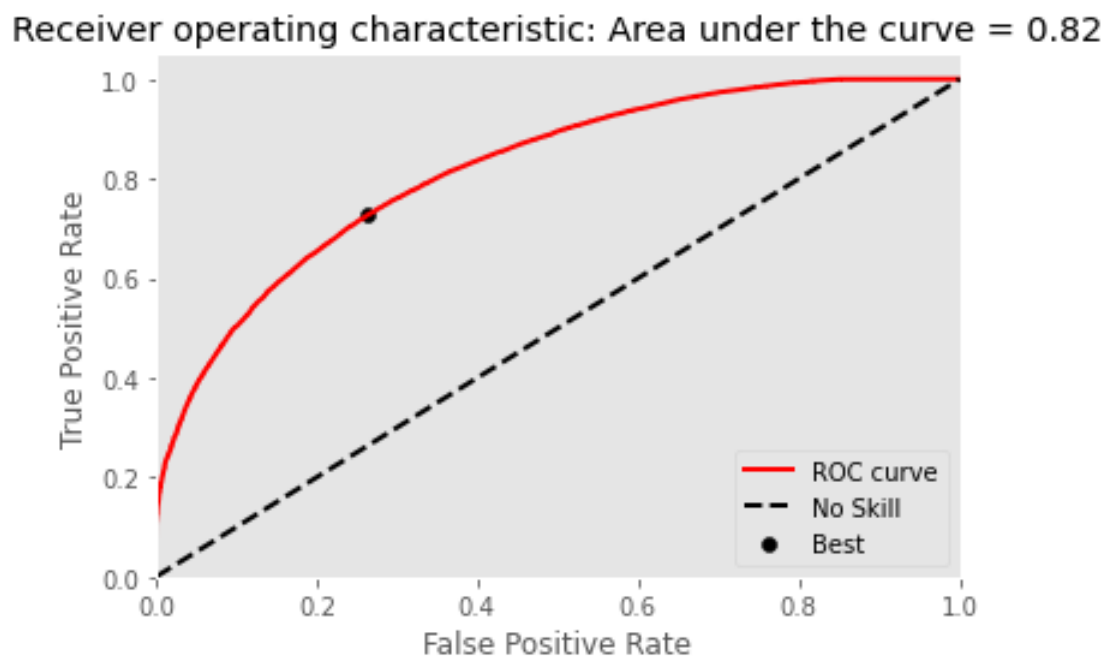
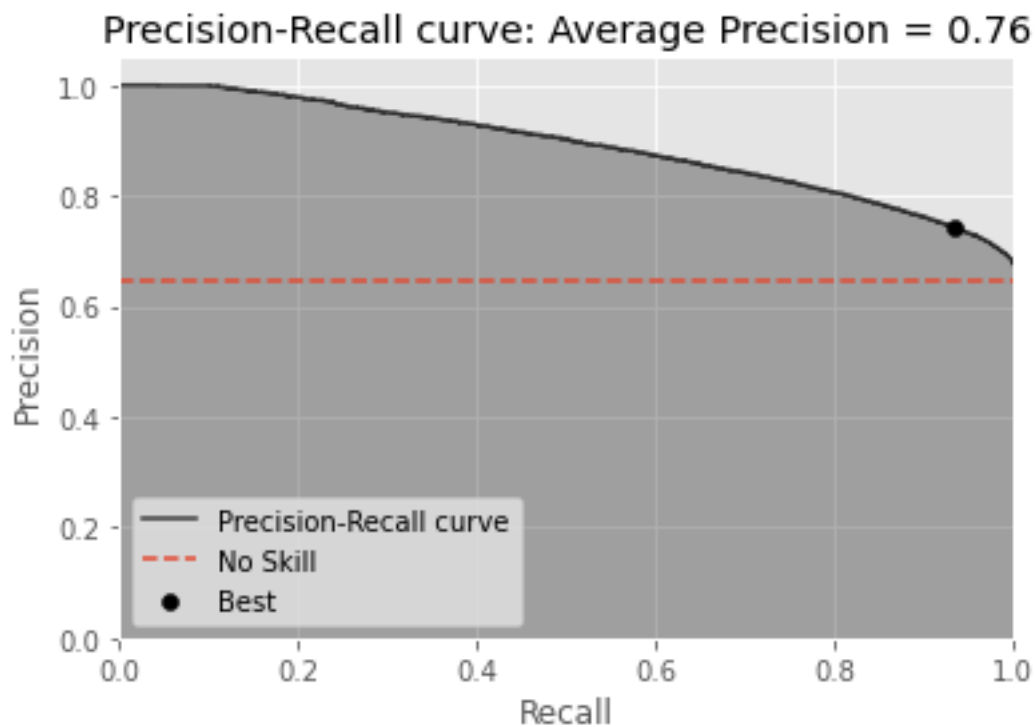
 AUC of Precision-Recall Curve on Testing = 0.8893
 Best Threshold for Precision-Recall Curve = 0.426100
 F-Score = 0.828
 AUC of ROC = 0.8183

 Best Threshold for ROC = 0.636000
 G-Mean = 0.732
 Best Threshold with Youden's J statistic = 0.636000

 Cohens kappa = 0.4322
 Gini = 0.7786

 Expected Approval Rate = 0.733
 Expected Default Rate = 0.228

classification_report				
	precision	recall	f1-score	support
0.0	0.71	0.53	0.61	20403
1.0	0.77	0.88	0.82	36975
accuracy			0.75	57378
macro avg	0.74	0.70	0.71	57378
weighted avg	0.75	0.75	0.74	57378



time span= 0:00:42.855037

from steps above we got some results: AUC of ROC = 0.8191 for training data with Gradient Boosting model we use these parameters from hyperparameter tuning process: learning rate : 0.1 max depth : 5 n_estimators : 100 AUC of ROC = 0.8183 for validate data

10 Using Test dataset

10.1 Feature engineering for test dataset

```
[182]: col = ['session_no', 'topic', 'sub_topic',
            'learning_node', 'question_id', "question_type", 'session_question_no',
            'learning_node_question_no', 'question_difficulty',
            'question_number_of_choice']

[183]: test = test[col]

[184]: for i in test[~test['topic'].isin(train['topic'])]["topic"].values:
        topic_res = topic_res.append(pd.Series([0], index=[i]))

[185]: for i in test[~test['sub_topic'].isin(train['sub_topic'])]["sub_topic"].values:
        sub_topic_res = sub_topic_res.append(pd.Series([0], index=[i]))

[186]: for i in test[~test['question_id'].isin(train['question_id'])]["question_id"].
        ↪values:
        question_id_res = question_id_res.append(pd.Series([0], index=[i]))

[187]: for i in test[~test['learning_node'].
        ↪isin(train['learning_node'])]["learning_node"].values:
        learning_node_res = learning_node_res.append(pd.Series([0], index=[i]))

[189]: learning_node_res = learning_node_res.groupby(learning_node_res.index).first()
        question_id_res = question_id_res.groupby(question_id_res.index).first()

[190]: test.loc[:, 'topic_WoE_Encode'] = test['topic'].map(topic_res)
        test.loc[:, 'sub_topic_WoE_Encode'] = test['sub_topic'].map(sub_topic_res)
        test.loc[:, 'learning_node_WoE_Encode'] = test['learning_node'].
        ↪map(learning_node_res)
        test.loc[:, 'question_id_WoE_Encode'] = test['question_id'].map(question_id_res)

[191]: test = test.drop(columns = ["topic", 'sub_topic', 'learning_node', 'question_id'])

[192]: test['question_difficulty'] = test['question_difficulty'].replace(np.nan,
        ↪"None")
        test = fe.encode(test, ['question_difficulty'], "ohe")

[193]: test['question_type'].unique()

[193]: array(['Single choice', 'Multi choice'], dtype=object)
```

```
[194]: key = [{0.0:"Single choice", 1.0:'Multi choice'}]
test,dicts = fe.mapping(test,['question_type'], "def",key)
```

```
[195]: test
```

```
[195]:      session_no  question_type  session_question_no  \
0           2.0           0.0           2
1          11.0           0.0           6
2           4.0           0.0           8
3          10.0           0.0           7
4           3.0           0.0           9
...         ...           ...           ...
6995         18.0           0.0           1
6996          1.0           0.0           6
6997          6.0           0.0          14
6998          4.0           0.0          14
6999         57.0           0.0           4

      learning_node_question_no  question_number_of_choice  topic_WoE_Encode  \
0                2                4          1.284016
1                2                4          0.198851
2                2                4          0.173746
3                1                4          0.374049
4                3                4          0.127388
...                 ...                 ...
6995                1                5          0.312490
6996                1                4          0.186251
6997                2                5          0.530628
6998                2                4         -0.201866
6999                1                3          1.809824

      sub_topic_WoE_Encode  learning_node_WoE_Encode  question_id_WoE_Encode  \
0          1.351203          1.351203          1.306252
1         -0.048790          0.538997          1.252763
2          0.947891          0.243346          0.287682
3          0.947891          1.321756          0.451985
4          0.072162          0.451985          0.916291
...                 ...                 ...
6995          0.947891          0.274279         -0.305163
6996         -0.315853         -0.628609        -9999.000000
6997         13.815511         13.815511          0.000000
6998          0.000000          1.386294         13.815511
6999          0.947891          0.603916          0.603916

      question_difficulty_None  question_difficulty_easy  \
0                0                0
1                0                0
```

2	1	0
3	1	0
4	0	0
...
6995	1	0
6996	0	0
6997	0	0
6998	0	0
6999	1	0

	question_difficulty_hard	question_difficulty_hots \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
...
6995	0	0
6996	0	0
6997	0	0
6998	0	0
6999	0	0

	question_difficulty_medium
0	1
1	1
2	0
3	0
4	1
...	...
6995	0
6996	1
6997	1
6998	1
6999	0

[7000 rows x 14 columns]

```
[196]: describe.describe_data(test)
```

'table size 7000 x 14'

Dataframe has 14 columns.

There are 0 columns that have missing values.

```
[196]:
```

	column_names	Data Type	Missing Values	% missing	low Value	\
0	session_no	float64	0	0.0	1	
1	question_type	float64	0	0.0	0	

2	session_question_no	int64	0	0.0	1
3	learning_node_question_no	int64	0	0.0	1
4	question_number_of_choice	int64	0	0.0	2
5	topic_WoE_Encode	float64	0	0.0	-9999
6	sub_topic_WoE_Encode	float64	0	0.0	-9999
7	learning_node_WoE_Encode	float64	0	0.0	-9999
8	question_id_WoE_Encode	float64	0	0.0	-9999
9	question_difficulty_None	uint8	0	0.0	0
10	question_difficulty_easy	uint8	0	0.0	0
11	question_difficulty_hard	uint8	0	0.0	0
12	question_difficulty_hots	uint8	0	0.0	0
13	question_difficulty_medium	uint8	0	0.0	0

	Hi Value	stddev	Value	unique
0	1311	30	116.0	
1	1	0	2.0	
2	45	5	27.0	
3	33	1	9.0	
4	5	1	4.0	
5	14	585	851.0	
6	14	597	702.0	
7	14	1718	1138.0	
8	14	2634	872.0	
9	0	0	2.0	
10	0	0	2.0	
11	0	0	2.0	
12	0	0	2.0	
13	0	0	2.0	

10.2 apply model to test dataset

```
[197]: y_probs_test = models[0].predict_proba(test)[: , 1]
```

```
[200]: y_probs_test = pd.Series(y_probs_test)
```

10.3 create submission file

```
[206]: y_probs_test.to_csv( 'submission.  
→csv',index=True,index_label=['row_id'],header=['is_correct'])
```

11 Notes

this result is far from the best result and we can improve at some process, such as:

1. if we got correct value for “topic”, ‘sub_topic’, ‘learning_node’, ‘question_id’ there is probability to get better result.

2. Other supporting features can also be added (that need to be consulted back to the experts) to improve the generalization of the model
3. using more feature engineering to get more detail dataset.
4. I've done smote and near miss process but the result is lower than what we have in this result.
5. try to find the best value for hyperparameter and more wider value to get better result and dont stuck in the local optimum / minimum
6. try to use other hyperparameter tuning such as nature inspired algorithms (although the process will be longer)

[]: