



## MODULE 6: PREDICTIVE MODELING FOR TEMPORARY DATA

# CASE STUDY ACTIVITY TUTORIAL

### 6.2 PREDICTION ENGINEERING USING UK RETAIL DATASET

# UK Retail Dataset Case Study

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## 1 Prediction engineering case study using UK Retail Dataset

In this case study, we will study prediction engineering. Prediction engineering is a step in predictive modeling, where we: \* Define an outcome we are interested in predicting \* Scan the data to find the past occurrences of the outcome \* These past occurrences become training examples for machine learning/modeling \* We will then use featuretools to extract features and learn a predictive model.

In this particular case study, we are focusing a retail dataset openly available at

We will define the prediction problem as the one where the customer has more than k purchases

```
In [113]: import featuretools as ft
          from utils import (find_training_examples, load_uk_retail_data,
                             engineer_features_uk_retail, preview)

          import pandas as pd
          import numpy as np
          from sklearn.model_selection import train_test_split
          from sklearn.preprocessing import Imputer
          from sklearn.ensemble import RandomForestClassifier
          from sklearn.metrics import precision_recall_fscore_support, confusion_matrix
          ft.__version__
          %load_ext autoreload
          %autoreload 2
```

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

```
%reload_ext autoreload
```

## 2 Step 1: Load and prepare data

```
In [24]: item_purchases, invoices, items, customers = load_uk_retail_data()
```

The dataset has the following tables: \* item\_purchases \* invoices \* items \* customers

The following relations exist \* A customer may have multiple invoices \* An item may have been purchased multiple times \* An invoice may have multiple item purchases

```
In [25]: entities = {
    "item_purchases": (item_purchases, "item_purchase_id", "InvoiceDate" ),
    "items": (items, "StockCode"),
    "customers": (customers, "CustomerID"),
    "invoices": (invoices, "InvoiceNo", "first_item_purchases_time")
}

relationships = [
    ("customers", "CustomerID", "invoices", "CustomerID"),
    ("invoices", "InvoiceNo", "item_purchases", "InvoiceNo"),
    ("items", "StockCode", "item_purchases", "StockCode")]

```

### 3 Step 2 : Find training examples

In the code snippet below, we are trying to find training examples from the data. We set the following parameters: \* prediction\_window=14 days \* training\_window=21 days \* lead = 7 days \* threshold=2 --> specifies the number of purchases that the customer need to have in the future to be considered engaged

```
In [105]: label_times = find_training_examples(item_purchases, invoices,
    prediction_window=pd.Timedelta("14d"),
    training_window=pd.Timedelta("21d"),
    lead=pd.Timedelta("7d"),
    threshold=5)

In [123]: preview(label_times,5)

```

```
Out[123]:
```

	CustomerID	t_start	cutoff_time	purchases>threshold
0	17505.0	2011-05-18	2011-06-08	False
516	16444.0	2011-05-18	2011-06-08	False
517	16889.0	2011-05-18	2011-06-08	False
518	17613.0	2011-05-18	2011-06-08	True
519	17152.0	2011-05-18	2011-06-08	False

In the output above, we are showing the first 5 training examples. The first column is the CustomerID, the second column is the timestamp after which we can use the data for generating features. The third column is the last timestamp we can use the data from the customer. The fourth column is the label. It is True if the customer had more than 5 purchases in the period between (cutoff\_time+lead, cutoff\_time+lead+prediction\_window)

### 4 Step 3: Now lets generate features.

Next we generate features for each of the training examples. We use featuretools to generate the features. Featuretools is an automated feature engineering software. We go into detail about this software package in the NYC-Taxi case study. Here we simply use the tool to generate features.

```
In [107]: feature_matrix=engineer_features_uk_retail(entities,relationships,
    label_times,training_window='21d')
```

```
In [122]: preview(feature_matrix,10)
```

```
Out[122]:
```

	WEEK(first_invoices_time)	hour(first_invoices_time)	\
CustomerID			
12353.0	20	17	
12359.0	2	12	
12360.0	21	9	
12380.0	23	9	
12415.0	1	11	
12417.0	50	11	
12423.0	51	10	
12426.0	21	12	
12431.0	48	10	
12437.0	2	14	

  

	MAX(item_purchases.Quantity)	STD(item_purchases.UnitPrice)	\
CustomerID			
12353.0	NaN	NaN	
12359.0	NaN	NaN	
12360.0	NaN	NaN	
12380.0	NaN	NaN	
12415.0	600.0	2.367284	
12417.0	24.0	5.565414	
12423.0	NaN	NaN	
12426.0	NaN	NaN	
12431.0	24.0	2.658325	
12437.0	48.0	6.323762	

  

	DAY(first_invoices_time)	IS_WEEKEND(first_invoices_time)	\
CustomerID			
12353.0	19	False	
12359.0	12	False	
12360.0	23	False	
12380.0	7	False	
12415.0	6	False	
12417.0	17	False	
12423.0	21	False	
12426.0	29	True	
12431.0	1	False	
12437.0	12	False	

  

	MINUTE(first_invoices_time)	MONTH(first_invoices_time)	\
CustomerID			
12353.0	47	5	
12359.0	43	1	
12360.0	43	5	
12380.0	49	6	
12415.0	12	1	

12417.0	51	12
12423.0	54	12
12426.0	26	5
12431.0	3	12
12437.0	13	1

	MAX(item_purchases.UnitPrice)	MEAN(item_purchases.Quantity)	\
CustomerID			
12353.0	NaN		NaN
12359.0	NaN		NaN
12360.0	NaN		NaN
12380.0	NaN		NaN
12415.0	12.50		110.378378
12417.0	28.00		11.608696
12423.0	NaN		NaN
12426.0	NaN		NaN
12431.0	7.95		8.000000
12437.0	18.00		18.375000

	...	\
CustomerID	...	
12353.0	...	
12359.0	...	
12360.0	...	
12380.0	...	
12415.0	...	
12417.0	...	
12423.0	...	
12426.0	...	
12431.0	...	
12437.0	...	

	MAX(invoices.STD(item_purchases.UnitPrice))	\
CustomerID		
12353.0	NaN	
12359.0	NaN	
12360.0	NaN	
12380.0	NaN	
12415.0	2.376640	
12417.0	5.565414	
12423.0	NaN	
12426.0	NaN	
12431.0	2.658325	
12437.0	6.323762	

	STD(invoices.MAX(item_purchases.Quantity))	\
CustomerID		
12353.0	NaN	

12359.0	NaN
12360.0	NaN
12380.0	NaN
12415.0	350.0
12417.0	0.0
12423.0	NaN
12426.0	NaN
12431.0	0.0
12437.0	0.0

  

	MEAN(invoices.STD(item_purchases.UnitPrice)) \
CustomerID	
12353.0	NaN
12359.0	NaN
12360.0	NaN
12380.0	NaN
12415.0	1.188320
12417.0	5.565414
12423.0	NaN
12426.0	NaN
12431.0	2.658325
12437.0	6.323762

  

	MAX(invoices.MEAN(item_purchases.Quantity)) \
CustomerID	
12353.0	NaN
12359.0	NaN
12360.0	NaN
12380.0	NaN
12415.0	113.260274
12417.0	11.608696
12423.0	NaN
12426.0	NaN
12431.0	8.000000
12437.0	18.375000

  

	MAX(invoices.STD(item_purchases.Quantity)) \
CustomerID	
12353.0	NaN
12359.0	NaN
12360.0	NaN
12380.0	NaN
12415.0	131.485301
12417.0	6.761394
12423.0	NaN
12426.0	NaN
12431.0	6.947004
12437.0	14.247259

	MEAN(invoices.MAX(item_purchases.UnitPrice)) \
CustomerID	
12353.0	NaN
12359.0	NaN
12360.0	NaN
12380.0	NaN
12415.0	8.375
12417.0	28.000
12423.0	NaN
12426.0	NaN
12431.0	7.950
12437.0	18.000

	MEAN(invoices.MAX(item_purchases.Quantity)) \
CustomerID	
12353.0	NaN
12359.0	NaN
12360.0	NaN
12380.0	NaN
12415.0	250.0
12417.0	24.0
12423.0	NaN
12426.0	NaN
12431.0	24.0
12437.0	48.0

	MEAN(invoices.MEAN(item_purchases.Quantity)) \
CustomerID	
12353.0	NaN
12359.0	NaN
12360.0	NaN
12380.0	NaN
12415.0	6.630137
12417.0	11.608696
12423.0	NaN
12426.0	NaN
12431.0	8.000000
12437.0	18.375000

	STD(invoices.MAX(item_purchases.UnitPrice)) \
CustomerID	
12353.0	NaN
12359.0	NaN
12360.0	NaN
12380.0	NaN
12415.0	4.125
12417.0	0.000

12423.0	NaN
12426.0	NaN
12431.0	0.000
12437.0	0.000

  

```
STD(invoices.MEAN(item_purchases.UnitPrice))
```

CustomerID	
12353.0	NaN
12359.0	NaN
12360.0	NaN
12380.0	NaN
12415.0	0.773973
12417.0	0.000000
12423.0	NaN
12426.0	NaN
12431.0	0.000000
12437.0	0.000000

[10 rows x 27 columns]

## 5 Step 4: Let's train a model using Random Forests

Now we are ready to train a model and evaluate it. To do this, we:

- \* First split our training examples in train\_test\_split
- \* Impute missing values
- \* Train a model using training data
- \* Test on the data set aside for testing

We can split the data using the function `train_test_split` and specifying the proportion we want for testing. In this case we specified that as 35%

```
In [109]: y=label_times['purchases>threshold']
          X_train, X_test, y_train, y_test = train_test_split(feature_matrix,
                                                             y, test_size=0.35)
```

We can impute the missing values or NaN values in the `feature_matrix` using the `Imputer` in `scikit-learn`. It replaces the NaN values in a feature column with the mean of the rest of the entries in that column. This is a simple imputation strategy

```
In [116]: imp = Imputer(missing_values='NaN', strategy='mean', axis=0)
          imp = imp.fit(X_train)
          X_train_imp = imp.transform(X_train)
```

We can train a `RandomForest` classifier (a type of ensemble classifier). We make use of `scikit-learn` package for this as well.

```
In [117]: clf = RandomForestClassifier(random_state=0,n_estimators=10,
                                       class_weight="balanced",verbose=True)
          clf.fit(X_train_imp, y_train)
```

```
[Parallel(n_jobs=1)]: Done 10 out of 10 | elapsed: 0.0s finished
```



```
Out[117]: RandomForestClassifier(bootstrap=True, class_weight='balanced',
                                criterion='gini', max_depth=None, max_features='auto',
                                max_leaf_nodes=None, min_impurity_decrease=0.0,
                                min_impurity_split=None, min_samples_leaf=1,
                                min_samples_split=2, min_weight_fraction_leaf=0.0,
                                n_estimators=10, n_jobs=1, oob_score=False, random_state=0,
                                verbose=True, warm_start=False)
```

## 6 Step 5: Test the model

To test a model, we: \* First impute the missing values \* Use the trained classifier to predict the labels

```
In [118]: X_test_imp = imp.transform(X_test)
          predicted_labels = clf.predict(X_test_imp)
```

```
[Parallel(n_jobs=1)]: Done 10 out of 10 | elapsed: 0.0s finished
```

We evaluate by calculatin

```
In [120]: tn, fp, fn, tp = confusion_matrix(y_test, predicted_labels).ravel()
```

```
In [121]: tp,fp
```

```
Out[121]: (0, 10)
```