Assignment: DT

Please check below video before attempting this assignment

```
In [1]:
         from IPython.display import YouTubeVideo
         YouTubeVideo('ZhLXULFjIjQ', width="1000",height="500")
Out[1]:
```

TF-IDFW2V

```
Tfidf w2v (w1,w2...) = (tfidf(w1) * w2v(w1) + tfidf(w2) * w2v(w2) + ...) / (tfidf(w1) + tfidf(w2) + ...)
```

(Optional) Please check course video on AVgw2V and TF-IDFW2V for more details.

Glove vectors

In this assignment you will be working with glove vectors , please check [this] (https://en.wikipedia.org/wiki/GloVe_(machine_learning)) and [this] (https://en.wikipedia.org/wiki/GloVe_(machine_learning)) for more details.

Download glove vectors from this link

```
In [2]:
         #please use below code to load glove vectors
         import pickle
         with open('glove_vectors', 'rb') as f:
             model = pickle.load(f)
             glove_words = set(model.keys())
```

```
or else, you can use below code
# Reading glove vectors in python: https://stackoverflow.com/a/38230349/4084039
def loadGloveModel(gloveFile):
    print ("Loading Glove Model")
    f = open(gloveFile,'r', encoding="utf8")
    model = \{\}
    for line in tqdm(f):
        splitLine = line.split()
        word = splitLine[0]
        embedding = np.array([float(val) for val in splitLine[1:]])
        model[word] = embedding
    print ("Done.",len(model)," words loaded!")
```

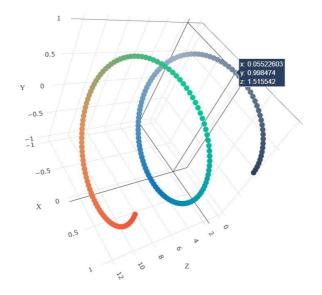
```
return model
model = loadGloveModel('glove.42B.300d.txt')
Output:
Loading Glove Model
1917495it [06:32, 4879.69it/s]
Done. 1917495 words loaded!
# -----
words = []
for i in preproced texts:
   words.extend(i.split(' '))
for i in preproced_titles:
   words.extend(i.split(' '))
print("all the words in the coupus", len(words))
words = set(words)
print("the unique words in the coupus", len(words))
inter_words = set(model.keys()).intersection(words)
print("The number of words that are present in both glove vectors and our coupus", \
      len(inter_words),"(",np.round(len(inter_words)/len(words)*100,3),"%)")
words_courpus = {}
words glove = set(model.keys())
for i in words:
    if i in words_glove:
       words courpus[i] = model[i]
print("word 2 vec length", len(words_courpus))
# stronging variables into pickle files python:
# http://www.jessicayung.com/how-to-use-pickle-to-save-and-load-variables-in-python/
import pickle
with open('glove_vectors', 'wb') as f:
    pickle.dump(words_courpus, f)
```

Task - 1

- 1. Apply Decision Tree Classifier(DecisionTreeClassifier) on these feature sets
 - Set 1: categorical, numerical features + preprocessed_essay (TFIDF) + Sentiment scores(preprocessed_essay)
 - Set 2: categorical, numerical features + preprocessed_essay (TFIDF W2V) + Sentiment scores(preprocessed_essay)
 - The hyper paramter tuning (best

```
depth in range [1, 3, 10, 30], and the best \min_s \ amp \leq s_s plit in range [5, 10, 100, 500])
```

- Find the best hyper parameter which will give the maximum AUC value
- find the best hyper paramter using k-fold cross validation(use gridsearch cv or randomsearch cv)/simple cross validation data(you can write your own for loops refer sample solution)
- Representation of results
 - You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure

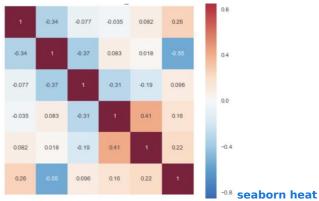


with X-axis as min_sample_split,

Y-axis as max_depth, and Z-axis as AUC Score , we have given the notebook which explains how to plot this 3d plot, you can find it in the same drive 3d_scatter_plot.ipynb



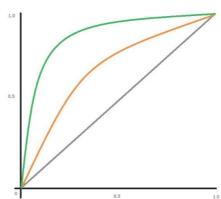
• You need to plot the performance of model both on train data and cross validation data for each



hyper parameter, like shown in the figure

maps with rows as min_sample_split, columns as max_depth, and values inside the cell representing AUC Score

- You choose either of the plotting techniques out of 3d plot or heat map
- Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test. Make sure that you are using predict_proba method to calculate AUC curves, because AUC is calcualted on class



probabilities and not on class labels.

• Along with plotting ROC curve, you need to print the confusion matrix with predicted and

	Predicted: NO	Predicted: YES		
Actual: NO	TN = ??	FP = ??		
Actual: YES	FN = ??	TP = ??		

Once after you plot the confusion matrix with the test data, get all the falsepositivedatap fs
 Plot the WordCloud(https://www.geeksforgeeks.org/generating-word-cloud-python/) with the words of essay text of these falsepositivedatap fs
 Plot the box plot with the price of these falsepositivedatap fs
 Plot the pdf with the teacher_vmber_of_previously_posted_projects of these

Task - 2

For this task consider set-1 features.

falsepositivedatap \(\psi \)

- Select all the features which are having non-zero feature importance. You can get the feature importance using 'featureimportances` (https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html), discard the all other remaining features and then apply any of the model of you choice i.e. (Dession tree, Logistic Regression, Linear SVM).
- You need to do hyperparameter tuning corresponding to the model you selected and procedure in step 2 and step 3

Note: when you want to find the feature importance make sure you don't use max_depth parameter keep it None.

You need to summarize the results at the end of the notebook, summarize it in the table format <code> </code>

Hint for calculating Sentiment scores

```
In [3]:
         import nltk
         from nltk.sentiment.vader import SentimentIntensityAnalyzer
         # nltk.download('vader_lexicon')
         sid = SentimentIntensityAnalyzer()
         sample_sentence_1='I am happy.'
         ss 1 = sid.polarity scores(sample sentence 1)
         print('sentiment score for sentence 1',ss_1)
         sample_sentence_2='I am sad.'
         ss_2 = sid.polarity_scores(sample_sentence_2)
         print('sentiment score for sentence 2',ss_2)
         sample_sentence_3='I am going to New Delhi tommorow.'
         ss_3 = sid.polarity_scores(sample_sentence_3)
         print('sentiment score for sentence 3',ss_3)
         # neg = sid.polarity_scores(sample_sentence_1)['neg']
         # neu = sid.polarity_scores(sample_sentence_1)['neu']
         # pos = sid.polarity_scores(sample_sentence_1)['pos']
         # comp = sid.polarity_scores(sample_sentence_1)['compound']
         # print(f"'neg': {neg}, 'neu': {neu}, 'pos': {pos}, 'compound': {comp}")
        sentiment score for sentence 1 {'neg': 0.0, 'neu': 0.213, 'pos': 0.787, 'compound': 0.5719}
        sentiment score for sentence 2 {'neg': 0.756, 'neu': 0.244, 'pos': 0.0, 'compound': -0.4767}
```

sentiment score for sentence 3 {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}

Task - 1

1.1 Loading Data

```
In [4]:
         #make sure you are loading atleast 50k datapoints
         #you can work with features of preprocessed data.csv for the assignment.
         import numpy as np
         import pandas as pd
         import seaborn as sns
         import plotly.graph_objs as go
         import matplotlib.pyplot as plt
         import plotly.offline as offline
         from prettytable import PrettyTable
         from tgdm.notebook import tgdm
         from wordcloud import WordCloud
         from scipy.sparse import hstack
         from sklearn.metrics import roc_curve, auc
         from sklearn.preprocessing import Normalizer
         from sklearn.metrics import confusion matrix
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.model_selection import GridSearchCV
         from sklearn.model selection import train test split
         from sklearn.model_selection import RandomizedSearchCV
         from sklearn.feature_extraction.text import TfidfVectorizer
         from sklearn.feature_extraction.text import CountVectorizer
         from nltk.sentiment.vader import SentimentIntensityAnalyzer
         data = pd.read_csv('preprocessed_data.csv', nrows = 50000)
In [5]:
         print(f'Input Data shape : {data.shape[0]} rows and {data.shape[1]} columns/dimentions')
         # print('Column names :', list(data.columns))
        Input Data shape : 50000 rows and 9 columns/dimentions
In [6]:
         # 1. calculate sentiment scores for the essay feature
         # https://www.analyticsvidhya.com/blog/2021/12/different-methods-for-calculating-sentiment-score-of-text/
         #https://github.com/llSourcell/Sentiment_Analysis/blob/master/Sentiment_Analysis.ipynb
         sid = SentimentIntensityAnalyzer()
         negative = []
         neutral = []
         positive = []
         compound = []
```

```
# 1. Catcutate SentIment Scores for the essay reature
# https://www.analyticsvidhya.com/blog/2021/12/different-methods-for-calculating-sentiment-score-of-text/
#https://github.com/llSourcell/Sentiment_Analysis/blob/master/Sentiment_Analysis.ipynb

sid = SentimentIntensityAnalyzer()

negative = []
neutral = []
positive = []
compound = []

print('Shape before adding Sentiment Scores : ', data.shape)

for a in tqdm(data['essay']) :
    neg = sid.polarity_scores(a)['neg']
    neu = sid.polarity_scores(a)['neu']
    pos = sid.polarity_scores(a)['pos']
    comp = sid.polarity_scores(a)['compound']
    negative.append(neg)
    neutral.append(neu)
    positive.append(pos)
    compound.append(comp)

data['negative'] = negative
data['positive'] = positive
data['neutral'] = neutral
data['compound'] = compound

print('Shape after adding Sentiment Scores : ', data.shape)

Shape before adding Sentiment Scores : (50000, 9)
```

Shape after adding Sentiment Scores: (50000, 13)

```
In [7]: # 2. Split your data.
         # https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.drop.html
         y_data = data['project_is_approved'].values
         x_data = data.drop('project_is_approved', axis = 1)
         #using `stratify` on `y_data` to ensure equal spliting
         x_train, x_test, y_train, y_test = train_test_split(x_data, y_data, test_size = 0.3, stratify = y_data)
In [8]:
         # 3. perform tfidf vectorization of text data.
         #3_Reference_Vectorization.ipynb
         tfidf_vectorizor = TfidfVectorizer(min_df = 10, ngram_range = (1,3), max_features = 15000)
         tfidf_vectorizor.fit(x_train['essay'].values)
         x_train_tfidf = tfidf_vectorizor.transform(x_train['essay'].values)
         x_test_tfidf = tfidf_vectorizor.transform(x_test['essay'].values)
         print(f"Shape of matrix before one hot encodig : {x_train.shape} {x_test.shape}")
         print(f"Shape of matrix after one hot encodig : {x_train_tfidf.shape} {x_test_tfidf.shape}")
        Shape of matrix before one hot encodig : (35000, 12) (15000, 12)
        Shape of matrix after one hot encodig : (35000, 15000) (15000, 15000)
In [91:
         # 4. perform tfidf w2v vectorization of text data.
         #3 Reference Vectorization.ipynb
         # Converting a dictionary with word as a key, and the idf as a value
         dictionary = dict(zip(tfidf_vectorizor.get_feature_names(), list(tfidf_vectorizor.idf_)))
         tfidf_words = set(tfidf_vectorizor.get_feature_names())
         tfidf_w2v_x_train = []
         for sentence in tqdm(x_train['essay']):
             vector = np.zeros(300) # as word vectors are of zero length
             tf_idf_weight =0
             for word in sentence.split():
                 if (word in glove_words) and (word in tfidf_words):
                     vec = model[word]
                     tf_idf = dictionary[word]*(sentence.count(word)/len(sentence.split()))
                     vector += (vec * tf_idf)
                     tf_idf_weight += tf_idf
             if tf idf weight != 0:
                 vector /= tf_idf_weight
             tfidf_w2v_x_train.append(vector)
         print(f'x_train TF-IDF-W2V shape is {len(tfidf_w2v_x_train) , len(tfidf_w2v_x_train[0])}')
         tfidf_w2v_x_test = []
         for sentence in tqdm(x_test['essay']):
             vector = np.zeros(300) # as word vectors are of zero length
             tf_idf_weight =0
             for word in sentence.split():
                 if (word in glove_words) and (word in tfidf_words):
                     vec = model[word]
                     tf_idf = dictionary[word]*(sentence.count(word)/len(sentence.split()))
                     vector += (vec * tf_idf)
                     tf_idf_weight += tf_idf
             if tf_idf_weight != 0:
                 vector /= tf_idf_weight
             tfidf_w2v_x_test.append(vector)
         print(f'x test TF-IDF-W2V shape is {len(tfidf w2v x test) , len(tfidf w2v x test[0])}')
        x_train TF-IDF-W2V shape is (35000, 300)
        x_test TF-IDF-W2V shape is (15000, 300)
```

```
'''https://stats.stackexchange.com/a/519081'''
          print('Shape of matrix after one hot encodig :')
          print('(Categorical features)')
          print('='*40)
           # school state
          school_state_vector = CountVectorizer(binary=True)
          school_state_vector.fit(x_train['school_state'].values)
          x_train_school_state = school_state_vector.transform(x_train['school_state'].values)
          x_test_school_state = school_state_vector.transform(x_test['school_state'].values)
          print('School State\t\t: ',x train school state.shape,',',x test school state.shape)
          # print(school state vector.get feature names()) # Code to printfeature names alone
           # teacher_prefix
          teacher_prefix_vector = CountVectorizer(binary=True)
           teacher_prefix_vector.fit(x_train['teacher_prefix'].values)
          x train_teacher_prefix = teacher_prefix_vector.transform(x_train['teacher_prefix'].values)
          x_test_teacher_prefix = teacher_prefix_vector.transform(x_test['teacher_prefix'].values)
          print('Teacher Prefix\t\t: ', x_train_teacher_prefix.shape,',',x_test_teacher_prefix.shape)
          # print(teacher_prefix_vector.get_feature_names()) # Code to printfeature names alone
          # project_grade_category
          project grade vector = CountVectorizer(binary=True)
          project_grade_vector.fit(x_train['project_grade_category'].values)
          x_train_project_grade = project_grade_vector.transform(x_train['project_grade_category'].values)
          x_test_project_grade = project_grade_vector.transform(x_test['project_grade_category'].values)
print('Project Grades\t\t: ', x_train_project_grade.shape,',',x_test_project_grade.shape)
          # print(project_grade_vector.get_feature_names()) # Code to printfeature names alone
          # clean categories
          clean_categories_vector = CountVectorizer(binary=True)
          clean_categories_vector.fit(x_train['clean_categories'].values)
          x_train_clean_categories = clean_categories_vector.transform(x_train['clean_categories'].values)
          x_test_clean_categories = clean_categories_vector.transform(x_test['clean_categories'].values)
          print( Project Categories\t: ', x train clean categories.shape, ', ', x test clean categories.shape)
          # print(clean_categories_vector.get_feature_names()) # Code to printfeature names alone
          # clean_subcategories
          clean subcategories vector = CountVectorizer(binary=True)
          clean_subcategories_vector.fit(x_train['clean_subcategories'].values)
          x_train_clean_subcategories = clean_subcategories_vector.transform(x_train['clean_subcategories'].values)
          x_test_clean_subcategories = clean_subcategories_vector.transform(x_test['clean_subcategories'].values)
          print('Project Subcategories\t: ', x_train_clean_subcategories.shape,',',x_test_clean_subcategories.shape)
          Shape of matrix after one hot encodig :
          (Categorical features)
          ______
                           : (35000, 51) , (15000, 51)
          School State
         Teacher Prefix : (35000, 5), (15000, 5)
Project Grades : (35000, 4), (15000, 4)
Project Categories : (35000, 9), (15000, 9)
Project Subcategories : (35000, 30), (15000, 30)
In [11]:
          # 6. perform encoding of numerical features
           # since we are giving only a single feature input so array.reshape(-1, 1)
          print('Shape of matrix after encodig :')
print('(Numerical features)')
print('='*40)
          # price
          price_normalizer = Normalizer()
          price_normalizer.fit(x_train['price'].values.reshape(-1, 1))
          x_train_price = price_normalizer.transform(x_train['price'].values.reshape(-1, 1))
          x_test_price = price_normalizer.transform(x_test['price'].values.reshape(-1, 1))
          print('Price\t\t: ', x_train_price.shape,',',x_test_price.shape)
           # teacher_number_of_previously_posted_projects
          pervious project normalizer = Normalizer()
          pervious_project_normalizer.fit(x_train['teacher_number_of_previously_posted_projects'].\
                                            values.reshape(-1, 1))
          x_train_previous_projects = pervious_project_normalizer.transform(
                           x\_train['teacher\_number\_of\_previously\_posted\_projects'].values.reshape(-1,\ 1))
```

In [10]: # 5. perform encoding of categorical features.

```
x_test_previous_projects = pervious_project_normalizer.transform(
                x_test['teacher_number_of_previously_posted_projects'].values.reshape(-1, 1))
print('Previous Projects\t: ', x train previous projects.shape,',',x test previous projects.shape)
# Normalizing Sentiment Scores
# negative
negative_normalizer = Normalizer()
negative normalizer.fit(x train['negative'].values.reshape(-1, 1))
x_train_negative = negative_normalizer.transform(x_train['negative'].values.reshape(-1, 1))
x_test_negative = negative_normalizer.transform(x_test['negative'].values.reshape(-1, 1))
print('Negative\t\t: ', x_train_negative.shape,',',x_test_negative.shape)
# neutral
neutral_normalizer = Normalizer()
neutral normalizer.fit(x train['neutral'].values.reshape(-1, 1))
x_train_neutral = neutral_normalizer.transform(x_train['neutral'].values.reshape(-1, 1))
x_test_neutral = neutral_normalizer.transform(x_test['neutral'].values.reshape(-1, 1))
print('Neutral\t\t: ', x_train_neutral.shape,',',x_test_neutral.shape)
# positive
positive_normalizer = Normalizer()
positive_normalizer.fit(x_train['positive'].values.reshape(-1, 1))
x_train_positive = positive_normalizer.transform(x_train['price'].values.reshape(-1, 1))
x_test_positive = positive_normalizer.transform(x_test['price'].values.reshape(-1, 1))
print('Positive\t\t: ', x_train_positive.shape,',',x_test_positive.shape)
# compound
compound_normalizer = Normalizer()
compound_normalizer.fit(x_train['compound'].values.reshape(-1, 1))
x\_train\_price = compound\_normalizer.transform(x\_train['compound'].values.reshape(-1, 1))
x_test_price = compound_normalizer.transform(x_test['compound'].values.reshape(-1, 1))
print('Compound\t\t: ', x_train_price.shape,',',x_test_price.shape)
Shape of matrix after encodig:
(Numerical features)
_____
Price
                      : (35000, 1) , (15000, 1)
Previous Projects : (35000, 1) , (15000, 1)
Negative : (35000, 1) , (15000, 1)
Negative
                      : (35000, 1) , (15000, 1)
Neutral
                      : (35000, 1) , (15000, 1)
Positive
                      : (35000, 1) , (15000, 1)
Compound
```

Set 1

```
In [12]:
          # 7. For task 1 set 1 stack up all the features
          # Stack up all the features using hstack() (TFIDF)
          When should I use hstack/vstack vs append vs concatenate vs column stack? :
                                                         https://stackoverflow.com/a/65470570
          Concatenate sparse matrices in Python using SciPy/Numpy:
                                                         https://stackoverflow.com/a/19710648/4084039
          Using `numpy.hstack` or `numpy.vstack` will create an array with two sparse matrix objects
          > scipy.sparse.hstack is also creating Stack sparse matrices horizontally (column wise)
          tfidf_x_train_stack = hstack((x_train_school_state, x_train_teacher_prefix, x_train_project_grade,
                                        x_train_clean_categories, x_train_clean_subcategories, x_train_price,
                                        x train previous_projects, x_train_tfidf, x_train_negative,
                                       x_train_neutral, x_train_positive, x_train_price, )).tocsr()
          tfidf_x_test_stack = hstack((x_test_school_state, x_test_teacher_prefix, x_test_project_grade,
                                         {\tt x\_test\_clean\_categories,\ x\_test\_clean\_subcategories,\ x\_test\_price,}
                                         x_test_previous_projects, x_test_tfidf, x_test_negative, x_test_neutral,
                                         x_test_positive, x_test_price)).tocsr()
          print('TFIDF stack train shape\t: ', tfidf_x_train_stack.shape)
print('TFIDF stack test shape\t: ', tfidf_x_test_stack.shape)
         TFIDF stack train shape: (35000, 15105)
         TFIDF stack test shape : (15000, 15105)
```

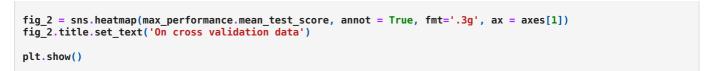
```
# 8. For task 1 set 2 stack up all the features (for stacking dense features you can use np.stack)
          # Stack up all the features using hstack() (TFIDF W2V)
           tfidf w2v x train stack = hstack((x train school state, x train teacher prefix, x train project grade,
                                        x_train_clean_categories, x_train_clean_subcategories, x_train_price,
                                        x_train_previous_projects, tfidf_w2v_x_train, x_train_negative,
                                       x_train_neutral, x_train_positive, x_train_price, )).tocsr()
          tfidf_w2v_x_test_stack = hstack((x_test_school_state, x_test_teacher_prefix, x_test_project_grade,
                                         x_test_clean_categories, x_test_clean_subcategories, x_test_price,
                                         x_test_previous_projects, tfidf_w2v_x_test, x_test_negative, x_test_neutral,
                                         x_test_positive, x_test_price)).tocsr()
          print('TFIDF-W2V stack train shape\t: ', tfidf_w2v_x_train_stack.shape)
print('TFIDF-W2V stack test shape\t: ', tfidf_w2v_x_test_stack.shape)
          TFIDF-W2V stack train shape : (35000, 405)
                                          : (15000, 405)
          TFIDF-W2V stack test shape
In [14]:
          # 9. Perform hyperparameter tuning and plot either heatmap or 3d plot.
          dt C = DecisionTreeClassifier()
          parameters= {'max_depth' : [1, 3, 10, 30], 'min_samples_split' : [5, 10, 100, 500]}
          clf = RandomizedSearchCV(dt_C, parameters, cv = 10, scoring = 'roc_auc',
                                     return_train_score = True, n_jobs =-1)
          r_search = clf.fit(tfidf_x_train_stack, y_train)
          best_params_tfidf = r_search.best_params_
          print(f'Best parameters from TF-IDF model : {best params tfidf}')
          tfidf min samp = best params tfidf['min samples split']
          tfidf depth = best params tfidf['max depth']
          data = {'param_max_depth' : r_search.cv_results_['param_max_depth'],
                    param_min_samples_split' : r_search.cv_results_['param_min_samples_split'],
                  'mean_train_score' : r_search.cv_results_['mean_train_score'],
'mean_test_score' : r_search.cv_results_['mean_test_score']}
          performance = pd.DataFrame(data)
          # performance.head()
          Best parameters from TF-IDF model : {'min_samples_split': 10, 'max_depth': 10}
In [15]:
          max_performance = performance.groupby(['param_min_samples_split', 'param_max_depth']).max().unstack()
          max performance
Out[15]:
                                                         mean_train_score
                                                                                                   mean test score
                                                    3
                                                             10
                                                                       30
                                                                                  1
                                                                                            3
                                                                                                     10
                                                                                                                30
                param max depth
                                          1
          param min samples split
                                5 0.521894 0.580248
                                                                     NaN 0.520299 0.569421
                               10 0.521894 0.580248 0.666438 0.801617 0.520299 0.569421 0.605287 0.549868
                             100 0.521894
                                                 NaN
                                                           NaN 0.774019 0.520299
                                                                                          NaN
                                                                                                    NaN 0.574166
                              500
                                       NaN 0.580207
                                                           NaN 0.742849
                                                                               NaN 0.569441
                                                                                                    NaN 0.598792
```

Heat Map

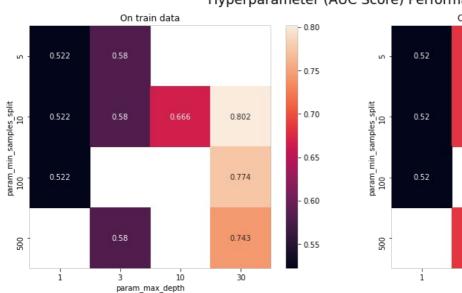
In [13]:

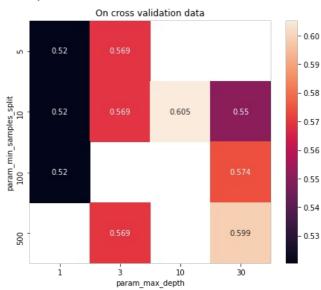
- · You need to plot the performance of model both on train data and cross validation data for each hyper
- Rows as min_sample_split, columns as max_depth, and values inside the cell representing AUC Score

```
In [16]:
          fig, axes = plt.subplots(1, 2, figsize = (16,6))
          fig.suptitle('Hyperparameter (AUC Score) Performance', fontsize = 18)
          # https://stackoverflow.com/a/39133654
          fig_1 = sns.heatmap(max_performance.mean_train_score, annot = True, fmt='.3g', ax = axes[0])
          fig_1.title.set_text('On train data')
```



Hyperparameter (AUC Score) Performance

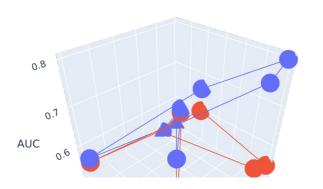




3d plot

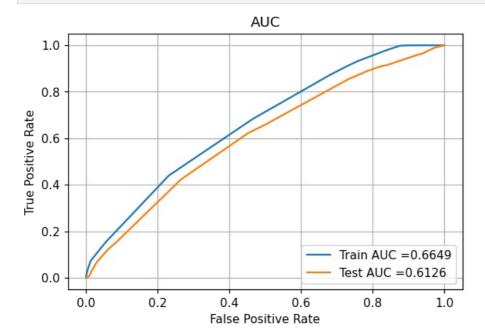
- You need to plot the performance of model both on train data and cross validation data for each hyper parameter
- With X-axis as min_sample_split, Y-axis as max_depth, and Z-axis as AUC Score





--- train
--- Cross validatio

```
In [18]:
          # 10. Find the best parameters and fit the model. Plot ROC-AUC curve(using predict proba method)
          # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc curve.html
          # https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html
          tfidf dt = DecisionTreeClassifier(criterion='gini', max depth = tfidf_depth,
                                                        min_samples_split = tfidf_min_samp)
          tfidf_dt.fit(tfidf_x_train_stack, y_train)
          y_train_tfidf_pred = tfidf_dt.predict_proba(tfidf_x_train_stack)[:,1]
          y_test_tfidf_pred = tfidf_dt.predict_proba(tfidf_x_test_stack)[:,1]
          # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html
          train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_tfidf_pred)
          test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_tfidf_pred)
          auc_train_set1 = auc(train_fpr, train_tpr)
          auc_test_set1 = auc(test_fpr, test_tpr)
          #Reference : DonorchooseNB assignment
          plt.figure(dpi =110)
          plt.plot(train_fpr, train_tpr, label="Train AUC ="+str(round(auc_train_set1,4)))
          plt.plot(test_fpr, test_tpr, label="Test AUC ="+str(round(auc_test_set1,4)))
          plt.xlabel('False Positive Rate')
          plt.ylabel('True Positive Rate')
          plt.title('AUC')
          plt.grid()
          plt.legend(loc=4)
          plt.show()
```



```
In [19]: # 11. Plot confusion matrix based on best threshold value
# Reference DonorchooseNB

def best_threshold_and_y_pred(threshould, proba, fpr, tpr):

    best_t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if fpr is very low and tpr is very high
    print("The maximum value of tpr*(1-fpr)", round(max(tpr*(1-fpr)),5), "for threshold", np.round(best_t,3))

    predictions = []
    for i in tqdm(proba):
```

```
if i >= best t:
          predictions.append(1)
       else:
          predictions.append(0)
    return best_t, predictions
# print('Train')
# print('=' * 5)
# thr_tfidf_tr, predictions_tfidf_tr = best_threshold_and_y_pred(tr_thresholds,
                                                        y_train_tfidf_pred, train_fpr, train_tpr)
# tr confusion mat tfidf = confusion matrix(y train, predictions tfidf tr)
print('\nTest')
print('=' * 4)
thr_tfidf_te, predictions_tfidf_te = best_threshold_and_y_pred(te_thresholds,
                                                         y_test_tfidf_pred, test_fpr, test_tpr)
te_confusion_mat_tfidf = confusion_matrix(y_test, predictions_tfidf_te)
```

Test

The maximum value of tpr*(1-fpr) 0.34117 for threshold 0.845

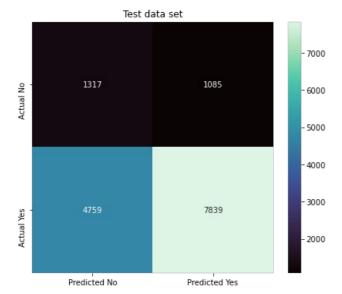
Test confusion matrix : [[1317 1085] [4759 7839]]

```
In [20]: # https://stackoverflow.com/a/61748695
# https://seaborn.pydata.org/tutorial/color_palettes.html
# https://matplotlib.org/stable/gallery/color/colormap_reference.html
# https://matplotlib.org/stable/tutorials/colors/colormaps.html

fig, axes = plt.subplots(figsize = (7,6))
fig.suptitle('Confusion Matrices', fontsize = 18)

fig = sns.heatmap(te_confusion_mat_tfidf, annot=True,fmt="d", cmap='mako')
fig.title.set_text('Test data set')
axes.set_xticklabels(['Predicted No', 'Predicted Yes'])
axes.set_yticklabels(['Actual No', 'Actual Yes'])
plt.show()
```

Confusion Matrices



```
In [21]: # 12. Find all the false positive data points and plot wordcloud of essay text and
# pdf of teacher_number_of_previously_posted_projects.

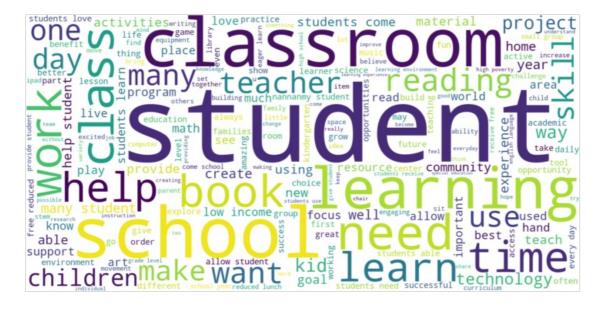
count = 0
fp_index = []

for idx, i in enumerate(tqdm(range(len(y_test)))):
    if y_test[i] == 0 and y_test_tfidf_pred[i] >= thr_tfidf_te :
        fp_index.append(idx)
        count += 1
print(f'No. of Fasle Positive date points : {count}')
```

```
# https://www.geeksforgeeks.org/generating-word-cloud-python/
{\it \# https://amueller.github.io/word\_cloud/generated/wordcloud.WordCloud.html}
word_cloud_words = ''
teacher_previous_posted_projects_fp = []
fp_price = []
for i in fp_index:
    word_cloud_words += x_test.iloc[i]['essay']
    teacher_previous_posted_projects_fp.append(
            x_test.iloc[i]['teacher_number_of_previously_posted_projects'])
    fp_price.append( x_test.iloc[i]['price'])
# https://matplotlib.org/stable/gallery/color/named_colors.html
word_cloud = WordCloud(width = 1600, height = 800,
                background_color ='white', min_font_size = 6).generate(word_cloud_words)
plt.figure(dpi = 120, facecolor = None)
plt.imshow(word_cloud, interpolation='bilinear')
plt.axis('off')
plt.title("Word Cloud on 'Essay' w.r.t False Positive data points\n", c = 'firebrick', size = 14,
         fontfamily = 'monospace')
plt.tight_layout(pad = 0)
plt.show()
```

No. of Fasle Positive date points : 1085

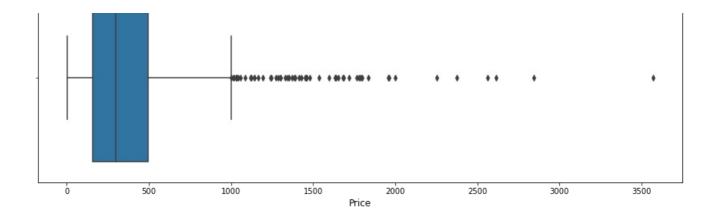
Word Cloud on 'Essay' w.r.t False Positive data points



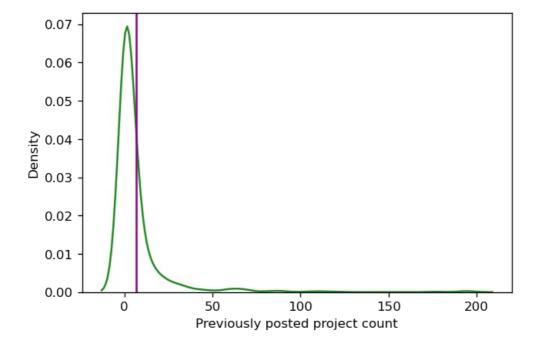
Observation

- From the word cloud it shows the most occured words are 'student', 'classroom', 'school', 'learning' and more.
- All the words are related to only the classroom environment
- The use of jargon or technical words are not common.
- Book and Reading are used more frequently.
- Most words used for the proposal are simple language words

Boxplot of 'price' (on false positive)



Probability Desnity Function: 'teacher_number_of_previously_posted_projects'



Observation

- The mean line (vertical line) is drawn are right side of the plot
- It's a right skewed plot, and most values are between 0 50
- In the teachers mostly submitted project proposales in a range interwel 0 -50
- Most frequent no. of project submission are in between 10 20
- The teachers who sumbitted projects more than 100 are less.
- In range $\,\theta\,$ $\,50$, the curve behaves like a $\,$ normal distribution $\,/\,$ bell curve

Set 2

Best parameters from TF-IDF W2V model : {'min_samples_split': 10, 'max_depth': 10}

```
In [25]:
          max_performance = performance.groupby(['param_min_samples_split', 'param_max_depth']).max().unstack()
          max_performance
Out[25]:
                                                      mean train score
                                                                                            mean test score
               param_max_depth
                                       1
                                                 3
                                                         10
                                                                   30
                                                                             1
                                                                                       3
                                                                                               10
                                                                                                         30
         param_min_samples_split
                              5 0.558538
                                                                 NaN 0.552578
                                              NaN 0.774764
                                                                                    NaN 0.577854
                                     NaN 0.611692 0.772669 0.991640
                                                                           NaN 0.591551 0.579815 0.510554
                             10
                            100
                                     NaN 0.611692
                                                        NaN 0.914616
                                                                           NaN 0.591551
                                                                                              NaN 0.551785
                                                                                    NaN 0.593520 0.589751
                                              NaN 0.713308 0.772543 0.552578
                            500 0.558538
```

Heat Map

- You need to plot the performance of model both on train data and cross validation data for each hyper parameter
- Rows as min_sample_split, columns as max_depth, and values inside the cell representing AUC Score

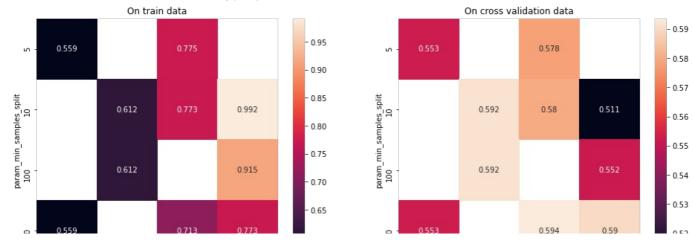
```
fig, axes = plt.subplots(1, 2, figsize = (16,6))
fig.suptitle('Hyperparameter (AUC Score) Performance', fontsize = 18)

# https://stackoverflow.com/a/39133654

fig_1 = sns.heatmap(max_performance.mean_train_score, annot = True, fmt='.3g', ax = axes[0])
fig_1.title.set_text('On train data')

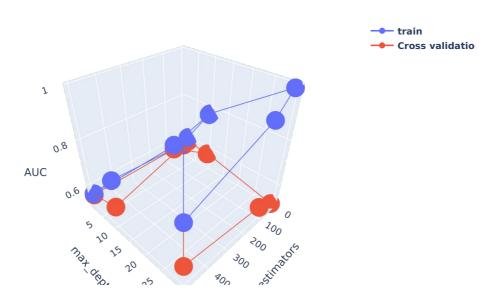
fig_2 = sns.heatmap(max_performance.mean_test_score, annot = True, fmt='.3g', ax = axes[1])
fig_2.title.set_text('On cross validation data')
plt.show()
```





3d plot

- You need to plot the performance of model both on train data and cross validation data for each hyper parameter
- With X-axis as min_sample_split, Y-axis as max_depth, and Z-axis as AUC Score

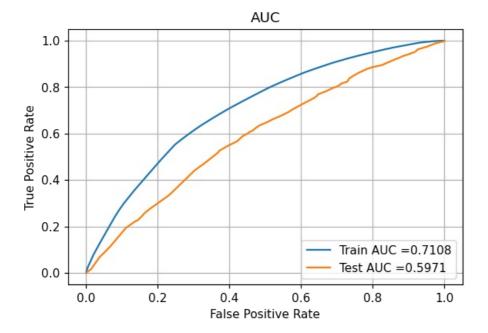


```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_tfidf_w2v_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_tfidf_w2v_pred)

auc_train_set2 = auc(train_fpr, train_tpr)
auc_test_set2 = auc(test_fpr, test_tpr)

#Reference : DonorchooseNB assignment
plt.figure(dpi =110)
plt.plot(train_fpr, train_tpr, label="Train AUC ="+str(round(auc_train_set2,4)))
plt.plot(test_fpr, test_tpr, label="Test AUC ="+str(round(auc_test_set2,4)))

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('AUC')
plt.title('AUC')
plt.legend(loc=4)
plt.show()
```



```
In [29]:
          # 11. Plot confusion matrix based on best threshold value
          # Reference DonorchooseNB
          def best_threshold_and_y_pred(threshould, proba, fpr, tpr):
              best_t = threshould[np.argmax(tpr*(1-fpr))]
              # (tpr*(1-fpr)) will be maximum if fpr is very low and tpr is very high
              print("The maximum value of tpr*(1-fpr)", round(max(tpr*(1-fpr)),5), "for threshold", np.round(best_t,3))
              predictions = []
              for i in tqdm(proba):
                  if i >= best_t:
                      predictions.append(1)
                      predictions.append(0)
              return best_t, predictions
          # print('Train')
          # print('=' * 5)
          # thr_tfidf_w2v_tr, predictions_tfidf_w2v_tr = best_threshold_and_y_pred(tr_thresholds,
                                                                          y_train_tfidf_w2v_pred, train_fpr, train_tpr)
          # tr_confusion_mat_tfidf_w2v = confusion_matrix(y_train, predictions_tfidf_w2v_tr)
          print('\nTest')
print('=' * 4)
          thr_tfidf_w2v_te, predictions_tfidf_w2v_te = best_threshold_and_y_pred(te_thresholds,
                                                                           y_test_tfidf_w2v_pred, test_fpr, test_tpr)
          te_confusion_mat_tfidf_w2v = confusion_matrix(y_test, predictions_tfidf_w2v_te)
          # print('\nTrain confusion matrix : \n', tr_confusion_mat_tfidf_w2v)
          print('\nTest confusion matrix : \n', te_confusion_mat_tfidf_w2v)
```

====
The maximum value of tpr*(1-fpr) 0.3318 for threshold 0.852

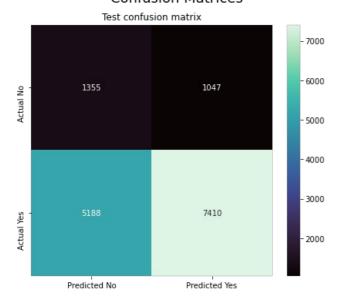
Test

```
# https://stackoverflow.com/a/61748695
# https://seaborn.pydata.org/tutorial/color_palettes.html
# https://matplotlib.org/stable/gallery/color/colormap_reference.html
# https://matplotlib.org/stable/tutorials/colors/colormaps.html

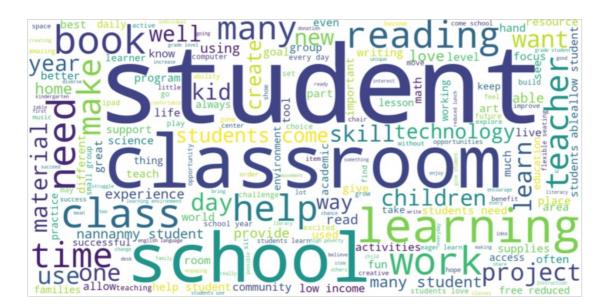
fig, axes = plt.subplots(figsize = (7,6))
fig.suptitle('Confusion Matrices', fontsize = 18)

fig = sns.heatmap(te_confusion_mat_tfidf_w2v, annot=True,fmt="d", cmap='mako')
fig.title.set_text('Test_confusion matrix')
axes.set_text('Test_confusion matrix')
axes.set_xticklabels(['Predicted No', 'Predicted Yes'])
axes.set_yticklabels(['Actual No', 'Actual Yes'])
plt.show()
```

Confusion Matrices



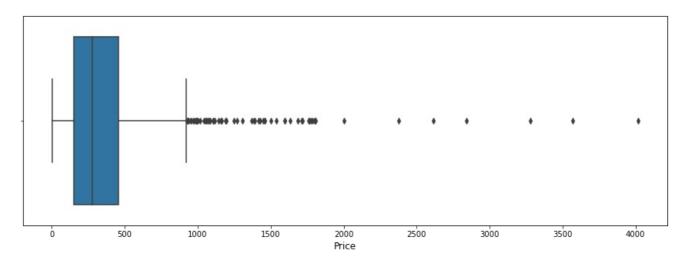
```
In [31]:
          # 12. Find all the false positive data points and plot wordcloud of essay text and
          # pdf of teacher_number_of_previously_posted_projects.
          count = 0
          fp_index = []
          for idx, i in enumerate(tqdm(range(len(y_test)))):
              if y_test[i]== 0 and y_test_tfidf_w2v_pred[i] >= thr_tfidf_w2v_te:
                  fp_index.append(idx)
                  count += 1
          # print(f'No. of Fasle Positive date points : {count}')
          # https://www.geeksforgeeks.org/generating-word-cloud-python/
          # https://amueller.github.io/word_cloud/generated/wordcloud.WordCloud.html
          word_cloud_words = ''
          teacher_previous_posted_project_fp = []
          fp_price = []
          for i in fp_index:
              word_cloud_words += x_test.iloc[i]['essay']
              teacher_previous_posted_project_fp.append(
                      x_test.iloc[i]['teacher_number_of_previously_posted_projects'])
              fp_price.append( x_test.iloc[i]['price'])
          # https://matplotlib.org/stable/gallery/color/named_colors.html
          word_cloud = WordCloud(width = 1600, height = 800,
                          background_color ='white', min_font_size = 6).generate(word_cloud_words)
          plt.figure(dpi = 120, facecolor = None)
          plt.imshow(word_cloud, interpolation='bilinear')
          plt.axis('off')
          plt.title("Word Cloud on 'Essay' w.r.t False Positive data points\n", c = 'firebrick', size = 14,
                   fontfamily = 'monospace')
          plt.tight_layout(pad = 0)
          plt.show()
```



Observation

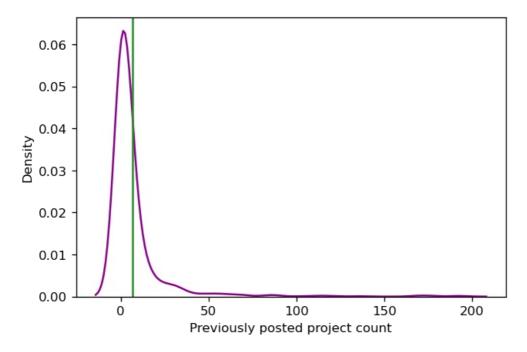
- From the word cloud it shows the most occured words are 'student', 'classroom', 'school', 'time' and more.
- All the words are related to only the classroom environment
- · Skill in here shows the importance of developing skills from the primary education
- The use of technical jargon are not common.
- · Book and Reading used alot.
- Words used for the proposal are simple once.
- Community, projects shows its importance

Boxplot of 'price' (on false positive)



```
plt.xlabel('Previously posted project count')
plt.axvline(mean_proj, c = 'forestgreen')
plt.show()
```

Probability Desnity Function: 'teacher number of previously posted projects'



Observation

- The mean line (vertical line) is drawn are right side of the plot
- It's a right skewed plot, and most values are between 0 50
- In the teachers mostly submitted project proposales in a range interwel 0 -50
- Most frequent no. of project submission are a range of 10.
- The teachers who sumbitted projects more than 100 are less.
- In range 0 50, the curve behaves like a normal distribution / bell curve

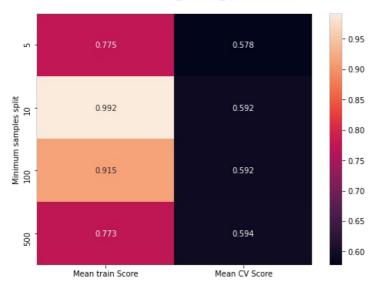
Task - 2

```
In [34]:
          # 1. write your code in following steps for task 2
          # 2. select all non zero features
          imp_features = tfidf_dt.feature_importances_ #Extracting imp. features from set-1
          # 3. Update your dataset i.e. X_train, X_test and X_cv so that it contains all rows and only
              # non zero features
          tfidf_x_train_stack_imp_feat = tfidf_x_train_stack[:, imp_features !=0]
          tfidf_x_test_stack_imp_feat = tfidf_x_test_stack[:, imp_features !=0]
          # print(tfidf_x_train_stack_imp_feat.shape)
          # print(tfidf_x_test_stack_imp_feat.shape)
In [35]:
          # 4. perform hyperparameter tuning and plot either heatmap or 3d plot.
          dt C = DecisionTreeClassifier()
          # 200 , 250 was added to `parameters` list beacuse the model performance was poor on initial
          # `parameters` values
          parameters = {'min_samples_split' : [5, 10, 100,200 , 250, 500]}
          clf = RandomizedSearchCV(dt_C, parameters, cv = 10, scoring = 'roc_auc',
                                   return_train_score = True, n_jobs =-1)
          /home/jishnu/anaconda3/lib/python3.8/site-packages/sklearn/model_selection/_search.py:285:UserWarning:
          The total space of parameters 4 is smaller than n iter=10. Running 4 iterations.
          For exhaustive searches, use GridSearchCV.
```

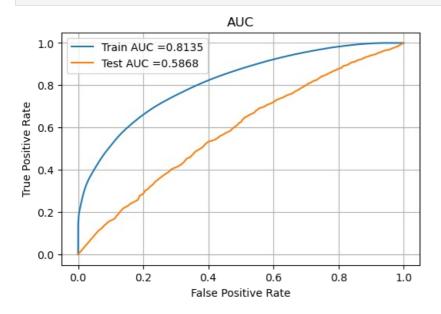
```
clf = GridSearchCV(dt_C, parameters, cv = 15, scoring = 'roc_auc',
                   return_train_score = True, n_jobs = -1)
g_search = clf.fit(tfidf_x_train_stack_imp_feat, y_train)
best_params_tfidf_imp = g_search.best_params_['min_samples_split']
print(f'Best parameters fron non-zero TF-IDF model : {best_params_tfidf_imp}')
# Taking the parameters
data = {'param_min_samples_split' : r_search.cv_results_['param_min_samples_split'],
       'mean_train_score' : r_search.cv_results_['mean_train_score'],
       'mean_test_score' : r_search.cv_results_['mean_test_score']}
df_hyper = pd.DataFrame(data)
df_hyper_gr = df_hyper.groupby(['param_min_samples_split']).max()
# Creating heatmap
fig, axes = plt.subplots(figsize = (8,6))
fig = sns.heatmap(df_hyper_gr, annot = True, fmt='.3g')
plt.title('\nHeat Map : min_samples_split\n')
axes.set_xticklabels(['Mean train Score', 'Mean CV Score'])
plt.ylabel('Minimum samples split')
plt.show()
```

Best parameters from non-zero TF-IDF model : 500





```
In [36]:
          # 5. Fit the best model. Plot ROC AUC curve and confusion matrix similar to model 1.
          final_dt = DecisionTreeClassifier(criterion='gini', min_samples_split = best_params_tfidf_imp)
          final dt.fit(tfidf x train stack imp feat, y train)
          y_train_final_pred = final_dt.predict_proba(tfidf_x_train_stack_imp_feat)[:,1]
          y_test_final_pred = final_dt.predict_proba(tfidf_x_test_stack_imp_feat)[:,1]
          # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html
          train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_final_pred)
          test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_final_pred)
          auc_train_set_f = auc(train_fpr, train_tpr)
          auc_test_set_f = auc(test_fpr, test_tpr)
          #Reference : DonorchooseNB assignment
          plt.figure(dpi =100)
          plt.plot(train_fpr, train_tpr, label="Train AUC ="+str(round(auc_train_set_f,4)))
          plt.plot(test_fpr, test_tpr, label="Test AUC ="+str(round(auc_test_set_f,4)))
          plt.xlabel('False Positive Rate')
          plt.ylabel('True Positive Rate')
          plt.title('AUC')
          plt.grid()
          plt.legend()
          plt.show()
```



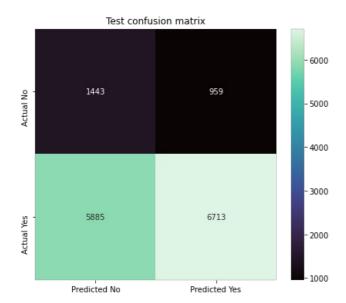
Observation

- The ROC-AUC Curve is not looking good.
- The train and test scores are far from each other.
- · Model behaves like, its over-fitted, because the gap is high
- By removing the zero valued freatures, we improved the train score but not the test score.

	TPR no Train data	TPR on Test data
FPR = ~0.1	~0.5	~0.175
FPR = 0.2	~0.7	~0.3
FPR = 0.6	~0.9	~0.7

https://stats.stackexchange.com/a/389884

```
In [37]:
          def best_threshold_and_y_pred(threshould, proba, fpr, tpr):
               best_t = threshould[np.argmax(tpr*(1-fpr))]
              \# (tpr*(1-fpr)) will be maximum if fpr is very low and tpr is very high
              print("The maximum value of tpr*(1-fpr)", round(max(tpr*(1-fpr)),5), "for threshold", np.round(best_t,3))
              predictions = []
               for i in tqdm(proba):
                   if i >= best_t:
                       predictions.append(1)
                   else:
                      predictions.append(θ)
               return best_t, predictions
          print('\nTest')
          print('=' * 4)
          thr_tfidf_te, predictions_tfidf_te = best_threshold_and_y_pred(te_thresholds,
                                                                            y_test_final_pred, test_fpr, test_tpr)
          te_confusion_mat_final = confusion_matrix(y_test, predictions_tfidf_te)
          print('\nTest confusion matrix : \n', te_confusion_mat_final)
          # https://stackoverflow.com/a/61748695
          fig, axes = plt.subplots(figsize = (7,6))
fig.suptitle('Confusion Matrices', fontsize = 18)
          fig = sns.heatmap(te_confusion_mat_final, annot=True,fmt="d", cmap='mako')
          fig.title.set_text('Test confusion matrix')
          axes.set_xticklabels(['Predicted No', 'Predicted Yes'])
          axes.set_yticklabels(['Actual No', 'Actual Yes'])
          plt.show()
         Test
         The maximum value of tpr*(1-fpr) 0.32012 for threshold 0.886
         Test confusion matrix :
           [[1443 959]
           [5885 6713]]
                          Confusion Matrices
```



Vectorizer	+Model	Hyper Para-min_sample	Hyper Para-max_depth	AUC	(train)	AUC	(test)
TFIDF TFIDF W2V TFIDF	DecisionTreeClassifier	10	10		0.6649	0	.613
	DecisionTreeClassifier	500	10	(0.7108	0	.597
	Non-Zero DT-Classifier	500	sk-learn default	(0.8135	0	.587