In [1]:

```
import pandas as pd
import numpy as np

import seaborn as sns
from matplotlib import pyplot as plt
%matplotlib inline
```

In [2]:

```
df = pd.read_csv('data/churn_data.csv')
```

In [3]:

```
#change dtype of 'TotalCharges' from object to numeric
#if there is an error, because the value has a space (" "), we use --> errors='coerce'
total_charges = pd.to_numeric(df.TotalCharges, errors='coerce')
```

In [4]:

```
#getting null (missing) values
df[total_charges.isnull()][['customerID', 'TotalCharges']]
```

	customerID	TotalCharges
488	4472-LVYGI	
753	3115-CZMZD	
936	5709-LVOEQ	
1082	4367-NUYAO	
1340	1371-DWPAZ	
3331	7644-OMVMY	
3826	3213-VVOLG	
4380	2520-SGTTA	
5218	2923-ARZLG	
6670	4075-WKNIU	
6754	2775-SEFEE	

In [5]:

```
#set missing values to zero
df.TotalCharges = pd.to_numeric(df.TotalCharges, errors='coerce')
df.TotalCharges = df.TotalCharges.fillna(0)
```

In [6]:

```
#column names & string values: lowercasing everything and replace spaces with underscore
df.columns = df.columns.str.lower().str.replace(' ', '_')
string_columns = list(df.dtypes[df.dtypes == 'object'].index)

for col in string_columns:
    df[col] = df[col].str.lower().str.replace(' ', '_')
```

In [7]:

```
df.head(3)
```

	customerid	gender	seniorcitizen	partner	dependents	tenure	phoneservice	multiplelines	internetservice	onlines
0	7590-vhveg	female	0	yes	no	1	no	no_phone_service	dsl	no
1	5575-gnvde	male	0	no	no	34	yes	no	dsl	yes
2	3668-qpybk	male	0	no	no	2	yes	no	dsl	yes

3 rows × 21 columns

In [8]:

```
#change target variable from object to integer (if yes, then 1; if no, then 0)
df.churn = (df.churn == 'yes').astype(int)
```

In [9]:

```
#splitting the dataset in different subsets
from sklearn.model_selection import train_test_split
```

In [10]:

```
#shuffling the data of df and splitting it into 2 sets
#df_train_full (80%), df_test(20%)
#random_state guarantees that the data is always shuffled in the same way
df_train_full, df_test = train_test_split(df, test_size=0.2, random_state=1)
```

In [11]:

```
#take df_train_full and split it into train and val
df_train, df_val = train_test_split(df_train_full, test_size=0.33, random_state=11)
#save target variable in a matrix array
y_train = df_train.churn.values
y_val = df_val.churn.values
#delete target variable from training and validation set
del df_train['churn']
del df_val['churn']
```

Feature Engineering

We compare 3 scenarios:

- Scenario 1: All features are included
- Scenario 2: The two least important features 'gender' and 'phoneservice' are excluded
- Scenario 3: The most important feature 'contract' is exluded

  The cell below gives the accuracy for each Scenario

In [12]:

```
#create variable lists
categorical = ['gender', 'seniorcitizen', 'partner', 'dependents',
'phoneservice', 'multiplelines', 'internetservice',
'onlinesecurity', 'onlinebackup', 'deviceprotection',
'techsupport', 'streamingtv', 'streamingmovies',
'contract', 'paperlessbilling', 'paymentmethod']

categ_ex_1 = ['seniorcitizen', 'partner', 'dependents',
'multiplelines', 'internetservice',
'onlinesecurity', 'onlinebackup', 'deviceprotection',
'techsupport', 'streamingtv', 'streamingmovies',
'contract', 'paperlessbilling', 'paymentmethod']

categ_ex_2 = ['gender', 'seniorcitizen', 'partner', 'dependents',
'phoneservice', 'multiplelines', 'internetservice',
'onlinesecurity', 'onlinebackup', 'deviceprotection',
'techsupport', 'streamingtv', 'streamingmovies',
'paperlessbilling', 'paymentmethod']

numerical = ['tenure', 'monthlycharges', 'totalcharges']

lists = [categorical, categ_ex_1, categ_ex_2]
scenario = ['Scenario 1:', 'Scenario 2:', 'Scenario 3:']
```

In [13]:

```
x = 0
for L in lists:
    def prepare_X(df, categ):
        #convert training set to dictionary
        train_dict = df[categ + numerical].to_dict(orient='rows')
        from sklearn.feature_extraction import DictVectorizer
        dv = DictVectorizer(sparse=False)
        dv.fit(train_dict)
        #use 'transform' method to convert dictionaries to matrix
        X = dv.transform(train_dict)
        return X

    #train logictic regression model
    from sklearn.linear_model import LogisticRegression
    #train model by calling the 'fit' method
    #X_train is derived from training set (besides we also have validation and testing set)
    model = LogisticRegression(solver='liblinear', random_state = 1)
    model.fit(prepare_X(df_train, L), y_train)

    def prepare_val(df, categ):
        #convert training set to dictionary
        train_dict = df[categ + numerical].to_dict(orient='rows')
        from sklearn.feature_extraction import DictVectorizer
        dv_new = DictVectorizer(sparse=False)
        dv_new.fit(train_dict)
        #use 'transform' method to convert dictionaries to matrix
        X = dv_new.transform(train_dict)
        return X

    #use the model to predict the target variable
    y_pred = model.predict_proba(prepare_val(df_val, L))[:, 1]
    y_pred >= 0.5
    churn = y_pred >= 0.5
    print('Accuracy for', scenario[x], (y_val == churn).mean())
    x += 1
```

```
Accuracy for Scenario 1: 0.8016129032258065
Accuracy for Scenario 2: 0.8026881720430108
Accuracy for Scenario 3: 0.7973118279569893
```

In [14]:

```
from sklearn.metrics import accuracy_score
```

In [15]:

```
#loop over different thresholds and see what has the best accuracy
#a threshold of 0.5 gives us the best accuracy
thresholds = np.linspace(0, 1, 11) #this gives 11 numbers starting with 0.0, 0.1, 0.2, ...
for t in thresholds:
    #compute accuracy
    churn = y_pred >= t
    acc = accuracy_score(y_val, churn)
    #print results
    print('%0.2f %0.3f' % (t, acc))
```

```
0.00 0.261
0.10 0.563
0.20 0.697
0.30 0.751
0.40 0.791
0.50 0.797
0.60 0.791
0.70 0.778
0.80 0.748
0.90 0.739
1.00 0.739
```

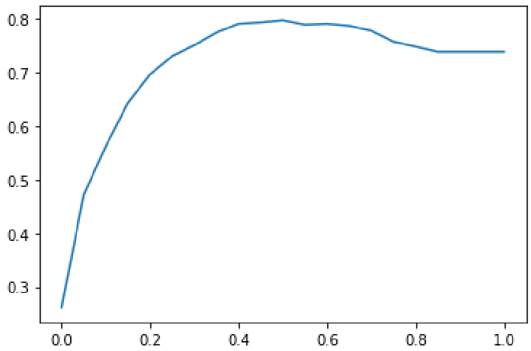
In [16]:

```
thresholds = np.linspace(0, 1, 21)
accuracies = []
for t in thresholds:
    acc = accuracy_score(y_val, y_pred >= t)
    accuracies.append(acc)
```

In [17]:

```
plt.plot(thresholds, accuracies)
plt.title('Threshold vs Accuracy', color='white')
plt.xlabel('Threshold', color='white')
plt.ylabel('Threshold', color='white')
```

```
Text(0, 0.5, 'Threshold')
```



Applying that to small model

In [18]:

```
small_subset = ['contract', 'tenure', 'totalcharges']
#convert to dictionary
train_dict_small = df_train[small_subset].to_dict(orient='rows')
#make use of DictVectorizer to perform one hot encoding
from sklearn.feature_extraction import DictVectorizer
dv_small = DictVectorizer(sparse=False)
#use fit method to apply DictVectorizer to dictionary
dv_small.fit(train_dict_small)
#transform dictionary to matrix array
X_small_train = dv_small.transform(train_dict_small)
```

In [19]:

```
model_small = LogisticRegression(solver='liblinear', random_state=1)
model_small.fit(X_small_train, y_train)

#train a simpler model
#apply one-hot-encoding to validation set
val_dict_small = df_val[small_subset].to_dict(orient='rows')
dv_small.fit(val_dict_small)
X_small_val = dv_small.transform(val_dict_small)
#predict churn using this small model
y_pred_small = model_small.predict_proba(X_small_val)[:, 1]
churn_small = y_pred_small >= 0.5
#calculate accuracy
accuracy_score(y_val, churn_small)
```

```
0.7672043010752688
```

Is an accuracy of 0.77 now a good value? We need to compare it. One possibility could be the **Dummy Baseline**, what

- always predicts the majority class: here "no churn (False)"

In [20]:

```
#making a baseline prediction
#get number of customers in validation set
size_val = len(y_val)
#create array with only false elements
baseline = np.repeat(False, size_val)
```

In [21]:

```
#check the accuracy
accuracy_score(baseline, y_val)
```

```
0.7387096774193549
```

the smaller model is only 2% better and the big model is only 6% better than the dummy baseline.
We need another metric: the **Confusion Table**

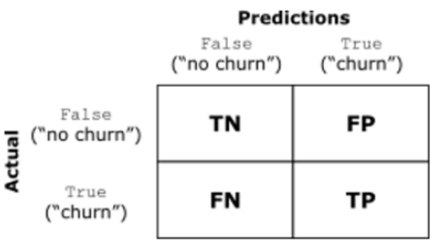


Figure 4.9 We can organize the outcomes in a table — the predicted values as columns and the actual values as rows. This way, we break down all prediction scenarios into four distinct groups: TN (true negative), TP (true positive), FN (false negative), and FP (false positive).

what the model is doing with the validation set:

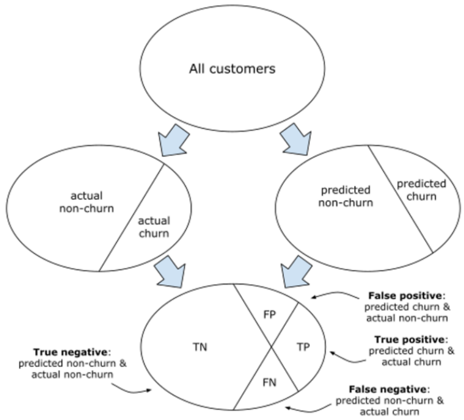


Figure 4.11 When we apply the model to the validation dataset, we get four different outcomes (TN, FP, TP, and FN)

In [22]:

```
#calculate the 4 outcomes
#make prediction at threshold 0.5
t = 0.5
predict_churn = (y_pred >= t)
predict_no_churn = (y_pred < t)

#get the actual target values
actual_churn = (y_val == 1)
actual_no_churn = (y_val == 0)

#calculate true and false positives
true_positive = (predict_churn & actual_churn).sum()
false_positive = (predict_churn & actual_no_churn).sum()

#calculate false and true negatives
#the logical "and" operator only evaluates to true if both values are true
false_negative = (predict_no_churn & actual_churn).sum()
true_negative = (predict_no_churn & actual_no_churn).sum()
```

Generating 2 arrays out of the predicated target values:

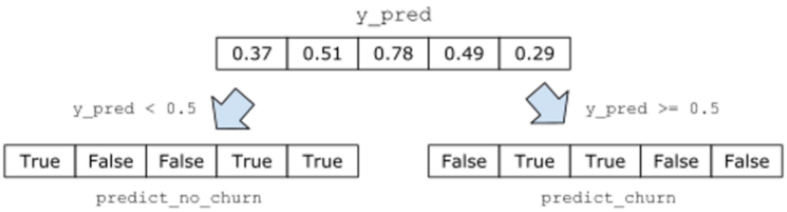


Figure 4.13 Splitting the predictions into two Boolean NumPy arrays: predict_churn if the probability is higher than 0.5, and predict_no_churn if it's lower

Generating 2 arrays out of the actual target values:

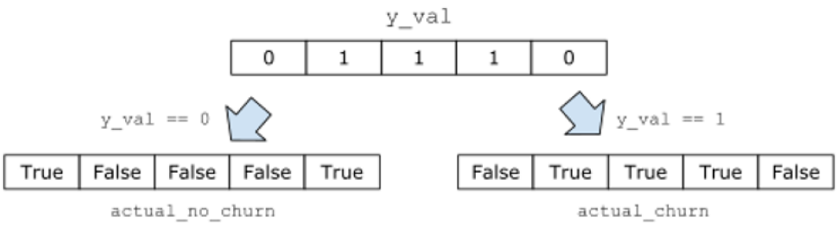


Figure 4.14 Splitting the array with actual values into two Boolean NumPy arrays: actual_no_churn if the customer didn't churn (y_val == 0) and actual_churn if the customer churned (y_val == 1)

In [23]:

```
#put all 4 values in one numpy array
confusion_table = np.array(
[[true_negative, false_positive],
[false_negative, true_positive]])
confusion_table
```

```
array([[1208,  166],
       [ 211,  275]])
```

In [24]:

```
#take fractions to better understand the values
confusion_table / confusion_table.sum()
```

```
array([[0.64946237, 0.08924731],
       [0.11344086, 0.14784946]])
```

In [25]:

```
#produce confusion table out of the small table

#calculate the 4 outcomes
#make prediction at threshold 0.5
t = 0.5
predict_churn = (y_pred_small >= t)
predict_no_churn = (y_pred_small < t)

#get the actual target values
actual_churn = (y_val == 1)
actual_no_churn = (y_val == 0)

#calculate true and false positives
true_positive = (predict_churn & actual_churn).sum()
false_positive = (predict_churn & actual_no_churn).sum()

#calculate false and true negatives
#the logical "and" operator only evaluates to true if both values are true
false_negative = (predict_no_churn & actual_churn).sum()
true_negative = (predict_no_churn & actual_no_churn).sum()
```

In [26]:

```
#put all 4 values in one numpy array
confusion_table = np.array(
[[true_negative, false_positive],
[false_negative, true_positive]])
confusion_table
```

```
array([[1189,  185],
       [ 248,  238]])
```

In [27]:

```
#take fractions to better understand the values
confusion_table / confusion_table.sum()
```

```
array([[0.63924731, 0.09946237],
       [0.13333333, 0.12795699]])
```

Precision and Recall
metrics that help us to better understand the quality of the model
in case of class imbalance.

Precision: How many of the positive predictions are correct

- P = TP/(TP + FP)

Recall: Positive predictions divided by the number of all positive examples
FN stands for a positive case, that was predicted negative

- R = TP/(TP + FN)

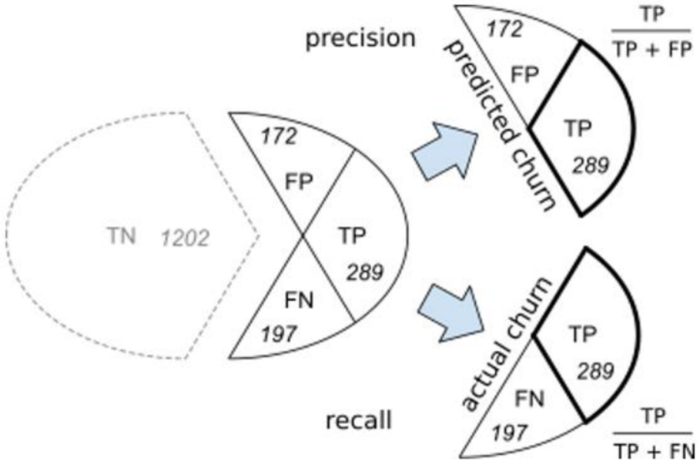


Figure 4.19 Both precision and recall look at the correct predictions (TP), but the denominators are different. For precision, it's the number of customers predicted as churning, while for recall it's the number of customers who churned.

- precision helps us to understand how many customers received promotional messages per mmistake (actually they are not going to churn)
- recall helps us to understand how many of the churning customers haven't been identified by the model

ROC curve
ROC stands of "receiver operating characteristics"
It tells us how well a model can separate two classes.
Here: churn and no churn
2 metrics are required:

- FPR (false positive rate; look at 1st row of conf. table --> FP / (FP + TN)
  fraction of false postives among all negative examples
  !! The smaller the FPR, the better
- TPR (true positive rate; look at 2nd row of conf. table) --> TP / (TP + FN)
  fraction of true postives among all positive examples
  !! The higher the TPR, the better (same as recall)

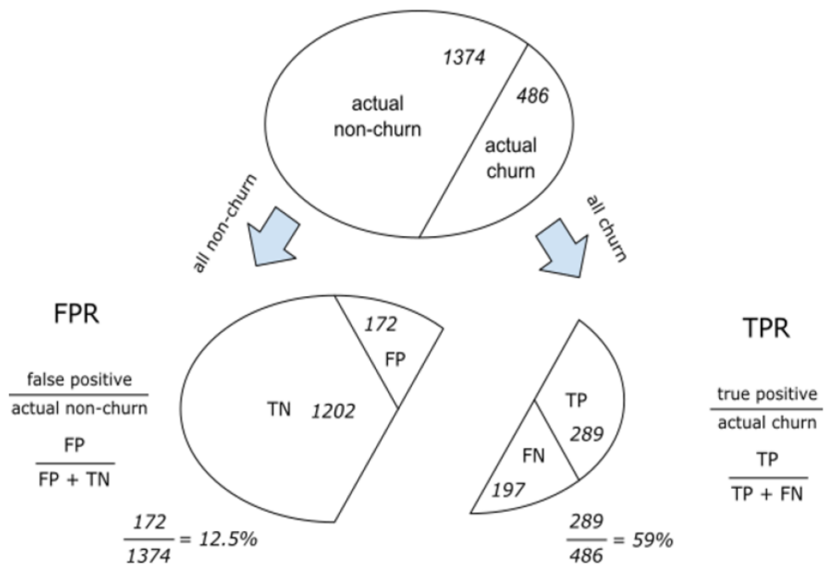


Figure 4.21 FPR is the fraction of false positives among all non-churning customers: the smaller the FPR is, the better. TPR is the fraction of true positives among all churning customers: the larger the TPR is, the better.

Evaluating a model at multiple thresholds

In [28]:

```
#computing confusion table for different thresholds

#result list
scores = []
#create array with different threshold values
thresholds = np.linspace(0, 1, 101)

#compute confusion table for predictions at each threshold
for t in thresholds:
    tp = ((y_pred >= t) & (y_val == 1)).sum()
    fp = ((y_pred >= t) & (y_val == 0)).sum()
    fn = ((y_pred < t) & (y_val == 1)).sum()
    tn = ((y_pred < t) & (y_val == 0)).sum()
    #append results to scores list
    scores.append((t, tp, fp, fn, tn))
```

In [29]:

```
#convert list of tuples to dataframe
df_scores = pd.DataFrame(scores)
#give names to the columns
df_scores.columns = ['threshold', 'tp', 'fp', 'fn', 'tn']
```

In [30]:

```
#[::10] selects every 10th record out of df
df_scores[::10]
```

	threshold	tp	fp	fn	tn
0	0.0	486	1374	0	0
10	0.1	457	784	29	590
20	0.2	413	491	73	883
30	0.3	365	342	121	1032
40	0.4	330	233	156	1141
50	0.5	275	166	211	1208
60	0.6	192	95	294	1279
70	0.7	117	44	369	1330
80	0.8	27	9	459	1365
90	0.9	0	0	486	1374
100	1.0	0	0	486	1374

In [31]:

```
#compute tpr and fpr
#and add it to the df
df_scores['tpr'] = df_scores.tp / (df_scores.tp + df_scores.fn)
df_scores['fpr'] = df_scores.fp / (df_scores.fp + df_scores.tn)
```

In [32]:

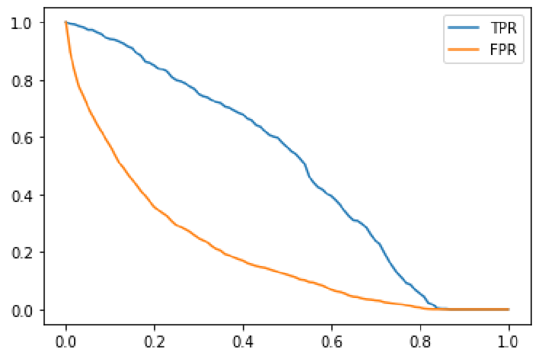
```
#[::10] selects every 10th record out of df
df_scores[::10]
```

	threshold	tp	fp	fn	tn	tpr	fpr
0	0.0	486	1374	0	0	1.000000	1.000000
10	0.1	457	784	29	590	0.940329	0.570597
20	0.2	413	491	73	883	0.849794	0.357351
30	0.3	365	342	121	1032	0.751029	0.248908
40	0.4	330	233	156	1141	0.679012	0.169578
50	0.5	275	166	211	1208	0.565844	0.120815
60	0.6	192	95	294	1279	0.395062	0.069141
70	0.7	117	44	369	1330	0.240741	0.032023
80	0.8	27	9	459	1365	0.055556	0.006550
90	0.9	0	0	486	1374	0.000000	0.000000
100	1.0	0	0	486	1374	0.000000	0.000000

In [33]:

```
#plot the values
plt.plot(df_scores.threshold, df_scores.tpr, label="TPR")
plt.plot(df_scores.threshold, df_scores.fpr, label="FPR")
plt.legend()
```

<matplotlib.legend.Legend at 0x28009a14408>



In [34]:

```
#get line, where difference between TPR and FPR is the biggest

#compute diff between tpr and fpr
#and add it to the df
df_scores['diff'] = df_scores.tpr - df_scores.fpr
```

In [35]:

```
#get row of df where diff is highest
df_scores.loc[df_scores['diff'] == df_scores['diff'].max()]
```

	threshold	tp	fp	fn	tn	tpr	fpr	diff
37	0.37	341	258	145	1116	0.701646	0.187773	0.513873

in order to better understand the meaning of TPR and FPR,
we compare it with 2 baseline models (random model & ideal model)

Random Baseline Model

In [36]:

```
#fix random seed for reproducibility
np.random.seed(1)
#generate array with random numbers between 0 and 1
#y_rand contains the "predictions of our model"
y_rand = np.random.uniform(0, 1, size=len(y_val))
```

In [37]:

```
#calculate TPR and FPR at different thresholds

#generate function what takes in actual and predicted values
def tpr_fpr_dataframe(y_val, y_pred):
    #calculate confusion table for different thresholds
    scores = []
    thresholds = np.linspace(0, 1, 101)
    for t in thresholds:
        tp = ((y_pred >= t) & (y_val == 1)).sum()
        fp = ((y_pred >= t) & (y_val == 0)).sum()
        fn = ((y_pred < t) & (y_val == 1)).sum()
        tn = ((y_pred < t) & (y_val == 0)).sum()
        scores.append((t, tp, fp, fn, tn))

    #convert confusion table numbers to dataframe and give columns a name
    df_scores = pd.DataFrame(scores)
    df_scores.columns = ['threshold', 'tp', 'fp', 'fn', 'tn']

    #calculate TPR & FPR
    df_scores['tpr'] = df_scores.tp / (df_scores.tp + df_scores.fn)
    df_scores['fpr'] = df_scores.fp / (df_scores.fp + df_scores.tn)

    return df_scores
```

In [38]:

```
#use the function to calculate TPR and FPR for random model
df_rand = tpr_fpr_dataframe(y_val, y_rand)
```

In [39]:

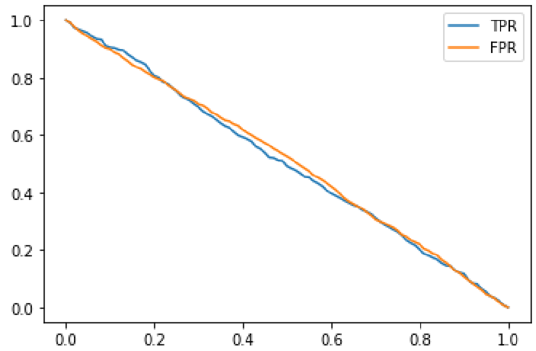
```
df_rand[::10]
```

	threshold	tp	fp	fn	tn	tpr	fpr
0	0.0	486	1374	0	0	1.000000	1.000000
10	0.1	440	1236	46	138	0.905350	0.899563
20	0.2	392	1101	94	273	0.806584	0.801310
30	0.3	339	972	147	402	0.697531	0.707424
40	0.4	288	849	198	525	0.592593	0.617904
50	0.5	239	723	247	651	0.491770	0.526201
60	0.6	193	579	293	795	0.397119	0.421397
70	0.7	152	422	334	952	0.312757	0.307132
80	0.8	98	302	388	1072	0.201646	0.219796
90	0.9	57	147	429	1227	0.117284	0.106987
100	1.0	0	0	486	1374	0.000000	0.000000

In [40]:

```
plt.plot(df_rand.threshold, df_rand.tpr, label='TPR')
plt.plot(df_rand.threshold, df_rand.fpr, label='FPR')
plt.legend()
#see also page 154 for explanation
```

<matplotlib.legend.Legend at 0x28009ce6f08>



findings of random baseline model:

- at threshold of 0.0, every is regarded as churning (the values of the target variable cannot be below 0 --> so TPR and FPR is 100%
- at threshold of 0.4, TPR and FPR are 60%
  for TPR: TP is 60%, FN is 40%
  for FPR: FP is 60%, TN is 40%
- at threshold of 1.0, everybody is regarded as non-churning
  so TPR and FPR are 0%
  for TPR: we have 0% TP and 100% FN
  for FPR: we have 0% FP and 100% TN

The ideal (ranking) model
That model always makes the right decisions.
Churning customers always have higher scores than non-churning ones.
--> predicted probability for all churned ones should be higher than predicted probabilty for non-churned ones

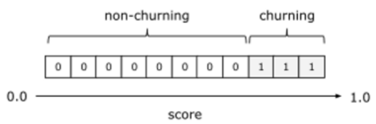


Figure 4.27 The ideal model orders customers such that first we have non-churning customers, and then churning ones.

In [41]:

```
#generate ideal predictions
#generate array with fake target variables, that are already ordered
#it firstly only contains 0's, then it only contains 1's

#calculate number of negative and positive examples in dataset
num_neg = (y_val == 0).sum()
num_pos = (y_val == 1).sum()

#generate array that firstly repeates 0s num_neg number of times,
#then generates 1s repeated num_pos number of times
y_ideal = np.repeat([0,1], [num_neg, num_pos])

#generate "predicitions of the model": numbers that grow
#from 0 in first cell to 1 in last cell
y_pred_ideal = np.linspace(0, 1, num_neg + num_pos)

#calculate TPR and FPR for this model
df_ideal = tpr_fpr_dataframe(y_ideal, y_pred_ideal)
```

In [43]:

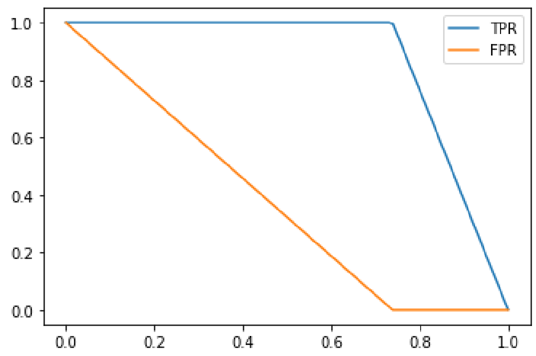
```
df_ideal[::10]
```

	threshold	tp	fp	fn	tn	tpr	fpr
0	0.0	486	1374	0	0	1.000000	1.000000
10	0.1	486	1188	0	186	1.000000	0.864629
20	0.2	486	1002	0	372	1.000000	0.729258
30	0.3	486	816	0	558	1.000000	0.593886
40	0.4	486	630	0	744	1.000000	0.458515
50	0.5	486	444	0	930	1.000000	0.323144
60	0.6	486	258	0	1116	1.000000	0.187773
70	0.7	486	72	0	1302	1.000000	0.052402
80	0.8	372	0	114	1374	0.765432	0.000000
90	0.9	186	0	300	1374	0.382716	0.000000
100	1.0	1	0	485	1374	0.002058	0.000000

In [44]:

```
plt.plot(df_ideal.threshold, df_ideal.tpr, label='TPR')
plt.plot(df_ideal.threshold, df_ideal.fpr, label='FPR')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x28009d4dbc8>
```



findings from above plot

- for threshold lower than 0.74, the model always correctly classifies churning customers, that's why TPR stays at 100%
- on other side, we incorrectly classify non-churning customers as churning (FP), with a growing threshold, the FPR goes down (so fewer and fewer non-churning customers are predicted as churning

In [ ]: