`Assignment-5` : Compute performance metrics for the given Y & Y_score w/o sklearn

1. Task-A
2. Task-B
3. Task-C
4. Task-D

In [1]:
```
import numpy as np
import pandas as pd

# Importing visualization libraries for plotting purpose
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

`Task-A`

```
A. Compute performance metrics for the given data 5_a.csv
   Note 1: in this data you can see number of positive points >> number of negatives points
   Note 2: use pandas or numpy to read the data from 5_a.csv
   Note 3: you need to derive the class labels from given score
```

$y^{pred}= \text{[0 if y_score < 0.5 else 1]}$

```
1. Compute Confusion Matrix

2. Compute F1 Score

3. Compute AUC Score, you need to compute different thresholds and
   for each threshold compute tpr,fpr and then use
   numpy.trapz(tpr_array, fpr_array)
   https://stackoverflow.com/q/53603376/4084039,
   https://stackoverflow.com/a/39678975/4084039 Note: it should be
   numpy.trapz(tpr_array, fpr_array) not numpy.trapz(fpr_array,
   tpr_array)

4. Compute Accuracy Score
```

In [2]:
```
task_a_scores = pd.read_csv("5_a.csv").rename(columns={'proba':'y_score'})
task_a_scores.head()
```

Out[2]:

	y	y_score
0	1.0	0.637387
1	1.0	0.635165
2	1.0	0.766586

	y	y_score
3	1.0	0.724564
4	1.0	0.889199

In [3]:
```
task_a_scores.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10100 entries, 0 to 10099
Data columns (total 2 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   y        10100 non-null  float64
 1   y_score  10100 non-null  float64
dtypes: float64(2)
memory usage: 157.9 KB
```

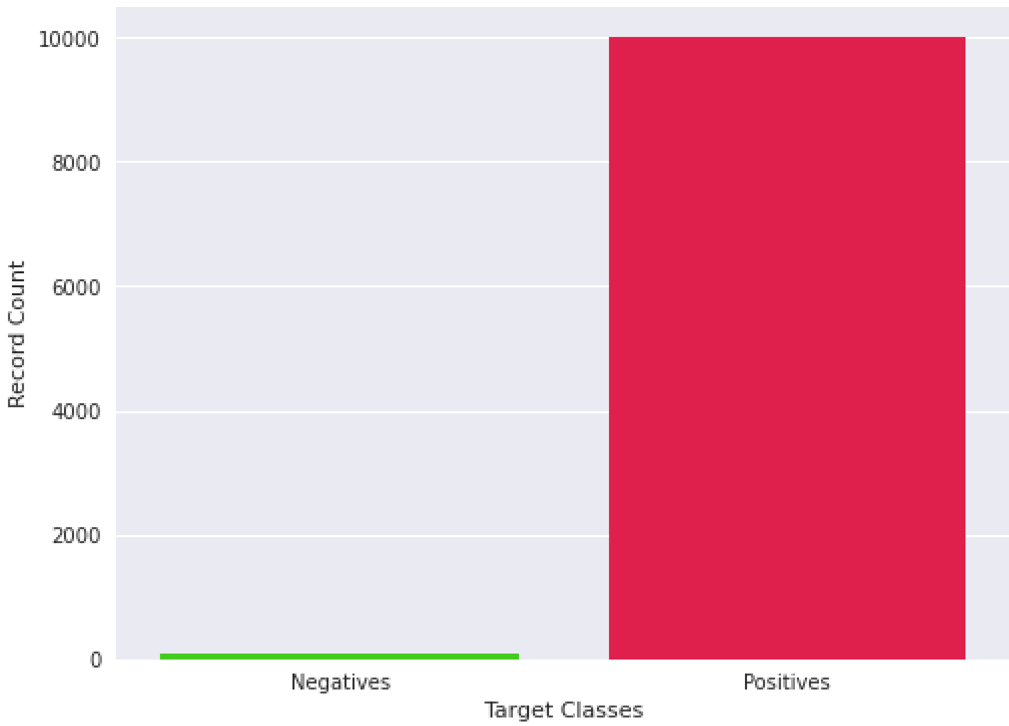
In [4]:
```
tgt_cls_rec_count = pd.DataFrame(task_a_scores['y'].value_counts()).reset_index().re
```

In [5]:
```
tgt_cls_rec_count
```

Out[5]:

	Tgt_Class	Record_Count
0	1.0	10000
1	0.0	100

In [6]:
```
with plt.style.context('seaborn'):
    plt.figure(figsize=(8,6))
    sns.barplot(x='Tgt_Class',y='Record_Count',data=tgt_cls_rec_count,palette='prism
    plt.xticks(ticks=(0,1),labels=('Negatives','Positives'))
    plt.xlabel('Target Classes')
    plt.ylabel('Record Count')
```



In [7]:
```
task_a_scores['y_pred'] = task_a_scores['y_score'].apply(lambda val: 0 if val < 0.5
```

In [8]:
```
y_pred_rec_cnt = pd.DataFrame(task_a_scores['y_pred'].value_counts()).reset_index().
```

In [9]:
```
y_pred_rec_cnt
```

Out[9]:

	y_pred_class	y_pred
0	1	10100

In [10]:
```
task_a_scores
```

Out[10]:

	y	y_score	y_pred
0	1.0	0.637387	1
1	1.0	0.635165	1
2	1.0	0.766586	1
3	1.0	0.724564	1
4	1.0	0.889199	1
...	...	...	...
10095	1.0	0.665371	1
10096	1.0	0.607961	1
10097	1.0	0.777724	1
10098	1.0	0.846036	1
10099	1.0	0.679507	1

10100 rows × 3 columns

In [11]:
```
task_a_scores.groupby(['y','y_pred']).count().reset_index()
```

Out[11]:

	y	y_pred	y_score
0	0.0	1	100
1	1.0	1	10000

In [12]:
```
def conf_mat_f1_scr(df_obj):
    """
    Desciprtion : This function is created for generating the Confusion Matrix and F

    Input Parameters: It accepts only one parameter:
        `df_obj`: Pandas Dataframe
            Dataframe containing the `actual y` named as 'y' and `predicted y` named

    Return: It returns the below performance metrics:
        Confusion Matrix
            [[tns,fns],
             [fps,tps]]
        F1 Score
            (2.0 * prec * recall)/(prec+recall)
        Accuracy Score
            (tps+tns)/(tps+tns+fps+fns)
    """
    tps_flg = []
    tns_flg = []
    fps_flg = []
    fns_flg = []
    temp_df = df_obj[['y','y_pred']].apply(lambda row: tps_flg.append('11') if row['
```

```
                                                tns_flg.append('00') if row['y']==0 and row['y_p
                                                fps_flg.append('01') if row['y']==0 and row['y_p
                                                fns_flg.append('10') if row['y']==1 and row['y_p
    tps = len(tps_flg)                               ## True +ve rate
    tns = len(tns_flg)                               ## True -ve rate
    fps = len(fps_flg)                               ## False +ve rate
    fns = len(fns_flg)                               ## False -ve rate
    conf_mat = np.array([[tns,fns],                  ## Generating Confusion Matrix
                         [fps,tps]])

    prec = np.divide(tps*1.0,(tps+fps))          ## Precision
    recall = np.divide(tps*1.0,(tps+fns))        ## Recall
    f1_scr = np.divide((2.0 * prec * recall),(prec+recall))    ## Calculating F1-Scor
    acc_scr = np.divide((tps+tns)*1.0,(tps+tns+fps+fns))       ## Calculating Accurac
    del temp_df
    return conf_mat, f1_scr, acc_scr
```

In [13]:
```
task_a_conf_mat, task_a_f1_scr, task_a_acc_scr = conf_mat_f1_scr(task_a_scores)
```

In [14]:
```
task_a_conf_mat
```

Out[14]:
```
array([[    0,     0],
       [  100, 10000]])
```

In [15]:
```
task_a_f1_scr
```

Out[15]:
```
0.9950248756218906
```

In [16]:
```
task_a_acc_scr
```

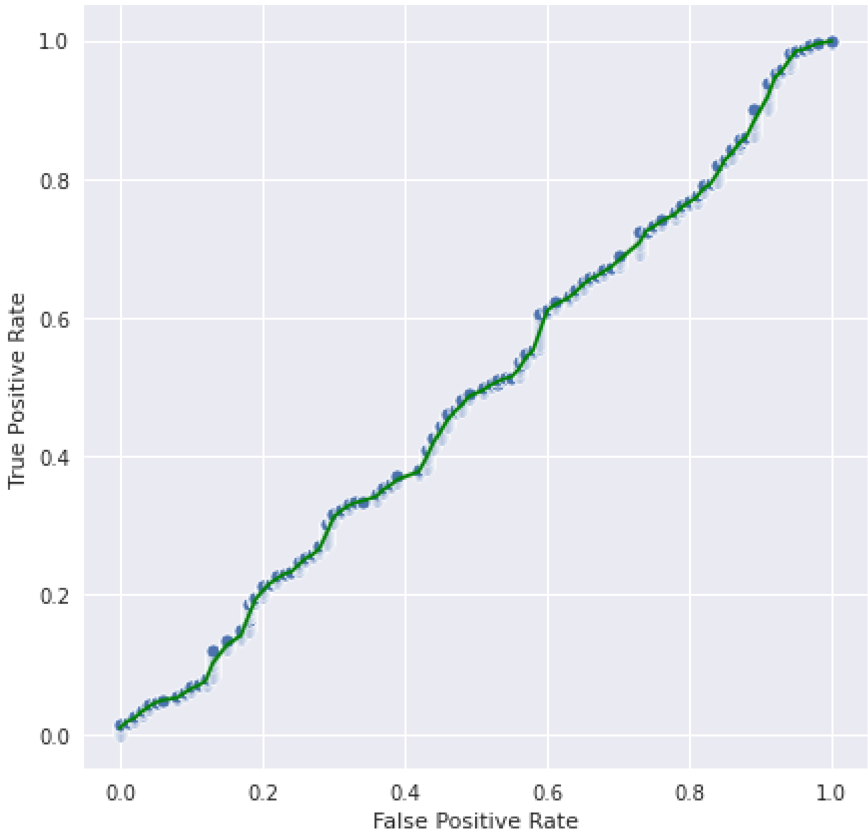
Out[16]:
```
0.9900990099009901
```

In [17]:
```
def roc_auc_scr(df_obj,y_prob_round_flg=3):
    """
    Desciprtion : This function is created for calculating the TPR and FPR based on

    Input Parameters: It accepts only one parameter:
        `df_obj`: Pandas Dataframe
            Dataframe containing the `actual y` named as 'y' and `y proba score` nam

        `y_prob_round_flg`: int
            By default 2. This is just a flag variable for controlling the number of

    Return: It returns the below arrays:
        TPR
        FPR
    """
    tpr_val = []
    fpr_val = []

    th_res_df = df_obj.copy(deep=True)
    # Rounding-off the scores for controlling the number of unique scores
    th_res_df['y_score'] = np.round(th_res_df['y_score'],y_prob_round_flg)
    # Sorting the unique score in descending order
    thres_vals = th_res_df.sort_values(by='y_score',ascending=False)['y_score'].uniq
    # Sorting the df in descending order based on rounded-off scores
    th_res_df.sort_values(by='y_score',ascending=False,ignore_index=True,inplace=Tru

    # Generating the y outcome threshold columns based on threshold value
    for i,th_val in enumerate(thres_vals):
        th_tps = []
        th_tns = []
        th_fps = []
```

```
        th_fns = []
        th_res_df['y_tao'+str(i)] = th_res_df['y_score'].apply(lambda row_val: 1 if
        tmp_tsk2 = th_res_df[['y','y_tao'+str(i)]].apply(lambda row: th_tps.append('
                                                th_tns.append('00') if row['y']==0 and row['
                                                th_fps.append('01') if row['y']==0 and row['
                                                th_fns.append('10') if row['y']==1 and row['
        th_tpr = np.divide(len(th_tps),(len(th_tps)+len(th_fns)))     ## Calculating
        th_fpr = np.divide(len(th_fps),(len(th_fps)+len(th_tns)))     ## Calculating
        tpr_val.append(th_tpr)
        fpr_val.append(th_fpr)

    del th_res_df, tmp_tsk2
    return tpr_val, fpr_val
```

In [18]:
```
tpr_arr, fpr_arr = roc_auc_scr(task_a_scores)
```

In [19]:
```
with plt.style.context('seaborn'):
    plt.figure(figsize=(7,7))
    sns.scatterplot(x=fpr_arr,y=tpr_arr,palette='twilight')
    sns.lineplot(x=fpr_arr,y=tpr_arr,color='green')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
```



In [20]:
```
len(tpr_arr),len(fpr_arr)
```

Out[20]: (401, 401)

In [21]:
```
## AUC Score
np.trapz(tpr_arr,fpr_arr)
```

Out[21]: 0.48827050000000005

Task-B

B. Compute performance metrics for the given data **5_b.csv**
Note 1: in this data you can see number of positive points << number of negatives points
Note 2: use pandas or numpy to read the data from **5_b.csv**
Note 3: you need to derive the class labels from given score

$y^{pred}= \text{[0 if y_score < 0.5 else 1]}$

1. Compute Confusion Matrix

2. Compute F1 Score

3. Compute AUC Score, you need to compute different thresholds and for each threshold compute tpr,fpr and then use numpy.trapz(tpr_array, fpr_array) https://stackoverflow.com/q/53603376/4084039, https://stackoverflow.com/a/39678975/4084039

4. Compute Accuracy Score

In [22]:
```
task_b_scores = pd.read_csv("5_b.csv").rename(columns={'proba':'y_score'})
task_b_scores.head()
```

Out[22]:

	y	y_score
0	0.0	0.281035
1	0.0	0.465152
2	0.0	0.352793
3	0.0	0.157818
4	0.0	0.276648

In [23]:
```
task_b_scores.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10100 entries, 0 to 10099
Data columns (total 2 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   y        10100 non-null  float64
 1   y_score  10100 non-null  float64
dtypes: float64(2)
memory usage: 157.9 KB
```

In [24]:
```
tgt_cls_rec_count = pd.DataFrame(task_b_scores['y'].value_counts()).reset_index().re
```

In [25]:
```
tgt_cls_rec_count
```

Out[25]:

	Tgt_Class	Record_Count
0	0.0	10000
1	1.0	100

In [26]:
```
with plt.style.context('seaborn'):
    plt.figure(figsize=(8,6))
    sns.barplot(x='Tgt_Class',y='Record_Count',data=tgt_cls_rec_count,palette='prism
    plt.xticks(ticks=(0,1),labels=('Negatives','Positives'))
    plt.xlabel('Target Classes')
    plt.ylabel('Record Count')
```

In [27]:
```
task_b_scores['y_pred'] = task_b_scores['y_score'].apply(lambda val: 0 if val < 0.5
```

In [28]:
```
y_pred_rec_cnt = pd.DataFrame(task_b_scores['y_pred'].value_counts()).reset_index().
```

In [29]:
```
y_pred_rec_cnt
```

Out[29]:

	y_pred_class	y_pred
0	0	9806
1	1	294

In [30]:
```
task_b_conf_mat, task_b_f1_scr, task_b_acc_scr = conf_mat_f1_scr(task_b_scores)
```

In [31]:
```
task_b_conf_mat
```

Out[31]:
```
array([[9761,   45],
       [ 239,   55]])
```

In [32]:
```
task_b_f1_scr
```

Out[32]:
```
0.2791878172588833
```

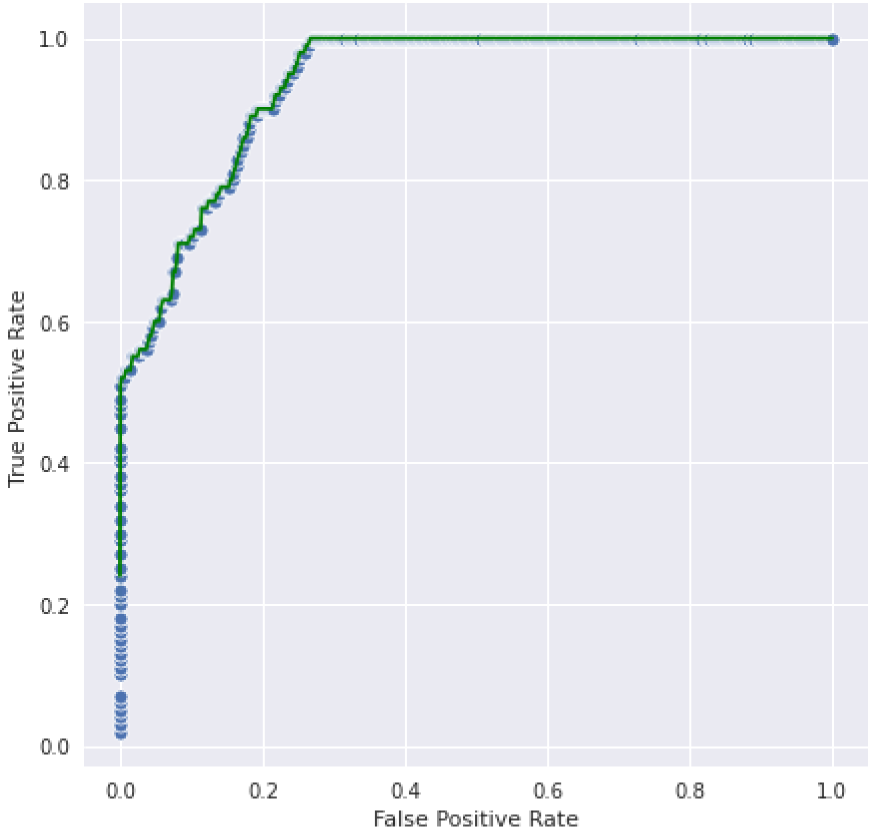
In [33]:
```
task_b_acc_scr
```

Out[33]:
```
0.9718811881188119
```

In [34]:
```
tpr_arr, fpr_arr = roc_auc_scr(task_b_scores)
```

In [35]:
```
with plt.style.context('seaborn'):
```

```
    plt.figure(figsize=(7,7))
    sns.scatterplot(x=fpr_arr,y=tpr_arr,palette='twilight')
    sns.lineplot(x=fpr_arr,y=tpr_arr,color='green')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
```



In [36]:
```
len(tpr_arr),len(fpr_arr)
```

Out[36]: (446, 446)

In [37]:
```
## AUC Score
np.trapz(tpr_arr,fpr_arr)
```

Out[37]: 0.937801

Task-C

C. Compute the best threshold (similarly to ROC curve computation) of probability which gives lowest values of metric **A** for the given data **5_c.csv**

you will be predicting label of a data points like this: $y^{pred}= \text{[0 if y_score < threshold else 1]}$

$ A = 500 \times \text{number of false negative} + 100 \times \text{numebr of false positive}$

```
    Note 1: in this data you can see number of negative points > number
 of positive points
    Note 2: use pandas or numpy to read the data from 5_c.csv
```

In [38]:
```
task_c_scores = pd.read_csv("5_c.csv").rename(columns={'prob':'y_score'})
task_c_scores.head()
```

Out[38]:

	y	y_score

	y	y_score
0	0	0.458521
1	0	0.505037
2	0	0.418652
3	0	0.412057
4	0	0.375579

In [39]:
```
task_c_scores.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2852 entries, 0 to 2851
Data columns (total 2 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   y        2852 non-null   int64  
 1   y_score  2852 non-null   float64
dtypes: float64(1), int64(1)
memory usage: 44.7 KB
```

In [40]:
```
tgt_cls_rec_count = pd.DataFrame(task_c_scores['y'].value_counts()).reset_index().re
```

In [41]:
```
tgt_cls_rec_count
```

Out[41]:

	Tgt_Class	Record_Count
0	0	1805
1	1	1047

In [42]:
```
with plt.style.context('seaborn'):
    plt.figure(figsize=(8,6))
    sns.barplot(x='Tgt_Class',y='Record_Count',data=tgt_cls_rec_count,palette='magma
    plt.xticks(ticks=(0,1),labels=('Negatives','Positives'))
    plt.xlabel('Target Classes')
    plt.ylabel('Record Count')
```

In [43]:
```
def Calc_Min_A(df_obj,y_prob_round_flg=3):
    """
    Desciprtion : This function is created for calculating minimum of A based FNS an

    Input Parameters: It accepts only one parameter:
        `df_obj`: Pandas Dataframe
            Dataframe containing the `actual y` named as 'y' and `y proba score` nam

        `y_prob_round_flg`: int
            By default 2. This is just a flag variable for controlling the number of

    Return:
        `Min_A_df` : Pandas Dataframe
    It returns the pandas dataframe sorted as per the minimum value of A for differe
    """
    fns_val = []
    fps_val = []
    A_op = []
    thresholds = []

    th_res_df = df_obj.copy(deep=True)
    # Rounding-off the scores for controlling the number of unique scores
    th_res_df['y_score'] = np.round(th_res_df['y_score'],y_prob_round_flg)
    # Sorting the unique score in descending order
    thres_vals = th_res_df.sort_values(by='y_score',ascending=False)['y_score'].uniq
    # Sorting the df in descending order based on rounded-off scores
    th_res_df.sort_values(by='y_score',ascending=False,ignore_index=True,inplace=Tru

    # Generating the y outcome threshold columns based on threshold value
    for i,th_val in enumerate(thres_vals):
        th_fps = []
        th_fns = []
        th_res_df['y_tao'+str(i)] = th_res_df['y_score'].apply(lambda row_val: 1 if
        tmp_tsk3 = th_res_df[['y','y_tao'+str(i)]].apply(lambda row: th_fps.append('
                                                    th_fns.append('10') if row['y']==1 and r
        n_fns = len(th_fns)
        n_fps = len(th_fps)
        A = (500.0 * n_fns) + (100.0 * n_fps)
        thresholds.append(th_val)
        fns_val.append(n_fns)
        fps_val.append(n_fps)
        A_op.append(A)

    Min_A_df = pd.DataFrame({'A_op':A_op,'fns':fns_val,'fps':fps_val,'th_val':thresh
    Min_A_df.sort_values(by='A_op',ascending=True,ignore_index=True,inplace=True)
    del th_res_df, tmp_tsk3
    return Min_A_df
```

In [44]:
```
task3_op_df = Calc_Min_A(df_obj=task_c_scores)
```

In [45]:
```
task3_op_df
```

Out[45]:

	A_op	fns	fps	th_val
0	141400.0	78	1024	0.230
1	141600.0	78	1026	0.229
2	141700.0	100	917	0.252
3	141700.0	99	922	0.251
4	141800.0	78	1028	0.228

	A_op	fns	fps	th_val
...	...	...	...	...
777	521000.0	1042	0	0.941
778	521500.0	1043	0	0.944
779	522000.0	1044	0	0.949
780	522500.0	1045	0	0.951
781	523000.0	1046	0	0.958

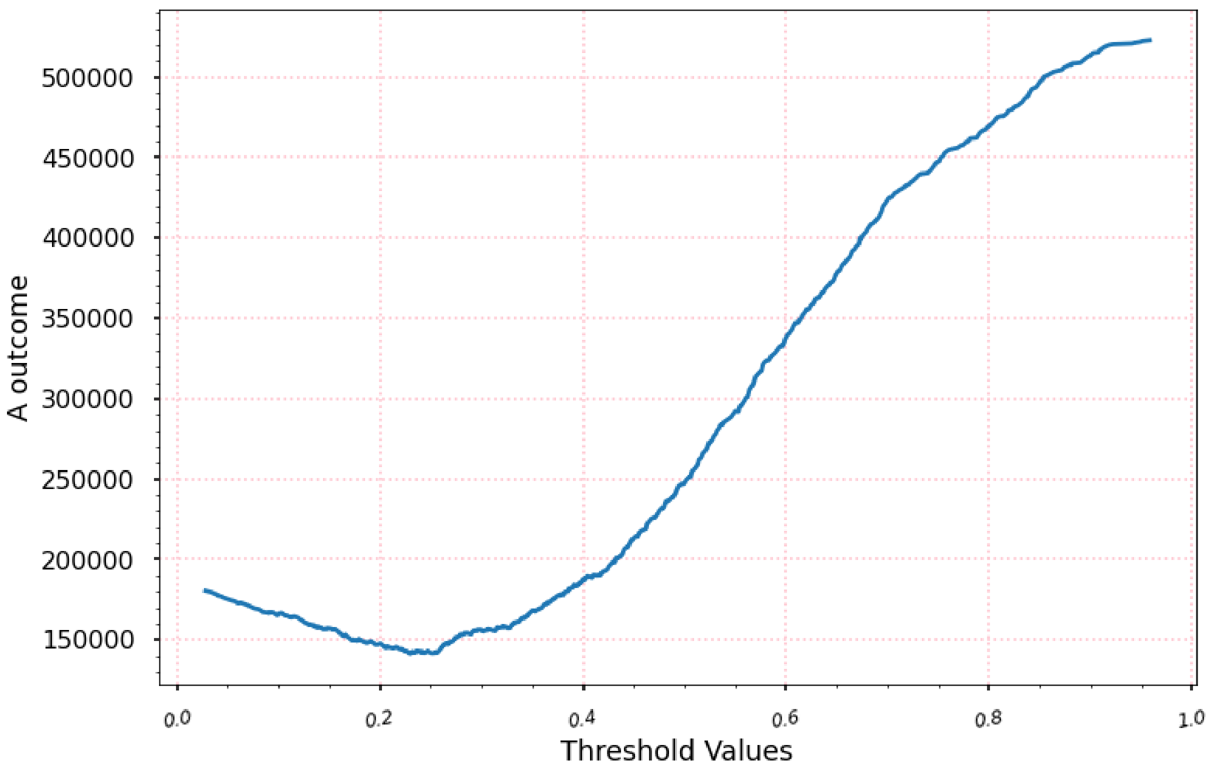
782 rows × 4 columns

In [46]:
```
## Minimum value of A
task3_op_df.head(1)
```

Out[46]:

	A_op	fns	fps	th_val
0	141400.0	78	1024	0.23

In [47]:
```
with plt.style.context('seaborn-poster'):
    plt.figure(figsize=(12,8))
    sns.lineplot(x='th_val',y='A_op',data=task3_op_df,palette='twilight')
    plt.grid(which='major',linestyle=':',color='pink')
    plt.minorticks_on()
    plt.xticks(rotation=10,size=12,style='oblique')
    plt.xlabel('Threshold Values')
    plt.ylabel('A outcome')
```



Task-D

D. Compute performance metrics(for regression) for the given data **5_d.csv**

Note 2: use pandas or numpy to read the data from **5_d.csv**

Note 1: 5_d.csv will having two columns Y and predicted_Y both are real valued features

1. Compute Mean Square Error
2. Compute MAPE: https://www.youtube.com/watch?v=ly6ztgIkUxk
3. Compute R^2 error: https://en.wikipedia.org/wiki/Coefficient_of_determination#Definitions

In [48]:

```
task_d_scores = pd.read_csv("5_d.csv").rename(columns={'pred':'y_pred'})
task_d_scores.head()
```

Out[48]:

	y	y_pred
0	101.0	100.0
1	120.0	100.0
2	131.0	113.0
3	164.0	125.0
4	154.0	152.0

In [49]:

```
task_d_scores.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 157200 entries, 0 to 157199
Data columns (total 2 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   y       157200 non-null  float64
 1   y_pred  157200 non-null  float64
dtypes: float64(2)
memory usage: 2.4 MB
```

In [52]:

```
task_d_scores['Err'] = task_d_scores['y'] - task_d_scores['y_pred']
task_d_scores['Err_sqr'] = np.square(task_d_scores['Err'])
task_d_scores['Err_abs'] = np.abs(task_d_scores['Err'])
```

In [55]:

```
task_d_scores
```

Out[55]:

	y	y_pred	Err	Err_sqr	Err_abs
0	101.0	100.0	1.0	1.0	1.0
1	120.0	100.0	20.0	400.0	20.0
2	131.0	113.0	18.0	324.0	18.0
3	164.0	125.0	39.0	1521.0	39.0
4	154.0	152.0	2.0	4.0	2.0
...	...	...	...	...	...
157195	87.0	83.0	4.0	16.0	4.0
157196	97.0	86.0	11.0	121.0	11.0

	y	y_pred	Err	Err_sqr	Err_abs
157197	106.0	93.0	13.0	169.0	13.0
157198	105.0	101.0	4.0	16.0	4.0
157199	81.0	104.0	-23.0	529.0	23.0

157200 rows × 5 columns

In [57]:
```
mean_task_d_y = np.mean(task_d_scores['y'])
mean_task_d_y
```

Out[57]:
```
66.56208651399491
```

In [67]:
```
task_d_scores['ST'] = np.square(task_d_scores['y'] - mean_task_d_y)
```

In [56]:
```
task_d_scores['Mod_Abs_Err'] = task_d_scores[['y','Err_abs']].apply(lambda row: row[
                                                                    row['Err_abs']/ro
```

In [58]:
```
## Mean Squared Error
MSE = np.sum(task_d_scores['Err'])/task_d_scores.shape[0]
print("Mean Squared Error is {}".format(MSE))
```

```
Mean Squared Error is 0.07837150127226464
```

In [64]:
```
## Modified Mean Absolute Percentage Error
MMAPE = np.sum(task_d_scores['Mod_Abs_Err'])/task_d_scores.shape[0]
print("Mean Squared Error is {:.2f}%".format(MMAPE*100))
```

```
Mean Squared Error is 28.20%
```

In [69]:
```
## Sum of Squares of Residuals and Total Sum of squares
SS_res = np.sum(task_d_scores['Err_sqr'])
SS_tot = np.sum(task_d_scores['ST'])
SS_res, SS_tot
```

Out[69]:
```
(27850448.0, 638161080.0356234)
```

In [70]:
```
## Coeff. of determination
R_sqr = 1 - (SS_res/SS_tot)
R_sqr
```

Out[70]:
```
0.9563582786990937
```