Homework 4: Predictive Process Monitoring

This task uses the Turnaround process event log that we used in Practice 8 of the course. The link has been provided in Slack (Event log link: http://kodu.ut.ee/~chavez85/pm_course/data/turnaround_anon_sla.csv)

This goal of this homework is to train and use predictive process monitoring techniques to predict the outcome of a process from a log of events. Make the necessary modifications to the framework proposed by Taineema et al. reviewed in class to meet this goal (framework link: https://github.com/Mcamargo85/predictive-monitoring-benchmark.git).

Notes

All of the code can be found in this notebook (including the ngram generation method).

Homework repository: https://github.com/antialman/predictive-monitoring-benchmark

Task 1

(1 point) As part of the log preprocessing, it is necessary to categorize the process traces as deviant or regular. This log contains a column called SLA. it is a "case attribute," which indicates how many minutes each case must complete.

You must create a new column in the log that contains a case attribute called *label*, which contains a value of 1 for deviant cases or 0 for regular ones. This column's value is 0 if the duration of the case (in minutes) is less than or equal to the SLA; otherwise, this column's value must be 1 (the SLA has not been met).

NB! If there are cases that do not have SLA, categorize them as 0.

In [1]:
```
##Imports
import pandas as pd
import math
from nltk import ngrams
from sklearn.model_selection import StratifiedKFold
import seaborn as sns
from matplotlib import pyplot as plt
```

In [2]:
```
##Loading the event log
file_path = 'hw_input/turnaround_anon_sla.csv'
df = pd.read_csv(file_path)
df.head()
```

Out[2]:

	caseid	activity	start_timestamp	end_timestamp	SLA MIN
0	Case00	A0	2017-07-12 11:47:00	2017-07-12 11:48:00	35.0
1	Case00	A1	2017-07-12 11:57:00	2017-07-12 11:57:00	35.0
2	Case00	A2	2017-07-12 12:34:00	2017-07-12 12:34:00	35.0
3	Case00	A3	2017-07-12 11:57:00	2017-07-12 11:59:00	35.0
4	Case00	A4	2017-07-12 11:43:00	2017-07-12 11:43:00	35.0

In [3]:
```
##Checking the initial datatypes
df.dtypes
```

Out[3]:
```
caseid              object
activity            object
start_timestamp     object
end_timestamp       object
SLA MIN            float64
dtype: object
```

In [4]:
```
##Fixing data types of timestamp columns
df['start_timestamp'] = pd.to_datetime(df['start_timestamp'], format='%Y-%m-%d %H:%M:%S')
df['end_timestamp'] = pd.to_datetime(df['end_timestamp'], format='%Y-%m-%d %H:%M:%S')
#df.head()
df.dtypes
```

Out[4]:
```
caseid                     object
activity                   object
start_timestamp    datetime64[ns]
end_timestamp      datetime64[ns]
SLA MIN                   float64
dtype: object
```

In [5]:
```
##Creating a dictionary of case durations
###(note that the events of a trace are sometimes not in cronological order, but that does not matter when usi
case_durations = {}

for id, group in df.groupby('caseid'):
    case_durations[id] = (group['end_timestamp'].max() - group['start_timestamp'].min()).total_seconds()/60

print (case_durations['Case00'], case_durations['Case01'], case_durations['Case02'])
```

```
56.0 73.0 47.0
```

In [6]:
```
##Creating case duration column
df['case_duration'] = df['caseid'].map(case_durations)
df.head()
```

Out[6]:

	caseid	activity	start_timestamp	end_timestamp	SLA MIN	case_duration
0	Case00	A0	2017-07-12 11:47:00	2017-07-12 11:48:00	35.0	56.0
1	Case00	A1	2017-07-12 11:57:00	2017-07-12 11:57:00	35.0	56.0
2	Case00	A2	2017-07-12 12:34:00	2017-07-12 12:34:00	35.0	56.0
3	Case00	A3	2017-07-12 11:57:00	2017-07-12 11:59:00	35.0	56.0
4	Case00	A4	2017-07-12 11:43:00	2017-07-12 11:43:00	35.0	56.0

In [7]:
```
##Adding the column 'label' to distinguish deviant and regular cases
def sla_fulfilled(x):
    if math.isnan(x['SLA MIN']):
        return 0
    elif x['case_duration'] <= x['SLA MIN']:
        return 0
    else:
        return 1

df['label'] = df.apply(sla_fulfilled, axis=1)
df.head()
```

Out[7]:

	caseid	activity	start_timestamp	end_timestamp	SLA MIN	case_duration	label
0	Case00	A0	2017-07-12 11:47:00	2017-07-12 11:48:00	35.0	56.0	1
1	Case00	A1	2017-07-12 11:57:00	2017-07-12 11:57:00	35.0	56.0	1
2	Case00	A2	2017-07-12 12:34:00	2017-07-12 12:34:00	35.0	56.0	1
3	Case00	A3	2017-07-12 11:57:00	2017-07-12 11:59:00	35.0	56.0	1
4	Case00	A4	2017-07-12 11:43:00	2017-07-12 11:43:00	35.0	56.0	1

In [8]:
```
##Checking how many deviant and regular cases there are
print("Deviant cases:", df.loc[df['label'] == 1].caseid.nunique(), "Regular cases:", df.loc[df['label'] == 0].c
```

```
Deviant cases: 51 Regular cases: 17
```

Task 2

(2 points) Add a column to the event log that captures the WIP of the process at the moment where the last event in the prefix occurs. Remember that the WIP refers to the number of active cases, meaning the number of cases that have started but not yet completed.

In [9]:
```
##Creating a dictionary of case start and end timestamps
###(used for creating artificial case start and end events, which will then be used to track the number of act
case_start_timestamps = {}
case_end_timestamps = {}

for id, group in df.groupby('caseid'):
    case_start_timestamps[id] = group['start_timestamp'].min()
    case_end_timestamps[id] = group['end_timestamp'].max()

print (case_start_timestamps['Case00'], case_end_timestamps['Case00'])
print (case_start_timestamps['Case01'], case_end_timestamps['Case01'])
print (case_start_timestamps['Case02'], case_end_timestamps['Case02'])
```

```
2017-07-12 11:43:00 2017-07-12 12:39:00
2017-07-12 14:21:00 2017-07-12 15:34:00
2017-07-13 11:19:00 2017-07-13 12:06:00
```

In [10]:
```
##Creating a list of the artificial case start and end events
###(row_order is used to make sure that the artificial start/end events will be first/last events of each trace
caseStartEndList = []

for caseid in df.caseid.unique():
    caseStartEndList.append([caseid, 'caseStart', case_start_timestamps[caseid], 1])
    caseStartEndList.append([caseid, 'caseEnd', case_end_timestamps[caseid], 3])

caseStartEndEvents = pd.DataFrame(caseStartEndList, columns=['caseid', 'activity', 'start_timestamp', 'row_orde

caseStartEndEvents.head()
```

Out[10]:

	caseid	activity	start_timestamp	row_order
0	Case00	caseStart	2017-07-12 11:43:00	1
1	Case00	caseEnd	2017-07-12 12:39:00	3
2	Case01	caseStart	2017-07-12 14:21:00	1
3	Case01	caseEnd	2017-07-12 15:34:00	3
4	Case02	caseStart	2017-07-13 11:19:00	1

In [11]:
```
##Concatenating start/end events to the dataframe
###(using row_order 2 for all original events)
df['row_order'] = 2
df = pd.concat([df, caseStartEndEvents])
df.tail()
```

Out[11]:

	caseid	activity	start_timestamp	end_timestamp	SLA MIN	case_duration	label	row_order
129	Case64	caseEnd	2017-08-09 11:30:00	NaT	NaN	NaN	NaN	3
130	Case65	caseStart	2017-08-09 14:21:00	NaT	NaN	NaN	NaN	1
131	Case65	caseEnd	2017-08-09 15:56:00	NaT	NaN	NaN	NaN	3
132	Case66	caseStart	2017-08-10 15:00:00	NaT	NaN	NaN	NaN	1
133	Case66	caseEnd	2017-08-10 15:51:00	NaT	NaN	NaN	NaN	3

In [12]:
```
##Sorting the dataframe by start_timestamp
###(using mergesort because it preserves the original order of rows when the values used for sorting are equal)
df.sort_values(by=['start_timestamp', 'row_order'], inplace=True, kind='mergesort')
df.head()
```

Out[12]:

	caseid	activity	start_timestamp	end_timestamp	SLA MIN	case_duration	label	row_order
66	Case33	caseStart	2017-07-04 11:13:00	NaT	NaN	NaN	NaN	1
1232	Case33	A14	2017-07-04 11:13:00	2017-07-04 11:13:00	45.0	60.0	1.0	2
1226	Case33	A6	2017-07-04 11:16:00	2017-07-04 11:16:00	45.0	60.0	1.0	2
1220	Case33	A0	2017-07-04 11:19:00	2017-07-04 11:21:00	45.0	60.0	1.0	2
1223	Case33	A3	2017-07-04 11:19:00	2017-07-04 11:28:00	45.0	60.0	1.0	2

In [13]:
```
##Calculating WIP (the number of active cases) at the start of each event
W=0
WIP_list = []

for eventRow in df.itertuples(index=False):
    if eventRow.activity == 'caseStart':
        W=W+1
    elif eventRow.activity == 'caseEnd':
        W=W-1
    WIP_list.append(W)

df['WIP'] = WIP_list
df.head()
```

Out[13]:

	caseid	activity	start_timestamp	end_timestamp	SLA MIN	case_duration	label	row_order	WIP
66	Case33	caseStart	2017-07-04 11:13:00	NaT	NaN	NaN	NaN	1	1
1232	Case33	A14	2017-07-04 11:13:00	2017-07-04 11:13:00	45.0	60.0	1.0	2	1
1226	Case33	A6	2017-07-04 11:16:00	2017-07-04 11:16:00	45.0	60.0	1.0	2	1
1220	Case33	A0	2017-07-04 11:19:00	2017-07-04 11:21:00	45.0	60.0	1.0	2	1
1223	Case33	A3	2017-07-04 11:19:00	2017-07-04 11:28:00	45.0	60.0	1.0	2	1

In [14]:
```
##Cleaning up the dataframe
###(removing the artificial start/end events and the row_order column)
df = df[df.row_order == 2]
df.drop('row_order', axis=1, inplace=True)
df.reset_index()
df.head()
```

Out[14]:

	caseid	activity	start_timestamp	end_timestamp	SLA MIN	case_duration	label	WIP
1232	Case33	A14	2017-07-04 11:13:00	2017-07-04 11:13:00	45.0	60.0	1.0	1
1226	Case33	A6	2017-07-04 11:16:00	2017-07-04 11:16:00	45.0	60.0	1.0	1
1220	Case33	A0	2017-07-04 11:19:00	2017-07-04 11:21:00	45.0	60.0	1.0	1
1223	Case33	A3	2017-07-04 11:19:00	2017-07-04 11:28:00	45.0	60.0	1.0	1
1224	Case33	A4	2017-07-04 11:21:00	2017-07-04 11:21:00	45.0	60.0	1.0	1

Task 3

(4 points) Currently, the work proposed by Taineema et al. performs the extraction of the prefixes of the traces registered in the log to train the classification models. For large logs, this approach leads to an increase in the dimensionality of the models' input (too many features) without necessarily improving its precision, especially in cases in which the event traces are very long.

You must modify this technique to extract subsequences of size n (n-grams), where n is a user-defined parameter, instead of encoding entire prefixes. An n-gram is a contiguous sequence of n items from a given trace. Consider using the n-grams module from the nltk library for python (https://stackoverflow.com/questions/17531684/n-grams-in-python-four-five-six-grams)

In [15]:
```
##Parameters
train_ratio = 0.8
ngram_length = 5
n_splits = 2
random_state = 22
```

In [16]:
```
##Adding event numbers for use in ploting later
df['event_nr'] = df.groupby('caseid').cumcount() + 1
df
```

Out[16]:

	caseid	activity	start_timestamp	end_timestamp	SLA MIN	case_duration	label	WIP	event_nr
1232	Case33	A14	2017-07-04 11:13:00	2017-07-04 11:13:00	45.0	60.0	1.0	1	1
1226	Case33	A6	2017-07-04 11:16:00	2017-07-04 11:16:00	45.0	60.0	1.0	1	2
1220	Case33	A0	2017-07-04 11:19:00	2017-07-04 11:21:00	45.0	60.0	1.0	1	3
1223	Case33	A3	2017-07-04 11:19:00	2017-07-04 11:28:00	45.0	60.0	1.0	1	4
1224	Case33	A4	2017-07-04 11:21:00	2017-07-04 11:21:00	45.0	60.0	1.0	1	5
...	...	...	...	...	...	...	...	...	...
2419	Case66	A5	2017-08-10 15:40:00	2017-08-10 15:40:00	45.0	51.0	1.0	1	28
2439	Case66	A43	2017-08-10 15:40:00	2017-08-10 15:40:00	45.0	51.0	1.0	1	29
2423	Case66	A49	2017-08-10 15:42:00	2017-08-10 15:42:00	45.0	51.0	1.0	1	30
2416	Case66	A2	2017-08-10 15:51:00	2017-08-10 15:51:00	45.0	51.0	1.0	1	31
2445	Case66	A32	2017-08-10 15:51:00	2017-08-10 15:51:00	45.0	51.0	1.0	1	32

2446 rows × 9 columns

In [17]:
```
##Spliting the event log into train and test datasets
###(sligtly modified to work with the given event log
###(not using activity name in sorting, because I want to keep the original order of events if start timestamps
def split_data_strict(data, train_ratio):
    # split into train and test using temporal split and discard events that overlap the periods
    data = data.sort_values('start_timestamp', ascending=True, kind='mergesort')
    grouped = data.groupby('caseid')
    start_timestamps = grouped['start_timestamp'].min().reset_index()
    start_timestamps = start_timestamps.sort_values('start_timestamp', ascending=True, kind='mergesort')
    train_ids = list(start_timestamps['caseid'])[:int(train_ratio*len(start_timestamps))]
    train = data[data['caseid'].isin(train_ids)].sort_values('start_timestamp', ascending=True, kind='mergesort
    test = data[~data['caseid'].isin(train_ids)].sort_values('start_timestamp', ascending=True, kind='mergesort
    split_ts = test['start_timestamp'].min()
    #Using end timestamp here to also remove events which start before the split timestamp, but end after
    train = train[train['end_timestamp'] < split_ts]
    return (train, test)

train, test = split_data_strict(df, train_ratio)

print('Input event log length:', len(df))
print('Train split lenght:', len(train))
print('Test split lenght:', len(test))
```

```
Input event log length: 2446
Train split lenght: 1908
Test split lenght: 496
```

In [18]:
```
##Checking how many deviant and regular cases there are in train and in test
print("Train deviant cases:", train.loc[df['label'] == 1].caseid.nunique(), "Train regular cases:", train.loc[d
print("Test deviant cases:", test.loc[df['label'] == 1].caseid.nunique(), "Test regular cases:", test.loc[df['l
```

```
Train deviant cases: 40 Train regular cases: 13
Test deviant cases: 10 Test regular cases: 4
```

In [19]:
```
##Methods from practice 10 handout
###(sligtly modified to work with the given event log
def get_stratified_split_generator(data, n_splits=5, shuffle=True, random_state=22):
    grouped_firsts = data.groupby('caseid', as_index=False).first()
    skf = StratifiedKFold(n_splits=n_splits, shuffle=shuffle, random_state=random_state)

    for train_index, test_index in skf.split(grouped_firsts, grouped_firsts['label']):
        current_train_names = grouped_firsts['caseid'][train_index]
        train_chunk = data[data['caseid'].isin(current_train_names)].sort_values('start_timestamp', ascending=T
        test_chunk = data[~data['caseid'].isin(current_train_names)].sort_values('start_timestamp', ascending=T
        yield (train_chunk, test_chunk)

def get_class_ratio(data):
    class_freqs = data['label'].value_counts()
    return class_freqs[1.0] / class_freqs.sum()
```

In [20]:
```
##Method for extracting n-grams
def generate_ngrams(data, ngram_length):
    data['case_length'] = data.groupby('caseid')['activity'].transform(len) #len of each original case
    data = data[data['case_length'] >= ngram_length] #removing traces that are shorter than ngram_length

    dt_ngrams = []
    for id in data.caseid.unique():
        ngram_number=0
        for grams in ngrams(data[data.caseid==id].values.tolist(), ngram_length):
            ngram_number=ngram_number+1
            for gram in grams:
                dt_ngrams.append(gram + [ngram_number, gram[0]+ '-' + str(ngram_number)])
    data = data.rename(columns={'caseid': 'orig_caseid'})

    return pd.DataFrame(dt_ngrams, columns=data.columns.tolist() + ['ngram_nr', 'caseid'])
```

In [21]:
```
dt_ngrams = []
class_ratios = []
for train_chunk, test_chunk in get_stratified_split_generator(train, n_splits=n_splits):
    class_ratios.append(get_class_ratio(train_chunk))
    # generate data where each ngram is a separate instance
    dt_ngrams.append(generate_ngrams(test_chunk, ngram_length))
```

In [22]:
```
dt_ngrams[0].head(10)
```

Out[22]:

	orig_caseid	activity	start_timestamp	end_timestamp	SLA MIN	case_duration	label	WIP	event_nr	case_length	ngram_nr	caseid
0	Case33	A14	2017-07-04 11:13:00	2017-07-04 11:13:00	45.0	60.0	1.0	1	1	29	1	Case33-1
1	Case33	A6	2017-07-04 11:16:00	2017-07-04 11:16:00	45.0	60.0	1.0	1	2	29	1	Case33-1
2	Case33	A0	2017-07-04 11:19:00	2017-07-04 11:21:00	45.0	60.0	1.0	1	3	29	1	Case33-1
3	Case33	A3	2017-07-04 11:19:00	2017-07-04 11:28:00	45.0	60.0	1.0	1	4	29	1	Case33-1
4	Case33	A4	2017-07-04 11:21:00	2017-07-04 11:21:00	45.0	60.0	1.0	1	5	29	1	Case33-1
5	Case33	A6	2017-07-04 11:16:00	2017-07-04 11:16:00	45.0	60.0	1.0	1	2	29	2	Case33-2
6	Case33	A0	2017-07-04 11:19:00	2017-07-04 11:21:00	45.0	60.0	1.0	1	3	29	2	Case33-2
7	Case33	A3	2017-07-04 11:19:00	2017-07-04 11:28:00	45.0	60.0	1.0	1	4	29	2	Case33-2
8	Case33	A4	2017-07-04 11:21:00	2017-07-04 11:21:00	45.0	60.0	1.0	1	5	29	2	Case33-2
9	Case33	A1	2017-07-04 11:26:00	2017-07-04 11:26:00	45.0	60.0	1.0	1	6	29	2	Case33-2

In [23]:
```
print(len(dt_ngrams[0]), len(dt_ngrams[1]), sep=',')
print(dt_ngrams[0].ngram_nr.unique())
print(dt_ngrams[1].ngram_nr.unique())
```

```
4255,4245
[ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41]
[ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42]
```

In [24]:
```
print(dt_ngrams[0].orig_caseid.unique())
print(len(dt_ngrams[0].caseid.unique()))
```

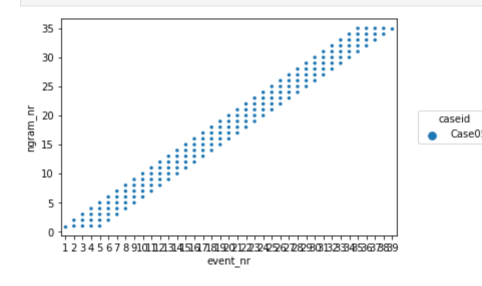
```
['Case33' 'Case32' 'Case29' 'Case27' 'Case05' 'Case07' 'Case06' 'Case37'
 'Case36' 'Case38' 'Case39' 'Case43' 'Case09' 'Case12' 'Case14' 'Case45'
 'Case46' 'Case16' 'Case15' 'Case18' 'Case49' 'Case21' 'Case20' 'Case52'
 'Case53' 'Case23']
851
```

In [25]:
```
eg_cases=dt_ngrams[0][dt_ngrams[0].orig_caseid == 'Case05']
eg_cases[['caseid', 'activity', 'orig_caseid', 'ngram_nr', 'event_nr']].head(10)
```

Out[25]:

	caseid	activity	orig_caseid	ngram_nr	event_nr
590	Case05-1	A0	Case05	1	1
591	Case05-1	A1	Case05	1	2
592	Case05-1	A3	Case05	1	3
593	Case05-1	A4	Case05	1	4
594	Case05-1	A6	Case05	1	5
595	Case05-2	A1	Case05	2	2
596	Case05-2	A3	Case05	2	3
597	Case05-2	A4	Case05	2	4
598	Case05-2	A6	Case05	2	5
599	Case05-2	A20	Case05	2	6

In [26]:
```
##Checking if the ngrams look as expected
ordered = eg_cases.sort_values(by=['orig_caseid', 'ngram_nr', 'caseid', 'event_nr'], ascending=[True ,True, Fal
ax = sns.swarmplot(data=ordered ,x='event_nr', y='ngram_nr', hue='orig_caseid', size=3.5)
ax.legend(loc='center left', bbox_to_anchor=(1.05, 0.5), ncol=2, title='caseid')
plt.show()
```



Task 4

(3 points) Test the results of your modifications with the Turnaround process event log using cluster bucketing, index encoding, and the XGboost model.

This task is incomplete

Divide prefixes into buckets

In [27]:
```
import BucketFactory #Taken from practice 10 code repository
```

In [28]:
```
# encoding_method = "last", "agg", "index"
# Bucketing prefixes based on control flow
bucketer_args = {'encoding_method': 'index',
                 'case_id_col': 'caseid',
                 'cat_cols':['activity'],
                 'num_cols':[],
                 'random_state':random_state}
```

In [29]:
```
cv_iter = 0
dt_test_ngrams = dt_ngrams[cv_iter]
dt_train_ngrams = pd.DataFrame()
for cv_train_iter in range(n_splits):
    if cv_train_iter != cv_iter:
        dt_train_ngrams = pd.concat([dt_train_ngrams, dt_ngrams[cv_train_iter]], axis=0)

#bucket_methods = "single", "prefix", "state", "cluster", "knn"
bucket_method = 'cluster'
if bucket_method == "cluster":
    bucketer_args["n_clusters"] = 3
bucketer = BucketFactory.get_bucketer(bucket_method, **bucketer_args)
bucket_assignments_train = bucketer.fit_predict(dt_train_ngrams)
bucket_assignments_test = bucketer.predict(dt_test_ngrams)
```

In [30]:
```
print('Train assignments:')
bucket_assignments_train
print(pd.DataFrame(bucket_assignments_train, columns=['bucket']).bucket.value_counts())
print('Test assignments:')
bucket_assignments_test
print(pd.DataFrame(bucket_assignments_test, columns=['bucket']).bucket.value_counts())
```

```
Train assignments:
0    422
2    276
1    151
Name: bucket, dtype: int64
Test assignments:
0    403
2    311
1    137
Name: bucket, dtype: int64
```

In [31]:
```
bucket_number = 2

bucket_indexes = dt_train_ngrams.groupby('caseid').first().index
bucket_indexes = bucket_indexes[bucket_assignments_train == bucket_number]
print(bucket_indexes)
bucket_data = dt_train_ngrams[dt_train_ngrams['caseid'].isin(bucket_indexes)]
bucket_data
def get_label_numeric(data):
    y = data.groupby('caseid').first()['label'] # one row per case
    return [1 if label == 1 else 0 for label in y]
train_y = get_label_numeric(bucket_data)
```

```
Index(['Case00-14', 'Case00-15', 'Case00-16', 'Case00-17', 'Case00-18',
       'Case00-19', 'Case00-20', 'Case00-21', 'Case00-22', 'Case00-23',
       ...
       'Case51-13', 'Case51-14', 'Case51-15', 'Case51-16', 'Case51-17',
       'Case51-18', 'Case51-20', 'Case51-21', 'Case51-22', 'Case51-23'],
      dtype='object', name='caseid', length=276)
```

In [32]:
```
bucket_indexes = dt_test_ngrams.groupby('caseid').first().index
bucket_indexes = bucket_indexes[bucket_assignments_test == bucket_number]
bucket_data_test = dt_test_ngrams[dt_test_ngrams['caseid'].isin(bucket_indexes)]
bucket_data_test
test_y = get_label_numeric(bucket_data_test)
```

Encode prefixes for classification

In [33]:
```
import EncoderFactory
from sklearn.pipeline import FeatureUnion, Pipeline
```