Compose Documentation

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Creating labels from raw data for a machine learning problem is difficult and time consuming. This is where *Compose* helps by making it easier to quickly generate complex labels from raw data.

Compose is advanced software for automating the prediction engineering process. Compose enables you to systematically define prediction problems by automatically extracting historical training examples to train machine learning algorithms.

CHAPTER 1

Install

In Python 3.6 or later, Compose can be installed by running the following commmand:

```
pip install composeml
```

CHAPTER 2

Getting Started

In this example, we will generate labels on a mock dataset of transactions. For each customer, we want to label whether the total purchase amount over the next hour of transactions will exceed $300. Additionally, we want to predict one hour in advance.

[1]:
```
import composeml as cp
```

2.1 Load Data

With the package installed, we load in the data. To get an idea on how the transactions looks, we preview the data frame.

[2]:
```
df = cp.demos.load_transactions()

df[df.columns[:7]].head()
```

[2]:

	transaction_id	session_id	transaction_time	product_id	amount	\
0	298	1	2014-01-01 00:00:00	5	127.64	
1	10	1	2014-01-01 00:09:45	5	57.39	
2	495	1	2014-01-01 00:14:05	5	69.45	
3	460	10	2014-01-01 02:33:50	5	123.19	
4	302	10	2014-01-01 02:37:05	5	64.47	

	customer_id	device
0	2	desktop
1	2	desktop
2	2	desktop
3	2	tablet
4	2	tablet

2.2 Create Labeling Function

To get started, we define the labeling function that will return the total purchase amount given a hour of transactions.

[3]:
```
def total_spent(df):
    total = df['amount'].sum()
    return total
```

2.3 Construct Label Maker

With the labeling function, we create the *LabelMaker* for our prediction problem. To process one hour of transactions for each customer, we set the `target_entity` to the customer ID and the `window_size` to one hour.

[4]:
```
label_maker = cp.LabelMaker(
    target_entity="customer_id",
    time_index="transaction_time",
    labeling_function=total_spent,
    window_size="1h",
)
```

2.4 Generate Labels

Next, we automatically search and extract the labels by using *LabelMaker.search()*.

[5]:
```
labels = label_maker.search(
    df.sort_values('transaction_time'),
    num_examples_per_instance=-1,
    gap=1,
    verbose=True,
)

labels.head()
```

```
Elapsed: 00:00 | Remaining: 00:00 | Progress: 100%|| customer_id: 5/5
```

[5]:

id	customer_id	time	total_spent
0	1	2014-01-01 00:45:30	914.73
1	1	2014-01-01 00:46:35	806.62
2	1	2014-01-01 00:47:40	694.09
3	1	2014-01-01 00:52:00	687.80
4	1	2014-01-01 00:53:05	656.43

2.5 Transform Labels

With the generated *LabelTimes*, we will apply specific transforms for our prediction problem.

2.5.1 Apply Threshold on Labels

To make the labels binary, *LabelTimes.threshold()* is applied for amounts exceeding $300.

[6]:
```
labels = labels.threshold(300)

labels.head()
```

[6]:
```
    customer_id                time  total_spent
id
0             1 2014-01-01 00:45:30         True
1             1 2014-01-01 00:46:35         True
2             1 2014-01-01 00:47:40         True
3             1 2014-01-01 00:52:00         True
4             1 2014-01-01 00:53:05         True
```

2.5.2 Lead Label Times

Additionally, the label times are shifted one hour earlier for predicting in advance by using *LabelTimes.apply_lead()*.

[7]:
```
labels = labels.apply_lead('1h')

labels.head()
```

[7]:
```
    customer_id                time  total_spent
id
0             1 2013-12-31 23:45:30         True
1             1 2013-12-31 23:46:35         True
2             1 2013-12-31 23:47:40         True
3             1 2013-12-31 23:52:00         True
4             1 2013-12-31 23:53:05         True
```

2.6 Describe Labels

After transforming the labels, we can use *LabelTimes.describe()* to print out the distribution with the settings and transforms that were used to make these labels. This is useful as a reference for understanding how the labels were generated from raw data. Also, the label distribution is helpful for determining if we have imbalanced labels.

[8]:
```
labels.describe()
```

```
Label Distribution
------------
False      56
True       44
Total:    100


Settings
-----
gap                                1
label_type                  discrete
labeling_function       total_spent
minimum_data                   None
num_examples_per_instance        -1
target_entity           customer_id
window_size                  <Hour>
```

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```
Transforms
-------
1. threshold
  - value:    300

2. apply_lead
  - value:    1h
```

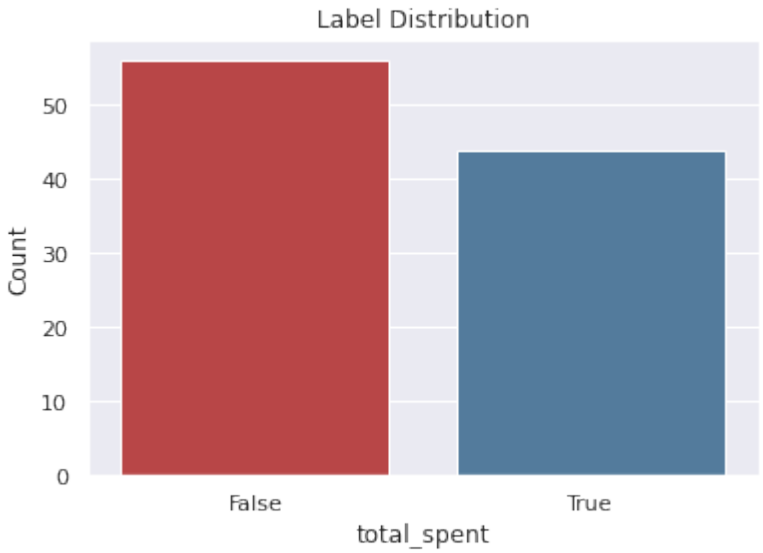
2.7 Plot Labels

Also, there are plots available for insight to the labels.

2.7.1 Distribution

This plot shows the label distribution.

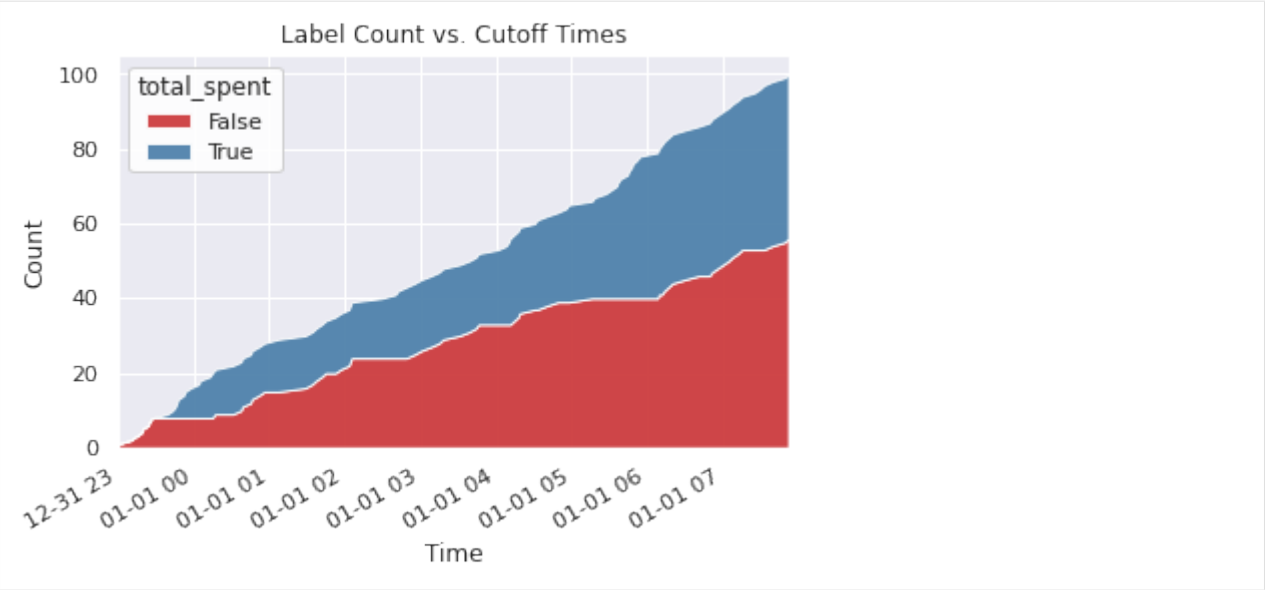
[9]:
```
%matplotlib inline
labels.plot.distribution();
```



2.7.2 Count by Time

This plot shows the label distribution across cutoff times.

[10]:
```
%matplotlib inline
labels.plot.count_by_time();
```


Label Count vs. Cutoff Times
total_spent
False
True
Count
100
80
60
40
20
0
12-31 23
01-01 00
01-01 01
01-01 02
01-01 03
01-01 04
01-01 05
01-01 06
01-01 07
Time

CHAPTER 3

Main Concepts

3.1 Label Maker

The label maker automatically extracts data along the time index to generate labels. The process starts by setting the first cutoff time after the minimum amount of data. Then subsequent cutoff times are spaced apart using **gaps**. Starting from each cutoff time, a window determines the amount of data, also referred to as a **data slice**, to pass into a labeling function.

The labeling function will then transform the extracted data slice into a label.

In cases where the labeling function returned continuous values, there are label transforms available to further process the labels into discrete values.

CHAPTER 4

Data Slice Generator

The data slice generator is the underlying function used to generate data slices for the labeling function. If the label maker raises an error during the search or the output labels doesn't seem right, then you will need to check the logic in the labeling function or inspect the data for any inherent errors. This is where the data slice generator can help us do both. Ideally, you also want to use the generator during the development of your labeling function for best practice. However, it is an optional step and not required to generate labels.

In this guide, we will use the data slice generator to inspect data slices and apply our labeling function. To get started, let's load a mock dataset of transactions and sample the data to see how the transactions look.

[1]:
```
import composeml as cp
```

[2]:
```
df = cp.demos.load_transactions()
df = df[df.columns[:7]]
df.sample(n=5, random_state=0)
```

[2]:
```
    transaction_id  session_id    transaction_time  product_id  amount  \
26              94          24 2014-01-01 05:55:20           5  100.42
86             274           7 2014-01-01 01:46:10           5   14.45
2              495           1 2014-01-01 00:14:05           5   69.45
55             275           4 2014-01-01 00:45:30           5  108.11
75             368          27 2014-01-01 06:36:30           5  139.43

    customer_id   device
26            5   tablet
86            3   tablet
2             2  desktop
55            1   mobile
75            1   mobile
```

4.1 Labeling Function

Let's define a labeling function that will return how much a customer spent given a slice of transactions.

[3]:
```
def total_spent(df):
    total = df['amount'].sum()
    return total
```

4.2 Data Slices

The *LabelMaker.slice()* method will create the data slice generator. The parameters of this method can be passed directly to *LabelMaker.search()* to generate the labels. In the following sections, we will see how to use the data slice generator to make data slices consecutive, overlap, or spread out.

See also:

For a conceptual explanation of the process, see *Main Concepts*.

4.2.1 Consecutive

When the the gap size is equal to the window size, the data slices are consecutive. In other words, the data slices do not overlap and are not spread out (e.g. don't skip any data). This is the default value for the gap size. To demonstrate this example, let's generate data slices using these parameters.

We create a label maker with the 2-hour window size.

[4]:
```
lm = cp.LabelMaker(
    target_entity="customer_id",
    time_index="transaction_time",
    labeling_function=total_spent,
    window_size="2h",
)
```

Then, we create a data slice generator with the 2-hour gap size. The default value for the gap size is the window size.

Tip: You can directly set `minimum_data` as the first cutoff time.

---

[5]:
```
slices = lm.slice(
    df.sort_values('transaction_time'),
    num_examples_per_instance=-1,
    minimum_data='2014-01-01',
)
```

Consecutive - Data Slice #1

By printing this data slice, we can see that it's the first slice of transactions (denoted by the `slice_number`) for customer 1. This data slice contains all of the customer's transactions that occurred within the 2-hour window between `2014-01-01 00:00:00` and `2014-01-01 02:00:00`. We can also see that the 2-hour gap aligns the cutoff times to the window. So, the next data slice will start at the end of this data slice.

[6]:
```
ds = next(slices)
print(ds)
ds
```

```
slice_number                                            1
customer_id                                             1
window           [2014-01-01 00:00:00, 2014-01-01 02:00:00)
gap              [2014-01-01 00:00:00, 2014-01-01 02:00:00)
```

[6]:
```
                     transaction_id  session_id  product_id  amount  \
transaction_time
2014-01-01 00:45:30             275           4           5  108.11
2014-01-01 00:46:35             101           4           5  112.53
2014-01-01 00:47:40              80           4           5    6.29
2014-01-01 00:52:00             163           4           5   31.37
2014-01-01 00:53:05             293           4           5   82.88
2014-01-01 00:57:25             103           4           5   20.79
2014-01-01 01:03:55             488           4           5  129.00
2014-01-01 01:05:00             413           4           5  119.98
2014-01-01 01:31:00             191           6           5  139.23
2014-01-01 01:37:30             372           6           5  114.84
2014-01-01 01:38:35             387           6           5   49.71

                     customer_id  device
transaction_time
2014-01-01 00:45:30            1  mobile
2014-01-01 00:46:35            1  mobile
2014-01-01 00:47:40            1  mobile
2014-01-01 00:52:00            1  mobile
2014-01-01 00:53:05            1  mobile
2014-01-01 00:57:25            1  mobile
2014-01-01 01:03:55            1  mobile
2014-01-01 01:05:00            1  mobile
2014-01-01 01:31:00            1  tablet
2014-01-01 01:37:30            1  tablet
2014-01-01 01:38:35            1  tablet
```

Let's apply our labeling function for the total spent on this data slice.

[7]:
```
total_spent(ds)
```

[7]:
```
914.7300000000001
```

Consecutive - Data Slice #2

In the second data slice, we can see the next 2 consecutive hours of transactions between `2014-01-01 02:00:00` and `2014-01-01 04:00:00`. This is useful for generating labels that will consecutively process the data only once.

[8]:
```
ds = next(slices)
print(ds)
ds
```

```
slice_number                                            2
customer_id                                             1
window           [2014-01-01 02:00:00, 2014-01-01 04:00:00)
gap              [2014-01-01 02:00:00, 2014-01-01 04:00:00)
```

[8]:
```
                     transaction_id  session_id  product_id  amount  \
transaction_time
2014-01-01 02:28:25             287           9           5   50.94
```

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```
2014-01-01 03:29:05              190          14           5  110.52
2014-01-01 03:39:55                7          14           5  107.42

                     customer_id   device
transaction_time
2014-01-01 02:28:25            1  desktop
2014-01-01 03:29:05            1   tablet
2014-01-01 03:39:55            1   tablet
```

Let's apply our labeling function for the total spent on this data slice.

[9]:
```
total_spent(ds)
```

[9]:
```
268.88
```

4.2.2 Overlap

When the the gap size is less than the window size, the data slices will overlap. We can use this for rolling window based labeling processes. The amount of overlap is the difference between the window and gap size. For example, if the window size is 3 hours and the gap size is 1 hour, then 2 hours will overlap on each data slice. To demonstrate this example, let's generate data slices using these parameters.

We create a label maker with the 3-hour window size.

[10]:
```
lm = cp.LabelMaker(
    target_entity="customer_id",
    time_index="transaction_time",
    labeling_function=total_spent,
    window_size="3h",
)
```

Then, we create a data slice generator with the 1-hour gap size.

[11]:
```
slices = lm.slice(
    df.sort_values('transaction_time'),
    num_examples_per_instance=-1,
    minimum_data='2014-01-01',
    gap="1h",
)
```

Overlap - Data Slice #1

The first data slice contains all of the customer's transactions that occurred within the 3-hour window between `2014-01-01 00:00:00` and `2014-01-01 03:00:00`. We can also see that the 1-hour gap spaces apart the cutoff time of this data slice at `2014-01-01 00:00:00` from the cutoff time of the next data slice at `2014-01-01 01:00:00`.

[12]:
```
ds = next(slices)
print(ds)
ds
```

```
slice_number                                                1
customer_id                                                 1
window           [2014-01-01 00:00:00, 2014-01-01 03:00:00)
gap              [2014-01-01 00:00:00, 2014-01-01 01:00:00)
```

[12]:
```
                     transaction_id  session_id  product_id  amount  \
transaction_time
2014-01-01 00:45:30             275           4           5  108.11
2014-01-01 00:46:35             101           4           5  112.53
2014-01-01 00:47:40              80           4           5    6.29
2014-01-01 00:52:00             163           4           5   31.37
2014-01-01 00:53:05             293           4           5   82.88
2014-01-01 00:57:25             103           4           5   20.79
2014-01-01 01:03:55             488           4           5  129.00
2014-01-01 01:05:00             413           4           5  119.98
2014-01-01 01:31:00             191           6           5  139.23
2014-01-01 01:37:30             372           6           5  114.84
2014-01-01 01:38:35             387           6           5   49.71
2014-01-01 02:28:25             287           9           5   50.94

                     customer_id   device
transaction_time
2014-01-01 00:45:30            1   mobile
2014-01-01 00:46:35            1   mobile
2014-01-01 00:47:40            1   mobile
2014-01-01 00:52:00            1   mobile
2014-01-01 00:53:05            1   mobile
2014-01-01 00:57:25            1   mobile
2014-01-01 01:03:55            1   mobile
2014-01-01 01:05:00            1   mobile
2014-01-01 01:31:00            1   tablet
2014-01-01 01:37:30            1   tablet
2014-01-01 01:38:35            1   tablet
2014-01-01 02:28:25            1  desktop
```

Let's apply our labeling function for the total spent on this data slice.

[13]:
```
total_spent(ds)
```

[13]:
```
965.6700000000001
```

Overlap - Data Slice #2

In the second data slice, we can see that there is a 2-hour overlap on the transactions that occurred between `2014-01-01 01:00:00` and `2014-01-01 03:00:00`. By adjusting the gap size, we can set the precise amount of overlap in the data slices. This is useful for generating labels with specific overlap.

[14]:
```
ds = next(slices)
print(ds)
ds
```

```
slice_number                                          2
customer_id                                           1
window           [2014-01-01 01:00:00, 2014-01-01 04:00:00)
gap              [2014-01-01 01:00:00, 2014-01-01 02:00:00)
```

[14]:
```
                     transaction_id  session_id  product_id  amount  \
transaction_time
2014-01-01 01:03:55             488           4           5  129.00
2014-01-01 01:05:00             413           4           5  119.98
2014-01-01 01:31:00             191           6           5  139.23
2014-01-01 01:37:30             372           6           5  114.84
```

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```
2014-01-01 01:38:35             387           6           5   49.71
2014-01-01 02:28:25             287           9           5   50.94
2014-01-01 03:29:05             190          14           5  110.52
2014-01-01 03:39:55               7          14           5  107.42

                     customer_id   device
transaction_time
2014-01-01 01:03:55            1   mobile
2014-01-01 01:05:00            1   mobile
2014-01-01 01:31:00            1   tablet
2014-01-01 01:37:30            1   tablet
2014-01-01 01:38:35            1   tablet
2014-01-01 02:28:25            1  desktop
2014-01-01 03:29:05            1   tablet
2014-01-01 03:39:55            1   tablet
```

Let's apply our labeling function for the total spent on this data slice.

[15]:
```
total_spent(ds)
```

[15]:
```
821.6400000000001
```

4.2.3 Spread Out

When the the gap size is greater than the window size, then there is data in-between data slices that will be skipped. We can use this for labeling data at specific intervals of time. The amount of data skipped is the difference between the gap and window size. For example, if the gap size is 3 hours and the window size is 1 hour, then 2 hours of data will be skipped in-between data slices. To demonstrate this example, let's generate data slices using these parameters.

We create a label maker with the 1-hour window size.

[16]:
```
lm = cp.LabelMaker(
    target_entity="customer_id",
    time_index="transaction_time",
    labeling_function=total_spent,
    window_size="1h",
)
```

Then, we create a data slice generator with the 3-hour gap size.

[17]:
```
slices = lm.slice(
    df.sort_values('transaction_time'),
    num_examples_per_instance=-1,
    minimum_data='2014-01-01',
    gap="3h",
)
```

Spread Out - Data Slice #1

The first data slice contains all of the customer's transactions that occurred within the 1-hour window between `2014-01-01 00:00:00` and `2014-01-01 01:00:00`. We can also see that the 3-hour gap spaces apart the cutoff time of this data slice at `2014-01-01 00:00:00` from the cutoff time of the next data slice at `2014-01-01 03:00:00`.

[18]:
```
ds = next(slices)
print(ds)
ds
```

```
slice_number                                              1
customer_id                                               1
window           [2014-01-01 00:00:00, 2014-01-01 01:00:00)
gap              [2014-01-01 00:00:00, 2014-01-01 03:00:00)
```

[18]:
```
                     transaction_id  session_id  product_id  amount  \
transaction_time
2014-01-01 00:45:30             275           4           5  108.11
2014-01-01 00:46:35             101           4           5  112.53
2014-01-01 00:47:40              80           4           5    6.29
2014-01-01 00:52:00             163           4           5   31.37
2014-01-01 00:53:05             293           4           5   82.88
2014-01-01 00:57:25             103           4           5   20.79

                     customer_id  device
transaction_time
2014-01-01 00:45:30            1  mobile
2014-01-01 00:46:35            1  mobile
2014-01-01 00:47:40            1  mobile
2014-01-01 00:52:00            1  mobile
2014-01-01 00:53:05            1  mobile
2014-01-01 00:57:25            1  mobile
```

Let's apply our labeling function for the total spent on this data slice.

[19]:
```
total_spent(ds)
```

[19]:
```
361.96999999999997
```

Spread Out - Data Slice #2

In the second data slice, we can see that 2 hours of transactions were skipped between `2014-01-01 01:00:00` and `2014-01-01 03:00:00`. By adjusting the gap size, we can set the precise amount of data to skip in-between data slices. This is useful for generating labels that target specific portions of a dataset.

[20]:
```
ds = next(slices)
print(ds)
ds
```

```
slice_number                                              2
customer_id                                               1
window           [2014-01-01 03:00:00, 2014-01-01 04:00:00)
gap              [2014-01-01 03:00:00, 2014-01-01 06:00:00)
```

[20]:
```
                     transaction_id  session_id  product_id  amount  \
transaction_time
2014-01-01 03:29:05             190          14           5  110.52
2014-01-01 03:39:55               7          14           5  107.42

                     customer_id  device
transaction_time
2014-01-01 03:29:05            1  tablet
2014-01-01 03:39:55            1  tablet
```

Let's apply our labeling function for the total spent on this data slice.

```
[21]: total_spent(ds)
```

```
[21]: 217.94
```

4.3 Data Slice Context

Each data slice has a `context` attribute to access its metadata. This is useful for integrating the context with the logic in the labeling function.

```
[22]: vars(ds.context)
```

```
[22]: {'gap': (Timestamp('2014-01-01 03:00:00'), Timestamp('2014-01-01 06:00:00')),
 'window': (Timestamp('2014-01-01 03:00:00'),
  Timestamp('2014-01-01 04:00:00')),
 'slice_number': 2,
 'target_entity': 'customer_id',
 'target_instance': 1}
```

From this guide, hopefully you have a better understanding on how to use the data slice generator to develop your labeling function.

CHAPTER 5

Using Compose with Featuretools

In this guide, we will generate labels and features on a mock dataset of transactions using Compose and Featuretools. Then create a machine learning model for predicting one hour in advance whether customers will spend over $1200 within the next hour of transactions.

[1]:
```
%matplotlib inline
import composeml as cp
import featuretools as ft
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
```

5.1 Load Data

To get an idea on how the transactions looks, we preview the data frame.

[2]:
```
transactions = ft.demo.load_mock_customer(
    return_single_table=True,
    random_seed=0,
)

transactions[transactions.columns[:7]].head()
```

[2]:
```
   transaction_id  session_id    transaction_time product_id  amount  \
0             298           1 2014-01-01 00:00:00          5  127.64
1              10           1 2014-01-01 00:09:45          5   57.39
2             495           1 2014-01-01 00:14:05          5   69.45
3             460          10 2014-01-01 02:33:50          5  123.19
4             302          10 2014-01-01 02:37:05          5   64.47

   customer_id   device
0            2  desktop
```

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```
1             2  desktop
2             2  desktop
3             2   tablet
4             2   tablet
```

5.2 Generate Labels

Now with the transactions loaded, we are ready to generate labels for our prediction problem.

5.2.1 Create Labeling Function

First, we define the function that will return the total purchase amount given a hour of transactions.

[3]:
```
def total_spent(df):
    total = df["amount"].sum()
    return total
```

5.2.2 Construct Label Maker

With our labeling function, we create the *LabelMaker* for the transactions. The `target_entity` is set to `customer_id` so that the labels are generated for each customer. The `window_size` is set to one hour to process one hour of transactions for a given customer.

[4]:
```
label_maker = cp.LabelMaker(
    target_entity='customer_id',
    time_index='transaction_time',
    labeling_function=total_spent,
    window_size='1h',
)
```

5.2.3 Create Labels

Next, we automatically search and extract the labels by using *LabelMaker.search()*.

See also:

For more details on how the label maker works, see *Main Concepts*.

[5]:
```
labels = label_maker.search(
    transactions.sort_values('transaction_time'),
    num_examples_per_instance=-1,
    gap=1,
)

labels.head()
```

```
Elapsed: 00:00 | Remaining: 00:00 | Progress: 100%|| customer_id: 5/5
```

[5]:
```
    customer_id                time  total_spent
id
0             1 2014-01-01 00:44:25      2880.53
1             1 2014-01-01 00:45:30      2859.18
2             1 2014-01-01 00:46:35      2751.07
3             1 2014-01-01 00:47:40      2638.54
4             1 2014-01-01 00:48:45      2632.25
```

5.2.4 Transform Labels

With the generated *LabelTimes*, we will apply specific transforms for our prediction problem.

Apply Threshold on Labels

We apply *LabelTimes.threshold()* to make the labels binary for total amounts exceeding $1200.

[6]:
```
labels = labels.threshold(1200)

labels.head()
```

[6]:
```
    customer_id                time  total_spent
id
0             1 2014-01-01 00:44:25         True
1             1 2014-01-01 00:45:30         True
2             1 2014-01-01 00:46:35         True
3             1 2014-01-01 00:47:40         True
4             1 2014-01-01 00:48:45         True
```

Lead Label Times

We also use *LabelTimes.apply_lead()* to shift the label times 1 hour earlier for predicting in advance.

[7]:
```
labels = labels.apply_lead('1h')

labels.head()
```

[7]:
```
    customer_id                time  total_spent
id
0             1 2013-12-31 23:44:25         True
1             1 2013-12-31 23:45:30         True
2             1 2013-12-31 23:46:35         True
3             1 2013-12-31 23:47:40         True
4             1 2013-12-31 23:48:45         True
```

5.2.5 Describe Labels

After transforming the labels, we could use *LabelTimes.describe()* to print out the distribution with the settings and transforms that were used to make the labels. This is useful as a reference for understanding how the labels were generated from raw data. Also, the label distribution is helpful for determining if we have imbalanced labels.

[8]:
```
labels.describe()
```

```
Label Distribution
------------
False     248
True      252
Total:    500


Settings
-----
gap                                    1
label_type                      discrete
labeling_function            total_spent
minimum_data                        None
num_examples_per_instance             -1
target_entity                customer_id
window_size                      <Hour>


Transforms
-------
1. threshold
  - value:    1200

2. apply_lead
  - value:    1h
```

5.3 Generate Features

Now with the generated labels, we are ready to generate features for our prediction problem.

5.3.1 Create Entity Set

Let's construct an `EntitySet` and load the transactions as an entity by using `EntitySet.entity_from_dataframe()`. Then extract additional entities by using `EntitySet.normalize_entity()`.

See also:

For more details on working with entity sets, see loading_data/using_entitysets .

[9]:
```
es = ft.EntitySet('transactions')

es.entity_from_dataframe(
    'transactions',
    transactions,
    index='transaction_id',
    time_index='transaction_time',
)

es.normalize_entity(
    base_entity_id='transactions',
    new_entity_id='sessions',
    index='session_id',
```

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```
    make_time_index='session_start',
    additional_variables=[
        'device',
        'customer_id',
        'zip_code',
        'session_start',
        'join_date',
        'date_of_birth',
    ],
)

es.normalize_entity(
    base_entity_id='sessions',
    new_entity_id='customers',
    index='customer_id',
    make_time_index='join_date',
    additional_variables=[
        'zip_code',
        'join_date',
        'date_of_birth',
    ],
)

es.normalize_entity(
    base_entity_id='transactions',
    new_entity_id='products',
    index='product_id',
    additional_variables=['brand'],
    make_time_index=False,
)

es.add_last_time_indexes()
```

5.3.2 Describe Entity Set

To get information on how the entity set is structured, we could print the entity set and use `EntitySet.plot()` to create a diagram.

[10]:
```
print(es, end='\n\n')

es.plot()
```

```
Entityset: transactions
  Entities:
    transactions [Rows: 500, Columns: 5]
    sessions [Rows: 35, Columns: 4]
    customers [Rows: 5, Columns: 4]
    products [Rows: 5, Columns: 2]
  Relationships:
    transactions.session_id -> sessions.session_id
    sessions.customer_id -> customers.customer_id
    transactions.product_id -> products.product_id
```

[10]:

5.3.3 Create Feature Matrix

Next, we generate features that correspond to the labels created previously by using `dfs()`. The `target_entity` is set to `customers` so that features are only calculated for customers. The `cutoff_time` is set to the labels so that features are calculated only using data up to and including the label cutoff times. Notice that the output of Compose integrates easily with Featuretools.

See also:

For more details on calculating features using cutoff times, see automated_feature_engineering/handling_time.

[11]:
```
feature_matrix, features_defs = ft.dfs(
    entityset=es,
    target_entity='customers',
    cutoff_time=labels,
    cutoff_time_in_index=True,
    verbose=True,
)
```

```
Built 77 features
Elapsed: 00:51 | Progress: 100%|
```

5.3.4 Describe Features

To get an idea on how the generated features look, we preview the feature definitions.

[12]:
```
features_defs[:20]
```

[12]:
```
[<Feature: zip_code>,
 <Feature: COUNT(sessions)>,
 <Feature: NUM_UNIQUE(sessions.device)>,
 <Feature: MODE(sessions.device)>,
 <Feature: SUM(transactions.amount)>,
 <Feature: STD(transactions.amount)>,
 <Feature: MAX(transactions.amount)>,
 <Feature: SKEW(transactions.amount)>,
 <Feature: MIN(transactions.amount)>,
 <Feature: MEAN(transactions.amount)>,
 <Feature: COUNT(transactions)>,
 <Feature: NUM_UNIQUE(transactions.product_id)>,
 <Feature: MODE(transactions.product_id)>,
 <Feature: DAY(date_of_birth)>,
 <Feature: DAY(join_date)>,
 <Feature: YEAR(date_of_birth)>,
 <Feature: YEAR(join_date)>,
 <Feature: MONTH(date_of_birth)>,
 <Feature: MONTH(join_date)>,
 <Feature: WEEKDAY(date_of_birth)>]
```

5.4 Machine Learning

Now with the generated labels and features, we are ready to create a machine learning model for our prediction problem.

5.4.1 Preprocess Features

In the feature matrix, let's extract the labels and fill any missing values with zeros. Then, one-hot encode all categorical features by using `encode_features()`.

[13]:
```
y = feature_matrix.pop(labels.label_name)
x = feature_matrix.fillna(0)
x, features_enc = ft.encode_features(x, features_defs)
```

5.4.2 Split Labels and Features

After preprocessing, we split the features and corresponding labels each into training and testing sets.

[14]:
```
x_train, x_test, y_train, y_test = train_test_split(
    x,
    y,
    train_size=.8,
    test_size=.2,
    random_state=0,
)
```

5.4.3 Train Model

Next, we train a random forest classifer on the training set.

[15]:
```
clf = RandomForestClassifier(n_estimators=10, random_state=0)

clf.fit(x_train, y_train)
```

[15]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, 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=None, oob_score=False, random_state=0, verbose=0,
                       warm_start=False)
```

5.4.4 Test Model

Lastly, we test the model performance by evaluating predictions on the testing set.

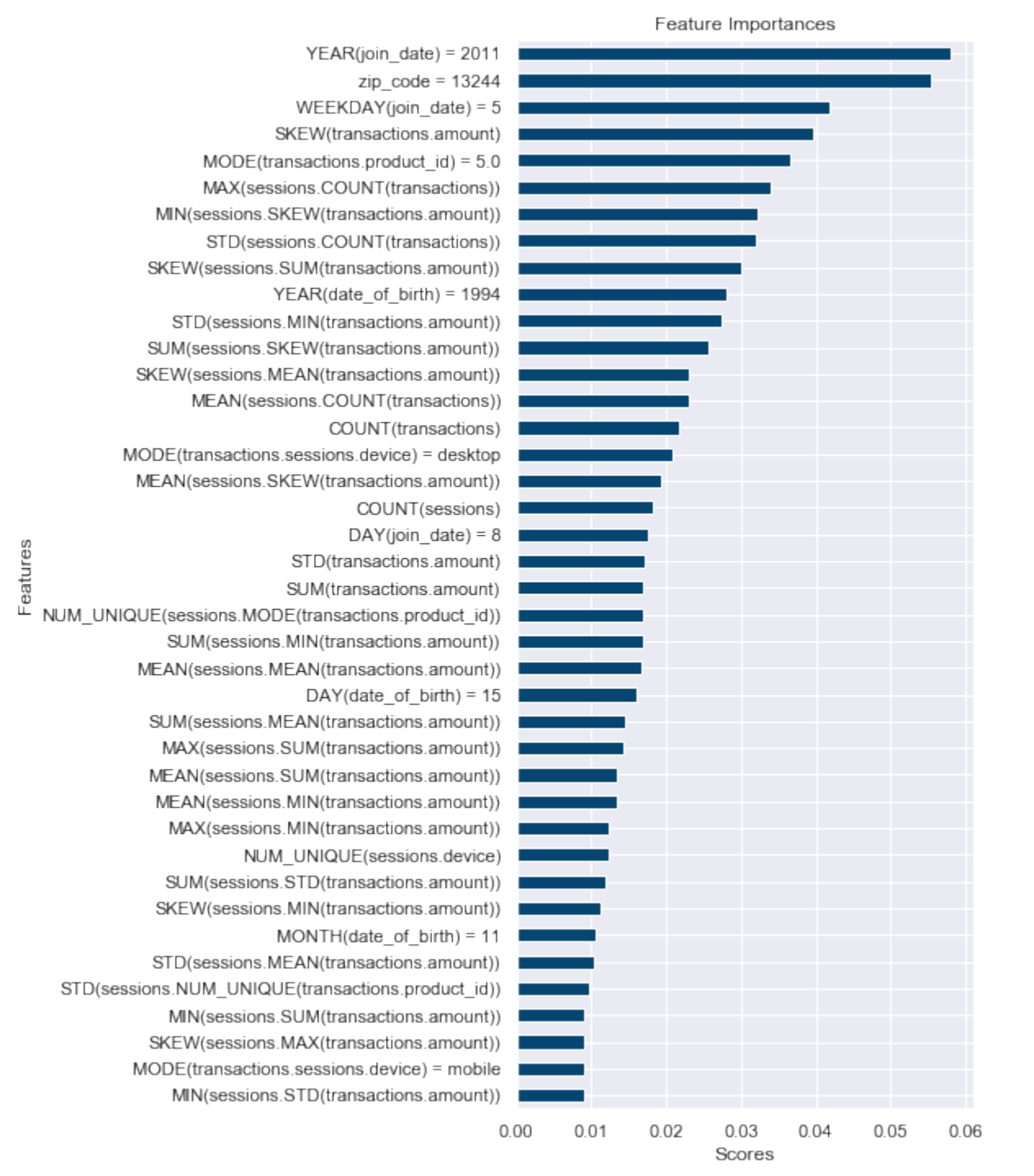
[16]:
```
y_hat = clf.predict(x_test)

print(classification_report(y_test, y_hat))
```

```
              precision    recall  f1-score   support

       False       0.79      0.90      0.84        49
        True       0.89      0.76      0.82        51

    accuracy                           0.83       100
   macro avg       0.84      0.83      0.83       100
weighted avg       0.84      0.83      0.83       100
```

5.4.5 Feature Importances

This plot is based on scores obtained by the model to illustrate which features are considered important for predictions.

[17]:
```
feature_importances = zip(x_train.columns, clf.feature_importances_)
feature_importances = pd.Series(dict(feature_importances))
feature_importances = feature_importances.rename_axis('Features')
feature_importances = feature_importances.sort_values()

top_features = feature_importances.tail(40)
plot = top_features.plot(kind='barh', figsize=(5, 12), color='#054571')
plot.set_title('Feature Importances')
plot.set_xlabel('Scores');
```


Feature Importances
YEAR(join_date) = 2011
zip_code = 13244
WEEKDAY(join_date) = 5
SKEW(transactions.amount)
MODE(transactions.product_id) = 5.0
MAX(sessions.COUNT(transactions))
MIN(sessions.SKEW(transactions.amount))
STD(sessions.COUNT(transactions))
SKEW(sessions.SUM(transactions.amount))
YEAR(date_of_birth) = 1994
STD(sessions.MIN(transactions.amount))
SUM(sessions.SKEW(transactions.amount))
SKEW(sessions.MEAN(transactions.amount))
MEAN(sessions.COUNT(transactions))
COUNT(transactions)
MODE(transactions.sessions.device) = desktop
MEAN(sessions.SKEW(transactions.amount))
COUNT(sessions)
DAY(join_date) = 8
STD(transactions.amount)
SUM(transactions.amount)
NUM_UNIQUE(sessions.MODE(transactions.product_id))
SUM(sessions.MIN(transactions.amount))
MEAN(sessions.MEAN(transactions.amount))
DAY(date_of_birth) = 15
SUM(sessions.MEAN(transactions.amount))
MAX(sessions.SUM(transactions.amount))
MEAN(sessions.SUM(transactions.amount))
MEAN(sessions.MIN(transactions.amount))
MAX(sessions.MIN(transactions.amount))
NUM_UNIQUE(sessions.device)
SUM(sessions.STD(transactions.amount))
SKEW(sessions.MIN(transactions.amount))
MONTH(date_of_birth) = 11
STD(sessions.MEAN(transactions.amount))
STD(sessions.NUM_UNIQUE(transactions.product_id))
MIN(sessions.SUM(transactions.amount))
SKEW(sessions.MAX(transactions.amount))
MODE(transactions.sessions.device) = mobile
MIN(sessions.STD(transactions.amount))
Features
0.00
0.01
0.02
0.03
0.04
0.05
0.06
Scores

CHAPTER 6

Using Label Transforms

In this guide, we will demonstrate how to use the transforms that are available on *LabelTimes*. Each transform will return a copy of the label times. This is useful for trying out multiple transforms in different settings without having to recalculate the labels. As a result, we could see which labels give a better performance in less time.

6.1 Generate Labels

Let's start by generating labels on a mock dataset of transactions. Each label is defined as the total spent by a customer given one hour of transactions.

[1]:
```
import composeml as cp

def total_spent(df):
    return df['amount'].sum()

label_maker = cp.LabelMaker(
    labeling_function=total_spent,
    target_entity='customer_id',
    time_index='transaction_time',
    window_size='1h',
)

labels = label_maker.search(
    cp.demos.load_transactions(),
    num_examples_per_instance=10,
    label_type='continuous',
    minimum_data='2h',
    gap='2min',
    verbose=True,
)
```

```
Elapsed: 00:00 | Remaining: 00:00 | Progress: 100%|| customer_id: 50/50
```

To get an idea on how the labels looks, we preview the data frame.

[2]:
```
labels.head()
```

[2]:
```
    customer_id                time  total_spent
id
0             1 2014-01-01 02:45:30       217.94
1             1 2014-01-01 02:47:30       217.94
2             1 2014-01-01 02:49:30       217.94
3             1 2014-01-01 02:51:30       217.94
4             1 2014-01-01 02:53:30       217.94
```

6.2 Threshold on Labels

LabelTimes.threshold() will create binary labels by testing if label values are above a threshold. In this example, a threshold is applied to determine which customers spent over 100.

[3]:
```
labels.threshold(100).head()
```

[3]:
```
    customer_id                time  total_spent
id
0             1 2014-01-01 02:45:30         True
1             1 2014-01-01 02:47:30         True
2             1 2014-01-01 02:49:30         True
3             1 2014-01-01 02:51:30         True
4             1 2014-01-01 02:53:30         True
```

6.3 Lead Labels Times

LabelTimes.apply_lead() will shift the label time earlier. This is useful for training a model to predict in advance. In this example, a one hour lead is applied to the label times.

[4]:
```
labels.apply_lead('1h').head()
```

[4]:
```
    customer_id                time  total_spent
id
0             1 2014-01-01 01:45:30       217.94
1             1 2014-01-01 01:47:30       217.94
2             1 2014-01-01 01:49:30       217.94
3             1 2014-01-01 01:51:30       217.94
4             1 2014-01-01 01:53:30       217.94
```

6.4 Bin Labels

LabelTimes.bin() will bin the labels into discrete intervals. There are two types of bins. Bins could either be based on values or quantiles. Additionally, the widths of the bins could either be defined by the user or divided equally. The following examples will go through each type.

6.4.1 Value Based

To use bins based on values, `quantiles` should be set to `False` which is the default value.

Equal Width

To group values into bins of equal width, set bins as a scalar value. In this example, the total spent is grouped into bins of equal width.

```
[5]: labels.bin(4, quantiles=False).head()
```

```
[5]:    customer_id                time         total_spent
id
0              1 2014-01-01 02:45:30  (198.455, 271.072]
1              1 2014-01-01 02:47:30  (198.455, 271.072]
2              1 2014-01-01 02:49:30  (198.455, 271.072]
3              1 2014-01-01 02:51:30  (198.455, 271.072]
4              1 2014-01-01 02:53:30  (198.455, 271.072]
```

Custom Widths

To group values into bins of custom widths, set bins as an array of values to define edges. In this example, the total spent is grouped into bins of custom widths.

```
[6]: inf = float('inf')
edges = [-inf, 34, 50, 67, inf]
labels.bin(edges, quantiles=False,).head()
```

```
[6]:    customer_id                time  total_spent
id
0              1 2014-01-01 02:45:30  (67.0, inf]
1              1 2014-01-01 02:47:30  (67.0, inf]
2              1 2014-01-01 02:49:30  (67.0, inf]
3              1 2014-01-01 02:51:30  (67.0, inf]
4              1 2014-01-01 02:53:30  (67.0, inf]
```

6.4.2 Quantile Based

To use bins based on quantiles, `quantiles` should be set to `True`.

Equal Width

To group values into quantile bins of equal width, set bins to the number of quantiles as a scalar value (e.g. 4 for quartiles, 10 for deciles, etc.). In this example, the total spent is grouped into bins based on the quartiles.

```
[7]: labels.bin(4, quantiles=True).head()
```

```
[7]:    customer_id                time        total_spent
id
0              1 2014-01-01 02:45:30  (196.25, 217.94]
1              1 2014-01-01 02:47:30  (196.25, 217.94]
2              1 2014-01-01 02:49:30  (196.25, 217.94]
3              1 2014-01-01 02:51:30  (196.25, 217.94]
4              1 2014-01-01 02:53:30  (196.25, 217.94]
```

To verify quartile values, we could check the descriptive statistics.

[8]:
```
stats = labels.total_spent.describe()
stats = stats.round(3).to_string()
print(stats)
```

```
count     50.000
mean     215.182
std       90.518
min       53.220
25%      196.250
50%      217.940
75%      290.390
max      343.690
```

Custom Widths

To group values into quantile bins of custom widths, set bins as an array of quantiles. In this example, the total spent is grouped into quantile bins of custom widths.

[9]:
```
quantiles = [0, .34, .5, .67, 1]
labels.bin(quantiles, quantiles=True).head()
```

[9]:
```
    customer_id                time       total_spent
id
0             1 2014-01-01 02:45:30  (196.25, 217.94]
1             1 2014-01-01 02:47:30  (196.25, 217.94]
2             1 2014-01-01 02:49:30  (196.25, 217.94]
3             1 2014-01-01 02:51:30  (196.25, 217.94]
4             1 2014-01-01 02:53:30  (196.25, 217.94]
```

6.4.3 Label Bins

To assign bins with custom labels, set `labels` to the array of values. The number of labels need to match the number of bins. In this example, the total spent is grouped into bins with custom labels.

[10]:
```
values = ['low', 'medium', 'high']
labels.bin(3, labels=values).head()
```

[10]:
```
    customer_id                time total_spent
id
0             1 2014-01-01 02:45:30      medium
1             1 2014-01-01 02:47:30      medium
2             1 2014-01-01 02:49:30      medium
3             1 2014-01-01 02:51:30      medium
4             1 2014-01-01 02:53:30      medium
```

6.5 Describe Labels

`LabelTimes.describe()` will print out the distribution with the settings and transforms that were used to make the labels. This is useful as a reference for understanding how the labels were generated from raw data. Also, the label distribution is helpful for determining if we have imbalanced labels. In this examlpe, a description of the labels is printed after transforming the labels into discrete values.

[11]:
```
labels.threshold(100).describe()
```

```
Label Distribution
------------
False      8
True      42
Total:    50


Settings
-----
gap                           <2 * Minutes>
label_type                         discrete
labeling_function               total_spent
minimum_data                             2h
num_examples_per_instance                10
target_entity                   customer_id
window_size                          <Hour>


Transforms
-------
1. threshold
  - value:    100
```

6.6 Sample Labels

LabelTimes.sample() will sample the labels based on a number or fraction. Samples can be reproduced by fixing `random_state` to an integer.

To sample 10 labels, `n` is set to 10.

[12]:
```
labels.sample(n=10, random_state=0)
```

[12]:

id	customer_id	time	total_spent
28	3	2014-01-01 04:01:05	196.25
11	2	2014-01-01 02:02:00	290.39
10	2	2014-01-01 02:00:00	290.39
41	5	2014-01-01 03:48:25	53.22
2	1	2014-01-01 02:49:30	217.94
27	3	2014-01-01 03:59:05	196.25
38	4	2014-01-01 02:55:00	225.18
31	4	2014-01-01 02:41:00	343.69
22	3	2014-01-01 03:49:05	196.25
4	1	2014-01-01 02:53:30	217.94

Similarly, to sample 10% of labels, `frac` is set to 10%.

[13]:
```
labels.sample(frac=.1, random_state=0)
```

[13]:

id	customer_id	time	total_spent
28	3	2014-01-01 04:01:05	196.25
11	2	2014-01-01 02:02:00	290.39

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```
10            2 2014-01-01 02:00:00       290.39
41            5 2014-01-01 03:48:25        53.22
2             1 2014-01-01 02:49:30       217.94
```

6.6.1 Categorical Labels

When working with categorical labels, the number or fraction of labels for each category can be sampled by using a dictionary. Let's bin the labels into 4 bins to make categorical.

[14]:
```
categorical = labels.bin(4, labels=['A', 'B', 'C', 'D'])
```

To sample 2 labels per category, map each category to the number 2.

[15]:
```
n = {'A': 2, 'B': 2, 'C': 2, 'D': 2}
categorical.sample(n=n, random_state=0)
```

[15]:
```
    customer_id                time total_spent
id
46            5 2014-01-01 03:58:25           A
42            5 2014-01-01 03:50:25           A
26            3 2014-01-01 03:57:05           B
48            5 2014-01-01 04:02:25           B
6             1 2014-01-01 02:57:30           C
38            4 2014-01-01 02:55:00           C
11            2 2014-01-01 02:02:00           D
16            2 2014-01-01 02:12:00           D
```

Similarly, to sample 10% of labels per category, map each category to 10%.

[16]:
```
frac = {'A': .1, 'B': .1, 'C': .1, 'D': .1}
categorical.sample(frac=frac, random_state=0)
```

[16]:
```
    customer_id                time total_spent
id
46            5 2014-01-01 03:58:25           A
26            3 2014-01-01 03:57:05           B
6             1 2014-01-01 02:57:30           C
11            2 2014-01-01 02:02:00           D
16            2 2014-01-01 02:12:00           D
```

CHAPTER 7

Predict Next Purchase

In this example, we will generate labels on online grocery orders provided by Instacart using Compose. The labels can be used to train a machine learning model to predict whether a customer will buy a specific product within the next month.

If you plan to run this notebook, you can use the following command at the root directory of the repository.

```
jupyter notebook docs/source/examples/predict-next-purchase/example.ipynb
```

7.1 Load Data

[1]:
```
%matplotlib inline
import composeml as cp
import data
```

The data hosted here will be downloaded automatically into the `data` module of this notebook unless it already exist. Once the data is in place, we can preview the grocery orders to see how they look.

[2]:
```
df = data.load_orders(nrows=1000000)

df.head()
```

[2]:

	order_id	product_id	add_to_cart_order	reordered	product_name	aisle_id	department_id	department
0	120	33120	13	0	Organic Egg Whites	86	16	dairy eggs
1	120	31323	7	0	Light Wisconsin String Cheese	21	16	dairy eggs
2	120	1503	8	0	Low Fat Cottage Cheese	108	16	dairy eggs
3	120	28156	11	0				
4	120	41273	4	0				

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```
3  Total 0% Nonfat Plain Greek Yogurt       120             16  dairy eggs
4                    Broccoli Florets       123              4     produce

   user_id          order_time
0    23750 2015-01-11 08:00:00
1    23750 2015-01-11 08:00:00
2    23750 2015-01-11 08:00:00
3    23750 2015-01-11 08:00:00
4    23750 2015-01-11 08:00:00
```

7.2 Generate Labels

Now with the grocery orders loaded, we are ready to generate labels for our prediction problem.

7.2.1 Create Labeling Function

To get started, we define the labeling function that will return whether a customer purchased the product in a given month.

[3]:
```
def bought_product(df, product_name):
    purchased = df.product_name.str.contains(product_name).any()
    return purchased
```

7.2.2 Construct Label Maker

With the labeling function, we create the label maker for our prediction problem. To process one month of orders for each customer, we set the `target_entity` to the customer ID and the `window_size` to one month. When window size is set to `1MS`, the window size will end on the first day of the next month. Alias definitions are listed here.

[4]:
```
lm = cp.LabelMaker(
    target_entity='user_id',
    time_index='order_time',
    labeling_function=bought_product,
    window_size='1MS',
)
```

7.2.3 Search Labels

Next, the label maker will search through the data continously to label whether a customer bought bananas in a given month. This happens when we use `LabelMaker.search` and set the `product_name` to bananas. If you are running this code yourself, feel free to expirement with other products (e.g. limes, avocados, etc.) and different time frames!

[5]:
```
lt = lm.search(
    df.sort_values('order_time'),
    minimum_data='2015-01-01',
    num_examples_per_instance=-1,
    product_name='Banana',
```

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```
    verbose=True,
)

lt.head()
```

```
Elapsed: 00:29 | Remaining: 00:00 | Progress: 100%|| user_id: 19477/19477
```

[5]:

id	user_id	time	bought_product
0	4	2015-01-01	False
1	7	2015-01-01	False
2	10	2015-01-01	False
3	10	2015-02-01	False
4	13	2015-01-01	False

7.2.4 Describe Labels

With the generate label times, we can use `LabelTimes.describe` to print out the distribution with the settings and transforms that were used to make these labels. This is useful as a reference for understanding how the labels were generated from raw data. Also, the label distribution is helpful for determining if we have imbalanced labels.

[6]:
```
lt.describe()
```

```
Label Distribution
------------
False     13752
True       7044
Total:    20796


Settings
-----
gap                              <MonthBegin>
label_type                           discrete
labeling_function             bought_product
minimum_data                     2015-01-01
num_examples_per_instance                -1
target_entity                       user_id
window_size                      <MonthBegin>


Transforms
-------
No transforms applied
```

7.2.5 Plot Labels

Additionally, there are plots available for insight to the labels.

Distribution

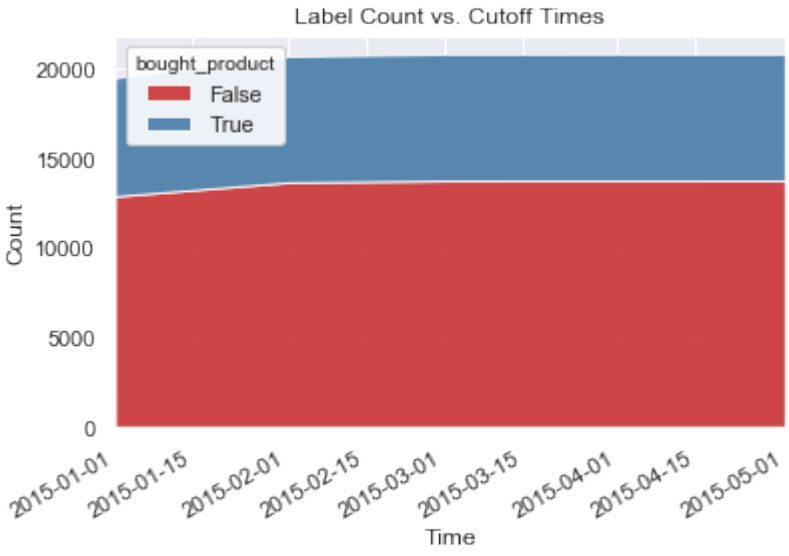
This plot shows the label distribution.

[7]:
```
lt.plot.distribution();
```

Count by Time

This plot shows the label distribution across cutoff times.

[8]:
```
lt.plot.count_by_time();
```



CHAPTER 8

Predict Remaining Useful Life

In this example, we will generate labels using Compose on data provided by NASA simulating turbofan engine degradation. Then, the labels are used to generate features and train a machine learning model to predict the Remaining Useful Life (RUL) of an engine.

[1]:
```
%matplotlib inline
import composeml as cp
import featuretools as ft
import pandas as pd
import data

from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
```

8.1 Load Data

In this dataset, we have 249 engines (`engine_no`) which are monitored over time (`time_in_cycles`). Each engine had `operational_settings` and `sensor_measurements` recorded for each cycle. The **Remaining Useful Life** (RUL) is the amount of cycles an engine has left before it needs maintenance. What makes this dataset special is that the engines run all the way until failure, giving us precise RUL information for every engine at every point in time.

You can download the data directly from NASA here. After downloading the data, you can set the `file` parameter as an absolute path to `train_FD004.txt`. With the file in place, we preview the data to get an idea on how to observations look.

[2]:
```
df = data.load('data/train_FD004.txt')
df[df.columns[:7]].head()
```

[2]:

	engine_no	time_in_cycles	operational_setting_1	operational_setting_2	\
0	1	1	42.0049	0.8400	
1	1	2	20.0020	0.7002	

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```
2          1               3                42.0038                0.8409
3          1               4                42.0000                0.8400
4          1               5                25.0063                0.6207

   operational_setting_3  sensor_measurement_1  sensor_measurement_2
0                  100.0                445.00                549.68
1                  100.0                491.19                606.07
2                  100.0                445.00                548.95
3                  100.0                445.00                548.70
4                   60.0                462.54                536.10
```

8.2 Generate Labels

Now with the observations loaded, we are ready to generate labels for our prediction problem.

8.2.1 Define Labeling Function

To get started, we define the labeling function that will return the RUL given the remaining observations of an engine.

[3]:
```
def remaining_useful_life(df):
    return len(df) - 1
```

8.2.2 Create Label Maker

With the labeling function, we create the label maker for our prediction problem. To process the RUL for each engine, we set the `target_entity` to the engine number. By default, the `window_size` is set to the total observation size to contain the remaining observations for each engine.

[4]:
```
lm = cp.LabelMaker(
    target_entity='engine_no',
    time_index='time',
    labeling_function=remaining_useful_life,
)
```

8.2.3 Search Labels

Let's imagine we want to make predictions on turbines that are up and running. Turbines in general don't fail before 120 cycles, so we will only make labels for engines that reach at least 100 cycles. To do this, the `minimum_data` parameter is set to 100. Using Compose, we can easily tweak this parameter as the requirements of our model changes. Additionally, we set `gap` to one to create labels on every cycle and limit the search to 10 examples for each engine.

See also:

For more details on how the label maker works, see *Main Concepts*.

[5]:
```
lt = lm.search(
    df.sort_values('time'),
    num_examples_per_instance=10,
    minimum_data=100,
    gap=1,
```

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```
    verbose=True,
)

lt.head()
```

```
Elapsed: 00:01 | Remaining: 00:00 | Progress: 100%|| engine_no: 2490/2490
```

[5]:

id	engine_no	time	remaining_useful_life
0	1	2000-01-01 16:40:00	220
1	1	2000-01-01 16:50:00	219
2	1	2000-01-01 17:00:00	218
3	1	2000-01-01 17:10:00	217
4	1	2000-01-01 17:20:00	216

8.2.4 Continuous Labels

The labeling function we defined returns continuous labels which can be used to train a regression model for our predictin problem. Alternatively, there are label transforms available to further process these labels into discrete values. In which case, can be used to train a classification model.

Describe Labels

Let's print out the settings and transforms that were used to make the continuous labels. This is useful as a reference for understanding how the labels were generated from raw data.

[6]:
```
lt.describe()
```

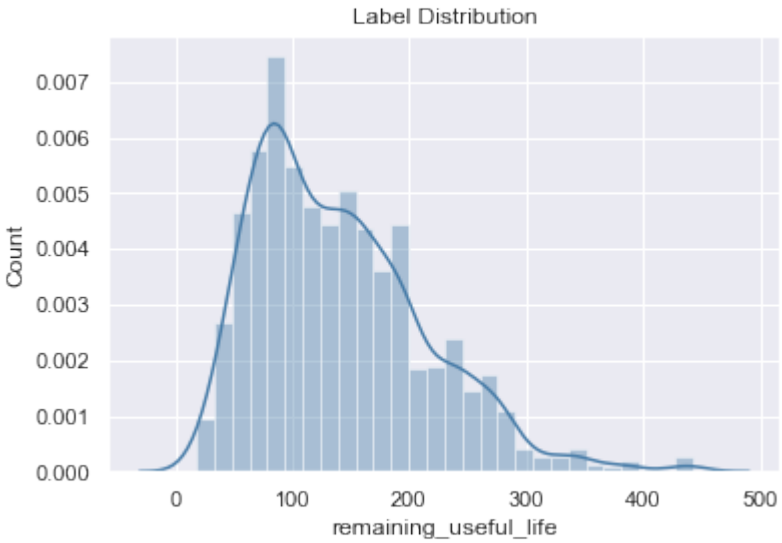
```
Settings
-----
gap                                        1
label_type                        continuous
labeling_function  remaining_useful_life
minimum_data                             100
num_examples_per_instance                 10
target_entity                      engine_no
window_size                            61249


Transforms
-------
No transforms applied
```

Let's plot the labels to get additional insight of the RUL.

Label Distribution

This plot shows the continuous label distribution.

[7]:
```
lt.plot.distribution();
```



8.2.5 Discrete Labels

Let's further process the labels into discrete values. We divide the RUL into quartile bins to predict which range an engine's RUL will fall in.

[8]:
```
lt = lt.bin(4, quantiles=True)
```

Describe Labels

Next, let's print out the settings and transforms that were used to make the discrete labels. This time we can see the label distribution which is useful for determining if we have imbalanced labels. Also, we can see that the label type changed from continuous to discrete and the binning transform used in the previous step is included below.

[9]:
```
lt.describe()
```

```
Label Distribution
------------
(128.0, 187.0]     629
(17.999, 83.0]     625
(187.0, 442.0]     614
(83.0, 128.0]      622
Total:            2490


Settings
-----
gap                                        1
label_type                          discrete
labeling_function     remaining_useful_life
minimum_data                             100
num_examples_per_instance                 10
target_entity                      engine_no
window_size                            61249
```

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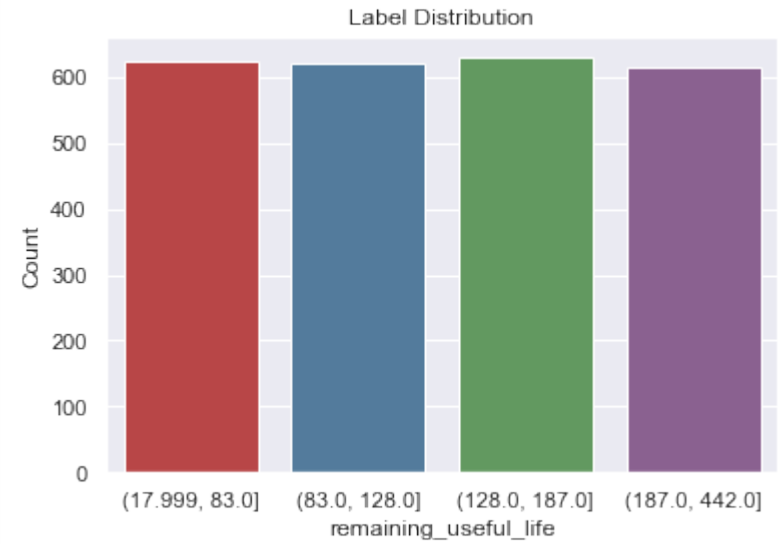
```
Transforms
-------
1. bin
  - bins:             4
  - labels:        None
  - quantiles:     True
  - right:         True
```

Let's plot the labels to get additional insight of the RUL.

Label Distribution

This plot shows the discrete label distribution.

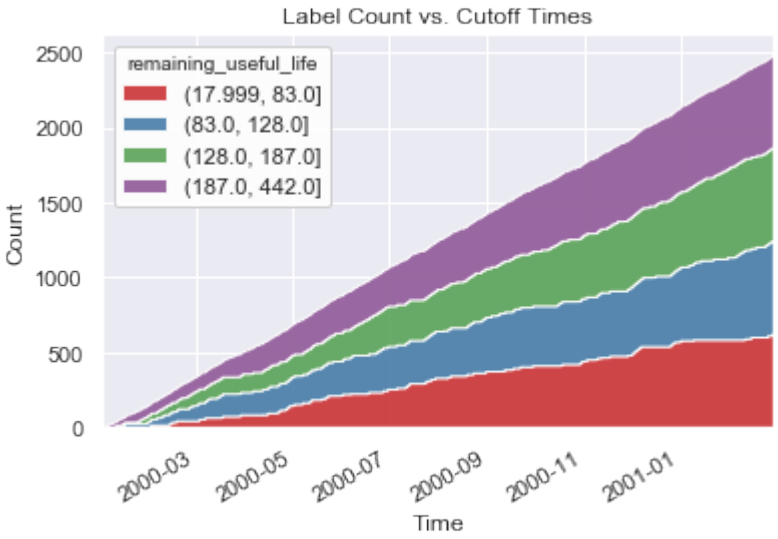
[10]:
```
lt.plot.distribution();
```



Count by Time

This plot shows the label count accumulated across cutoff times.

[11]:
```
lt.plot.count_by_time();
```



8.3 Generate Features

Now, we are ready to generate features for our prediction problem.

8.3.1 Create Entity Set

To get started, let's create an `EntitySet` for the observations.

See also:

For more details on working with entity sets, see loading_data/using_entitysets.

[12]:
```
es = ft.EntitySet('observations')

es.entity_from_dataframe(
    dataframe=df,
    entity_id='recordings',
    index='id',
    time_index='time',
    make_index=True,
)

es.normalize_entity(
    base_entity_id='recordings',
    new_entity_id='engines',
    index='engine_no',
)

es.normalize_entity(
    base_entity_id='recordings',
    new_entity_id='cycles',
    index='time_in_cycles',
)
```

[12]:
```
Entityset: observations
  Entities:
    recordings [Rows: 61249, Columns: 28]
    engines [Rows: 249, Columns: 2]
    cycles [Rows: 543, Columns: 2]
  Relationships:
    recordings.engine_no -> engines.engine_no
    recordings.time_in_cycles -> cycles.time_in_cycles
```

8.3.2 Describe Entity Set

To get an idea on how the entity set is structured, we can plot a diagram.

[13]:
```
es.plot()
```

[13]:

8.3.3 Create Feature Matrix

To simplify the calculation for the feature matrix, we only use 20 percent of the labels.

[14]:
```
lt = lt.sample(frac=.2, random_state=0)
```

Let's generate features that correspond to the labels. To do this, we set the `target_entity` to engines and the `cutoff_time` to our labels so that the features are calculated for each engine only using data up to and including the cutoff time of each label. Notice that the output of Compose integrates easily with Featuretools.

See also:

For more details on calculating features using cutoff times, see automated_feature_engineering/handling_time.

[15]:
```
fm, fd = ft.dfs(
    entityset=es,
    target_entity='engines',
    agg_primitives=['last', 'max', 'min'],
    trans_primitives=[],
    cutoff_time=lt,
    cutoff_time_in_index=True,
    max_depth=3,
    verbose=True,
)

fm.head()
```

```
Built 292 features
Elapsed: 03:05 | Progress: 100%|
```

[15]:
```
                             LAST(recordings.sensor_measurement_2)  \
engine_no time
233       2001-02-02 07:30:00                                643.08
146       2000-09-04 07:50:00                                554.79
105       2000-06-26 11:10:00                                549.28
240       2001-02-13 23:20:00                                642.73
229       2001-01-26 09:00:00                                536.44

                             LAST(recordings.sensor_measurement_21)  \
engine_no time
```

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```
233       2001-02-02 07:30:00                                  23.3473
146       2000-09-04 07:50:00                                   8.8768
105       2000-06-26 11:10:00                                   6.3080
240       2001-02-13 23:20:00                                  23.2631
229       2001-01-26 09:00:00                                   8.5711

                             LAST(recordings.sensor_measurement_1)  \
engine_no time
233       2001-02-02 07:30:00                                 518.67
146       2000-09-04 07:50:00                                 449.44
105       2000-06-26 11:10:00                                 445.00
240       2001-02-13 23:20:00                                 518.67
229       2001-01-26 09:00:00                                 462.54

                             LAST(recordings.sensor_measurement_4)  \
engine_no time
233       2001-02-02 07:30:00                                1399.84
146       2000-09-04 07:50:00                                1118.14
105       2000-06-26 11:10:00                                1127.19
240       2001-02-13 23:20:00                                1411.59
229       2001-01-26 09:00:00                                1047.57

                             LAST(recordings.sensor_measurement_5)  \
engine_no time
233       2001-02-02 07:30:00                                  14.62
146       2000-09-04 07:50:00                                   5.48
105       2000-06-26 11:10:00                                   3.91
240       2001-02-13 23:20:00                                  14.62
229       2001-01-26 09:00:00                                   7.05

                             LAST(recordings.sensor_measurement_11)  \
engine_no time
233       2001-02-02 07:30:00                                  47.49
146       2000-09-04 07:50:00                                  41.61
105       2000-06-26 11:10:00                                  42.03
240       2001-02-13 23:20:00                                  47.50
229       2001-01-26 09:00:00                                  36.54

                             LAST(recordings.sensor_measurement_7)  \
engine_no time
233       2001-02-02 07:30:00                                 554.09
146       2000-09-04 07:50:00                                 195.73
105       2000-06-26 11:10:00                                 139.18
240       2001-02-13 23:20:00                                 552.91
229       2001-01-26 09:00:00                                 174.64

                             LAST(recordings.sensor_measurement_9)  \
engine_no time
233       2001-02-02 07:30:00                                9068.13
146       2000-09-04 07:50:00                                8346.50
105       2000-06-26 11:10:00                                8332.78
240       2001-02-13 23:20:00                                9048.65
229       2001-01-26 09:00:00                                8008.89

                             LAST(recordings.sensor_measurement_19)  \
engine_no time
233       2001-02-02 07:30:00                                 100.00
```

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```
146       2000-09-04 07:50:00                                  100.00
105       2000-06-26 11:10:00                                  100.00
240       2001-02-13 23:20:00                                  100.00
229       2001-01-26 09:00:00                                   84.93

                             LAST(recordings.sensor_measurement_18)  ...  \
engine_no time                                                       ...
233       2001-02-02 07:30:00                                  2388  ...
146       2000-09-04 07:50:00                                  2223  ...
105       2000-06-26 11:10:00                                  2212  ...
240       2001-02-13 23:20:00                                  2388  ...
229       2001-01-26 09:00:00                                  1915  ...

                             MIN(recordings.cycles.LAST(recordings.sensor_
↪measurement_11))  \
engine_no time
233       2001-02-02 07:30:00                                        36.49
146       2000-09-04 07:50:00                                        36.45
105       2000-06-26 11:10:00                                        36.36
240       2001-02-13 23:20:00                                        36.39
229       2001-01-26 09:00:00                                        36.43

                             MIN(recordings.cycles.LAST(recordings.sensor_
↪measurement_3))  \
engine_no time
233       2001-02-02 07:30:00                                      1250.55
146       2000-09-04 07:50:00                                      1254.83
105       2000-06-26 11:10:00                                      1251.50
240       2001-02-13 23:20:00                                      1251.07
229       2001-01-26 09:00:00                                      1249.84

                             MIN(recordings.cycles.MIN(recordings.sensor_
↪measurement_16))  \
engine_no time
233       2001-02-02 07:30:00                                         0.02
146       2000-09-04 07:50:00                                         0.02
105       2000-06-26 11:10:00                                         0.02
240       2001-02-13 23:20:00                                         0.02
229       2001-01-26 09:00:00                                         0.02

                             MIN(recordings.cycles.MAX(recordings.operational_
↪setting_1))  \
engine_no time
233       2001-02-02 07:30:00                                      42.0070
146       2000-09-04 07:50:00                                      42.0067
105       2000-06-26 11:10:00                                      42.0067
240       2001-02-13 23:20:00                                      42.0070
229       2001-01-26 09:00:00                                      42.0070

                             MIN(recordings.cycles.LAST(recordings.sensor_
↪measurement_18))  \
engine_no time
233       2001-02-02 07:30:00                                         1915
146       2000-09-04 07:50:00                                         1915
105       2000-06-26 11:10:00                                         1915
240       2001-02-13 23:20:00                                         1915
229       2001-01-26 09:00:00                                         1915
```

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```
                              MIN(recordings.cycles.MIN(recordings.sensor_
↪measurement_17))  \
engine_no time
233       2001-02-02 07:30:00                                          302
146       2000-09-04 07:50:00                                          302
105       2000-06-26 11:10:00                                          302
240       2001-02-13 23:20:00                                          302
229       2001-01-26 09:00:00                                          302

                              MIN(recordings.cycles.MAX(recordings.operational_
↪setting_3))  \
engine_no time
233       2001-02-02 07:30:00                                        100.0
146       2000-09-04 07:50:00                                        100.0
105       2000-06-26 11:10:00                                        100.0
240       2001-02-13 23:20:00                                        100.0
229       2001-01-26 09:00:00                                        100.0

                              MIN(recordings.cycles.MIN(recordings.sensor_
↪measurement_10))  \
engine_no time
233       2001-02-02 07:30:00                                         0.93
146       2000-09-04 07:50:00                                         0.93
105       2000-06-26 11:10:00                                         0.93
240       2001-02-13 23:20:00                                         0.93
229       2001-01-26 09:00:00                                         0.93

                              MIN(recordings.cycles.MAX(recordings.sensor_
↪measurement_18))  \
engine_no time
233       2001-02-02 07:30:00                                         2388
146       2000-09-04 07:50:00                                         2388
105       2000-06-26 11:10:00                                         2388
240       2001-02-13 23:20:00                                         2388
229       2001-01-26 09:00:00                                         2388

                              remaining_useful_life
engine_no time
233       2001-02-02 07:30:00         (128.0, 187.0]
146       2000-09-04 07:50:00         (187.0, 442.0]
105       2000-06-26 11:10:00         (17.999, 83.0]
240       2001-02-13 23:20:00         (17.999, 83.0]
229       2001-01-26 09:00:00         (128.0, 187.0]

[5 rows x 293 columns]
```

8.4 Machine Learning

Now, we are ready to create a machine learning model for our prediction problem.

8.4.1 Preprocess Features

Let's extract the labels from the feature matrix and fill any missing values with zeros. Additionally, the categorical features are one-hot encoded.

[16]:
```
y = fm.pop(lt.label_name)
y = y.astype('str')

x = fm.fillna(0)
x, fe = ft.encode_features(x, fd)
```

8.4.2 Split Labels and Features

Then, we split the labels and features each into training and testing sets.

[17]:
```
x_train, x_test, y_train, y_test = train_test_split(
    x,
    y,
    train_size=.8,
    test_size=.2,
    random_state=0,
)
```

8.4.3 Train Model

Next, we train a random forest classifer on the training set.

[18]:
```
clf = RandomForestClassifier(n_estimators=10, random_state=0)
clf.fit(x_train, y_train)
```

[18]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, 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=None, oob_score=False, random_state=0, verbose=0,
                       warm_start=False)
```

8.4.4 Test Model

Lastly, we test the model performance by evaluating predictions on the testing set.

[19]:
```
y_hat = clf.predict(x_test)
print(classification_report(y_test, y_hat))
```

```
                precision    recall  f1-score   support

(128.0, 187.0]       0.65      0.79      0.71        28
(17.999, 83.0]       0.64      0.73      0.68        22
(187.0, 442.0]       0.81      0.84      0.82        25
 (83.0, 128.0]       0.67      0.40      0.50        25

      accuracy                           0.69       100
```

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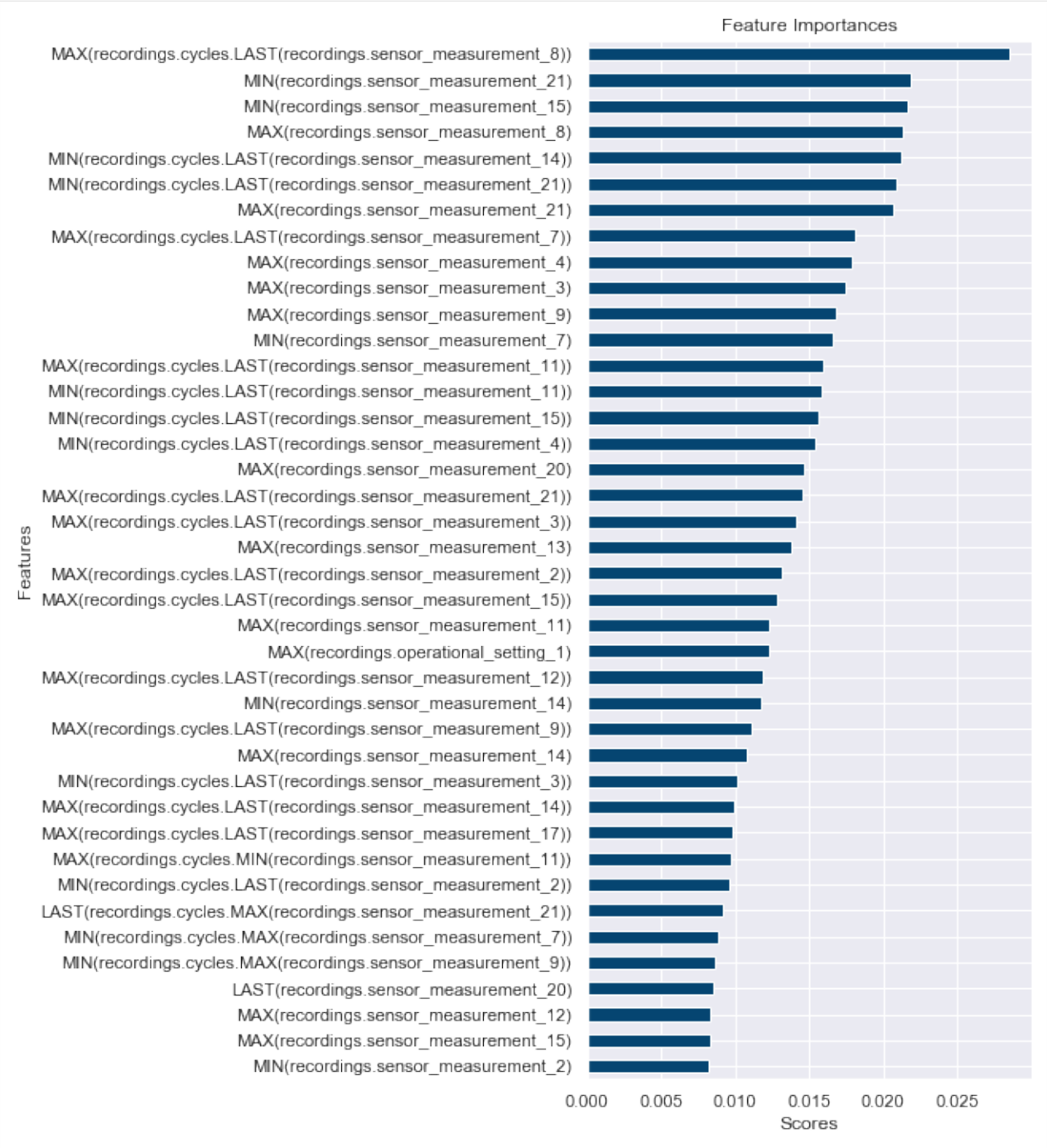
```
    macro avg       0.69      0.69      0.68       100
 weighted avg       0.69      0.69      0.68       100
```

8.4.5 Feature Importances

This plot is based on scores from the model to show which features are important for predictions.

[20]:
```
feature_importances = zip(x_train.columns, clf.feature_importances_)
feature_importances = pd.Series(dict(feature_importances))
feature_importances = feature_importances.rename_axis('Features')
feature_importances = feature_importances.sort_values()

top_features = feature_importances.tail(40)
plot = top_features.plot(kind='barh', figsize=(5, 12), color='#054571')
plot.set_title('Feature Importances')
plot.set_xlabel('Scores');
```


Feature Importances
MAX(recordings.cycles.LAST(recordings.sensor_measurement_8))
MIN(recordings.sensor_measurement_21)
MIN(recordings.sensor_measurement_15)
MAX(recordings.sensor_measurement_8)
MIN(recordings.cycles.LAST(recordings.sensor_measurement_14))
MIN(recordings.cycles.LAST(recordings.sensor_measurement_21))
MAX(recordings.sensor_measurement_21)
MAX(recordings.cycles.LAST(recordings.sensor_measurement_7))
MAX(recordings.sensor_measurement_4)
MAX(recordings.sensor_measurement_3)
MAX(recordings.sensor_measurement_9)
MIN(recordings.sensor_measurement_7)
MAX(recordings.cycles.LAST(recordings.sensor_measurement_11))
MIN(recordings.cycles.LAST(recordings.sensor_measurement_11))
MIN(recordings.cycles.LAST(recordings.sensor_measurement_15))
MIN(recordings.cycles.LAST(recordings.sensor_measurement_4))
MAX(recordings.sensor_measurement_20)
MAX(recordings.cycles.LAST(recordings.sensor_measurement_21))
MAX(recordings.cycles.LAST(recordings.sensor_measurement_3))
MAX(recordings.sensor_measurement_13)
MAX(recordings.cycles.LAST(recordings.sensor_measurement_2))
MAX(recordings.cycles.LAST(recordings.sensor_measurement_15))
MAX(recordings.sensor_measurement_11)
MAX(recordings.operational_setting_1)
MAX(recordings.cycles.LAST(recordings.sensor_measurement_12))
MIN(recordings.sensor_measurement_14)
MAX(recordings.cycles.LAST(recordings.sensor_measurement_9))
MAX(recordings.sensor_measurement_14)
MIN(recordings.cycles.LAST(recordings.sensor_measurement_3))
MAX(recordings.cycles.LAST(recordings.sensor_measurement_14))
MAX(recordings.cycles.LAST(recordings.sensor_measurement_17))
MAX(recordings.cycles.MIN(recordings.sensor_measurement_11))
MIN(recordings.cycles.LAST(recordings.sensor_measurement_2))
LAST(recordings.cycles.MAX(recordings.sensor_measurement_21))
MIN(recordings.cycles.MAX(recordings.sensor_measurement_7))
MIN(recordings.cycles.MAX(recordings.sensor_measurement_9))
LAST(recordings.sensor_measurement_20)
MAX(recordings.sensor_measurement_12)
MAX(recordings.sensor_measurement_15)
MIN(recordings.sensor_measurement_2)
Features
0.000
0.005
0.010
0.015
0.020
0.025
Scores

CHAPTER 9

Frequently Asked Questions

9.1 I have heard of autoML and automated feature engineering, how is this different?

AutoML targets solving the problem once the labels or targets one wants to predict are well defined and are already available. Feature engineering focuses on generating features given a dataset, labels or targets. Both assume that the target a user wants to predict is already defined and computed. In most real world scenarios, this is something a data scientist has to do - define an outcome to predict and create labeled training examples. We structured this process and called it prediction engineering (a play on an already well defined process - feature engineering). This library provides an easy way for a user to define the target outcome and generate training examples automatically - from relational, temporal, multi entity datasets.

9.2 I have used Featuretools for competing in KAGGLE, how can I use Compose?

In most KAGGLE competitions the target to predict is already defined. In many cases, they follow the same way to represent training examples as us - "label times" (see here and here). Compose is a step prior to where KAGGLE starts. Indeed, it is a step that KAGGLE or the company sponsoring the competition may have to do or would have done before publishing the competition.

9.3 Why have I not encountered the need for Compose yet?

In many cases, setting up prediction problem is done independently before even getting started on the machine learning. This has resulted in a very skewed availability of datasets with already defined prediction problems and labels. A number of times it also results in a data scientist not knowing how the label was defined. For example, when given a list of , the data scientist does not know how the churn was defined. In opening up this part of the process, we are enabling data scientists to more flexibly define problems, explore more problems and solve problems to maximize the end goal - ROI.

9.4 I already have "Label times" file, do I need Compose?

If you already have label times you don't need LabelMaker and search. However, you could use the label transforms functionality of Compose, to apply lead, threshold, balance labels and all the other cool things that are yet to come.

9.5 What is the best use of Compose?

Since we have automated feature engineering and autoML, the best recommended use for Compose is to closely couple *LabelMaker* and *Search* functionality of Compose with the rest of the machine learning pipeline. Certain parameters used in *Search*, and *LabelMaker* and *label transforms* can be tuned alongside machine learning model. We have an end to end demo on this here.

9.6 Where can I read about your technical approach in detail?

You can read about prediction engineering, the way we defined the search algorithm and technical details in this peer reviewed paper published in IEEE international conference on data science and advanced analytics. If you're interested, you can also watch a video here. Please note that some of our thinking and terminology has evolved as we built this library and applied Compose to different industrial scale problems.

9.7 Do you think Compose should be part of a data scientist's toolkit?

Yes. As we mentioned above, extracting value out of your data is dependent on how you set the prediction problem. Currently, data scientists do not iterate through the setting up of the prediction problem because there is no structured way of doing it or algorithms and library to help do it. We believe that prediction engineering should be taken even more seriously than any other part of actually solving a problem.

9.8 How can I contribute labeling functions, or use cases?

We are happy for anyone who can provide interesting labeling functions. To contribute an interesting new use case and labeling function, we request you create a representative synthetic data set, a labeling function and the parameters for label maker. Once you have these three, you can write a brief explanation about the use case and do a pull request. To get a template for the pull request please see here.

9.9 I have a transaction file with the label as the last column, what are my label times?

Your label times is the . However, when such a data set is given one should ask for how that label was generated. It could be one of very many cases: a human could have assigned it based on their assessment/analysis, it could have been automatically generated by a system, or it could have been computed using some data. If it is the third case one should ask for the function that computed the label or rewrite it. If it is (1), one should note that the ref_time would be slightly after the transaction timestamp.

CHAPTER 10

API Reference

10.1 Label Maker

LabelMaker	Automatically makes labels for prediction problems.

10.1.1 composeml.LabelMaker

class composeml.**LabelMaker**(*target_entity*, *time_index*, *labeling_function=None*, *window_size=None*, *label_type=None*)

Automatically makes labels for prediction problems.

Methods

__init__	Creates an instance of label maker.
search	Searches the data to calculates labels.
set_index	Sets the time index in a data frame (if not already set).
slice	Generates data slices of target entity.

composeml.LabelMaker.__init__

LabelMaker.**__init__**(*target_entity*, *time_index*, *labeling_function=None*, *window_size=None*, *label_type=None*)

Creates an instance of label maker.

Parameters

- **target_entity** (*str*) – Entity on which to make labels.
- **time_index** (*str*) – Name of time column in the data frame.

- **labeling_function** (*function or list(function) or dict(str=function)*) – Function, list of functions, or dictionary of functions that transform a data slice. When set as a dictionary, the key is used as the name of the labeling function.
- **window_size** (*str or int*) – Duration of each data slice. The default value for window size is all future data.

composeml.LabelMaker.search

LabelMaker.**search**(*df*, *num_examples_per_instance*, *minimum_data=None*, *gap=None*, *drop_empty=True*, *label_type=None*, *verbose=True*, **args*, ***kwargs*)

Searches the data to calculates labels.

Parameters

- **df** (*DataFrame*) – Data frame to search and extract labels.
- **num_examples_per_instance** (*int or dict*) – The expected number of examples to return from each entity group. A dictionary can be used to further specify the expected number of examples to return from each label.
- **minimum_data** (*str*) – Minimum data before starting search. Default value is first time of index.
- **gap** (*str or int*) – Time between examples. Default value is window size. If an integer, search will start on the first event after the minimum data.
- **drop_empty** (*bool*) – Whether to drop empty slices. Default value is True.
- **label_type** (*str*) – The label type can be "continuous" or "categorical". Default value is the inferred label type.
- **verbose** (*bool*) – Whether to render progress bar. Default value is True.
- ***args** – Positional arguments for labeling function.
- ****kwargs** – Keyword arguments for labeling function.

Returns Calculated labels with cutoff times.

Return type lt (*LabelTimes*)

composeml.LabelMaker.set_index

LabelMaker.**set_index**(*df*)

Sets the time index in a data frame (if not already set).

Parameters **df** (*DataFrame*) – Data frame to set time index in.

Returns Data frame with time index set.

Return type df (DataFrame)

composeml.LabelMaker.slice

LabelMaker.**slice**(*df*, *num_examples_per_instance*, *minimum_data=None*, *gap=None*, *drop_empty=True*, *verbose=False*)

Generates data slices of target entity.

Parameters

- **df** (*DataFrame*) – Data frame to create slices on.
- **num_examples_per_instance** (*int*) – Number of examples per unique instance of target entity.
- **minimum_data** (*str*) – Minimum data before starting search. Default value is first time of index.
- **gap** (*str or int*) – Time between examples. Default value is window size. If an integer, search will start on the first event after the minimum data.
- **drop_empty** (*bool*) – Whether to drop empty slices. Default value is True.
- **verbose** (*bool*) – Whether to print metadata about slice. Default value is False.

Returns Returns a generator of data slices.

Return type ds (generator)

10.2 Label Times

LabelTimes	A data frame containing labels made by a label maker.

10.2.1 composeml.LabelTimes

class composeml.**LabelTimes**(*data=None*, *target_entity=None*, *name=None*, *label_type=None*, *settings=None*, **args*, ***kwargs*)

A data frame containing labels made by a label maker.

settings

Methods

__init__	Initialize self.
apply_lead	Shifts the label times earlier for predicting in advance.
bin	Bin labels into discrete intervals.
copy	Makes a copy of this object.
describe	Prints out label info with transform settings that reproduce labels.
equals	Determines if two label time objects are the same.
infer_type	Infer label type.
sample	Return a random sample of labels.
threshold	Creates binary labels by testing if labels are above threshold.
to_csv	Write label times in csv format to disk.
to_parquet	Write label times in parquet format to disk.
to_pickle	Write label times in pickle format to disk.

composeml.LabelTimes.__init__

LabelTimes.**__init__**(*data=None*, *target_entity=None*, *name=None*, *label_type=None*, *settings=None*, **args*, ***kwargs*)
Initialize self. See help(type(self)) for accurate signature.

composeml.LabelTimes.apply_lead

LabelTimes.**apply_lead**(*value*, *inplace=False*)
Shifts the label times earlier for predicting in advance.

Parameters

- **value** (*str*) – Time to shift earlier.
- **inplace** (*bool*) – Modify labels in place.

Returns Instance of labels.

Return type labels (*LabelTimes*)

composeml.LabelTimes.bin

LabelTimes.**bin**(*bins*, *quantiles=False*, *labels=None*, *right=True*)
Bin labels into discrete intervals.

Parameters

- **bins** (*int or array*) – The criteria to bin by.
  - **bins (int)** [Number of bins either equal-width or quantile-based.] If *quantiles* is *False*, defines the number of equal-width bins. The range is extended by .1% on each side to include the minimum and maximum values. If *quantiles* is *True*, defines the number of quantiles (e.g. 10 for deciles, 4 for quartiles, etc.)
  - **bins (array)** [Bin edges either user defined or quantile-based.] If *quantiles* is *False*, defines the bin edges allowing for non-uniform width. No extension is done. If *quantiles* is *True*, defines the bin edges usings an array of quantiles (e.g. [0, .25, .5, .75, 1.] for quartiles)
- **quantiles** (*bool*) – Determines whether to use a quantile-based discretization function.
- **labels** (*array*) – Specifies the labels for the returned bins. Must be the same length as the resulting bins.
- **right** (*bool*) – Indicates whether bins includes the rightmost edge or not. Does not apply to quantile-based bins.

Returns Instance of labels.

Return type *LabelTimes*

Examples

Using bins of *equal-widths*:

```
>>> labels.bin(2).head(2).T
label_id                                0                     1
customer_id                             1                     1
time                  2014-01-01 00:45:00  2014-01-01 00:48:00
my_labeling_function      (157.5, 283.46]      (31.288, 157.5]
```

Using bins of *custom-widths*:

```
>>> values = labels.bin([0, 200, 400])
>>> values.head(2).T
label_id                                0                     1
customer_id                             1                     1
time                  2014-01-01 00:45:00  2014-01-01 00:48:00
my_labeling_function           (200, 400]             (0, 200]
```

Using *quantile-based* bins:

```
>>> values = labels.bin(4, quantiles=True) # (i.e. quartiles)
>>> values.head(2).T
label_id                                0                     1
customer_id                             1                     1
time                  2014-01-01 00:45:00  2014-01-01 00:48:00
my_labeling_function    (137.44, 241.062]     (43.848, 137.44]
```

Assigning *labels* to bins:

```
>>> values = labels.bin(3, labels=['low', 'medium', 'high'])
>>> values.head(2).T
label_id                                0                     1
customer_id                             1                     1
time                  2014-01-01 00:45:00  2014-01-01 00:48:00
my_labeling_function                 high                   low
```

composeml.LabelTimes.copy

LabelTimes.**copy**(***kwargs*)

Makes a copy of this object.

Parameters ****kwargs** – Keyword arguments to pass to underlying pandas.DataFrame.copy method

Returns Copy of label times.

Return type *LabelTimes*

composeml.LabelTimes.describe

LabelTimes.**describe**()

Prints out label info with transform settings that reproduce labels.

composeml.LabelTimes.equals

LabelTimes.**equals**(*other*, ***kwargs*)

Determines if two label time objects are the same.

Parameters

- **other** (LabelTimes) – Other label time object for comparison.
- ****kwargs** – Keyword arguments to pass to underlying pandas.DataFrame.equals method

Returns Whether label time objects are the same.

Return type bool

composeml.LabelTimes.infer_type

LabelTimes.**infer_type**()

Infer label type.

Returns Inferred label type. Either "continuous" or "discrete".

Return type str

composeml.LabelTimes.sample

LabelTimes.**sample**(*n=None*, *frac=None*, *random_state=None*, *replace=False*)

Return a random sample of labels.

Parameters

- **n** (*int or dict*) – Sample number of labels. A dictionary returns the number of samples to each label. Cannot be used with frac.
- **frac** (*float or dict*) – Sample fraction of labels. A dictionary returns the sample fraction to each label. Cannot be used with n.
- **random_state** (*int*) – Seed for the random number generator.
- **replace** (*bool*) – Sample with or without replacement. Default value is False.

Returns Random sample of labels.

Return type *LabelTimes*

Examples

Create mock data:

```
>>> labels = {'labels': list('AABBBAA')}
>>> labels = LabelTimes(labels, name='labels')
>>> labels
  labels
0      A
1      A
2      B
3      B
4      B
5      A
6      A
```

Sample number of labels:

```
>>> labels.sample(n=3, random_state=0).sort_index()
  labels
1      A
2      B
6      A
```

Sample number per label:

```
>>> n_per_label = {'A': 1, 'B': 2}
>>> labels.sample(n=n_per_label, random_state=0).sort_index()
  labels
3      B
4      B
5      A
```

Sample fraction of labels:

```
>>> labels.sample(frac=.4, random_state=2).sort_index()
  labels
1      A
3      B
4      B
```

Sample fraction per label:

```
>>> frac_per_label = {'A': .5, 'B': .34}
>>> labels.sample(frac=frac_per_label, random_state=2).sort_index()
  labels
4      B
5      A
6      A
```

composeml.LabelTimes.threshold

LabelTimes.**threshold**(*value*, *inplace=False*)

Creates binary labels by testing if labels are above threshold.

Parameters

- **value** (*float*) – Value of threshold.
- **inplace** (*bool*) – Modify labels in place.

Returns Instance of labels.

Return type labels (*LabelTimes*)

composeml.LabelTimes.to_csv

LabelTimes.**to_csv**(*path*, *filename='label_times.csv'*, *save_settings=True*, ***kwargs*)

Write label times in csv format to disk.

Parameters

- **path** (*str*) – Location on disk to write to (will be created as a directory).
- **filename** (*str*) – Filename for label times. Default value is *label_times.csv*.

- **save_settings** (*bool*) – Whether to save the settings used to make the label times.
- ****kwargs** – Keyword arguments to pass to underlying pandas.DataFrame.to_csv method

composeml.LabelTimes.to_parquet

LabelTimes.**to_parquet**(*path*, *filename='label_times.parquet'*, *save_settings=True*, ***kwargs*)
Write label times in parquet format to disk.

Parameters

- **path** (*str*) – Location on disk to write to (will be created as a directory).
- **filename** (*str*) – Filename for label times. Default value is *label_times.parquet*.
- **save_settings** (*bool*) – Whether to save the settings used to make the label times.
- ****kwargs** – Keyword arguments to pass to underlying pandas.DataFrame.to_parquet method

composeml.LabelTimes.to_pickle

LabelTimes.**to_pickle**(*path*, *filename='label_times.pickle'*, *save_settings=True*, ***kwargs*)
Write label times in pickle format to disk.

Parameters

- **path** (*str*) – Location on disk to write to (will be created as a directory).
- **filename** (*str*) – Filename for label times. Default value is *label_times.pickle*.
- **save_settings** (*bool*) – Whether to save the settings used to make the label times.
- ****kwargs** – Keyword arguments to pass to underlying pandas.DataFrame.to_pickle method

10.2.2 Transform Methods

LabelTimes.apply_lead	Shifts the label times earlier for predicting in advance.
LabelTimes.bin	Bin labels into discrete intervals.
LabelTimes.sample	Return a random sample of labels.
LabelTimes.threshold	Creates binary labels by testing if labels are above threshold.

10.3 Label Plots

LabelPlots	Creates plots for Label Times.

10.3.1 composeml.label_plots.LabelPlots

class composeml.label_plots.**LabelPlots**(*label_times*)
Creates plots for Label Times.

Methods

__init__	Initializes Label Plots.
count_by_time	Plots the label distribution across cutoff times.
distribution	Plots the label distribution.

composeml.label_plots.LabelPlots.__init__

LabelPlots.**__init__**(*label_times*)
Initializes Label Plots.

Parameters **label_times** (LabelTimes) – instance of Label Times

composeml.label_plots.LabelPlots.count_by_time

LabelPlots.**count_by_time**(*ax=None*, ***kwargs*)
Plots the label distribution across cutoff times.

composeml.label_plots.LabelPlots.distribution

LabelPlots.**distribution**(***kwargs*)
Plots the label distribution.

10.3.2 Plotting Methods

LabelPlots.count_by_time	Plots the label distribution across cutoff times.
LabelPlots.distribution	Plots the label distribution.

CHAPTER 11

Changelog

v0.3.0 June 1, 2020

- **Enhancements**
  - Label Search for Multiple Targets (#130)
- **Changes**
  - Column renamed from `cutoff_time` to `time` (#139)

v0.2.0 April 23, 2020

- **Changes**
  - Dropped Support for Python 3.5 (#128)
  - Rename LabelTimes.name to LabelTimes.label_name (#126)
  - Support keyword arguments in Pandas methods. (#121)
- **Documentation Changes**
  - Improved data download in Predict Next Purchase (#76)
- **Testing Changes**
  - Added tests that use Python 3.8 in CirlceCI (#128)

Breaking Changes

- `LabelTimes.name` has been renamed to `LabelTimes.label_name`

v0.1.8 March 11, 2020

- **Fixes**
  - Support for Pandas 1.0

v0.1.7 January 31, 2020

- **Enhancements**
  - Added higher-level mappings to offsets.

  - Track settings for sample transforms.
- **Fixes**
  - Pinned Pandas version.
- **Testing Changes**
  - Moved Featuretools to test requirements.

v0.1.6 October 22, 2019

- **Enhancements**
  - Serialization for Label Times
- **Fixes**
  - Matplotlib Backend Fix
  - Sampling Label Times
- **Documentation Changes**
  - Added Data Slice Generator Guide
- **Testing Changes**
  - Integration Tests for Python Versions 3.6 and 3.7

v0.1.5 September 16, 2019

- **Enhancements**
  - Added Slice Generator
  - Added Seaborn Plots
  - Added Data Slice Context
  - Added Count per Group
- **Documentation Changes**
  - Updated README
  - Added Example: Predict Next Purchase
  - Added Example: Predict RUL

v0.1.4 August 7, 2019

- **Enhancements**
  - Added Sample Transform
  - Improved Progress Bar
  - Improved Label Times description

v0.1.3 July 9, 2019

- **Enhancements**
  - Improved documentation
  - Added testing for Featuretools compatibility
  - Improved description of Label Times
  - Refactored search in Label Maker

  - Improved testing for Label Transforms

v0.1.2 June 19, 2019

- **Enhancements**
  - Add dynamic progress bar
  - Add label transform for binning labels
  - Improve code coverage
  - Update documentation

v0.1.1 May 31, 2019

- Initial Release

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