Component Wear Anomalies

Skinwrapper Machines

Let's consider the Vega skinwrapper family of packaging machines by OCME

- They work by wrapping products (bottles) in a plastic film
- ...Which is cut and heated, so that the film shrinks and stabilizes the content

OCME Vega Shrinker

A public dataset for a skinwrapper is available from Kaggle

- The dataset contains a single run-to-failure experiment
- I.e. the machine was left running until its blade became unusable

This is an example of anomaly due to component wear

- It's a common type of anomaly
- ...And run-to-failure experiments are a typical way to investigate them

OCME Vega Shrinker

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All problems in this class share a few properties

- There is a critical anomaly at the end of the experiment
- The behavior becomes more and more distant from normal over time

...Meaning that they are good fit for many of the techniques we have studied

The Dataset

Let's have a first look at the dataset

In [2]:
```
data = pd.read_csv(data_file)
data
```

Out[2]:

	mode	segment	smonth	sday	stime	timestamp	pCut::Motor_Torque	pCut::CTRL_Position_controller::Lag_error	pCut::CTR
0	1	0	1	4	184148	0.008000	0.199603	0.027420	62839262
1	1	0	1	4	184148	0.012000	0.281624	0.002502	62839262
2	1	0	1	4	184148	0.016000	0.349315	-0.018085	62839262
3	1	0	1	4	184148	0.020000	0.444450	-0.054680	62839261
4	1	0	1	4	184148	0.024000	0.480923	-0.042770	62839261
...	...	...	...	...	...	...	...	...	...
1062907	2	518	12	28	185909	8.179999	-0.277697	-0.023948	19492447
1062908	2	518	12	28	185909	8.183999	-0.285098	-0.022138	19492450
1062909	2	518	12	28	185909	8.187999	-0.155192	-0.034412	19492453
1062910	2	518	12	28	185909	8.191999	-0.371426	0.031594	19492456
1062911	2	518	12	28	185909	8.195999	-0.284030	0.010178	19492459

1062912 rows × 14 columns

- The data refers to disjoint measurement windows
- Each segment contains data sampled every 4ms

The Dataset

Let's check some statistics

In [3]:
```
data.describe()
```

Out[3]:

	mode	segment	smonth	sday	stime	timestamp	pCut::Motor_Torque	pCut::CTRL_Pos
count	1.062912e+06	1.062912e+06	1.062912e+06	1.062912e+06	1.062912e+06	1.062912e+06	1.062912e+06	1.062912e+06
mean	2.323699e+00	2.590000e+02	5.271676e+00	1.654143e+01	1.362122e+05	4.102069e+00	-1.206338e-01	-5.472746e-05
std	1.649207e+00	1.498222e+02	3.505212e+00	8.490150e+00	3.226381e+04	2.364827e+00	6.078708e-01	1.212122e-01
min	1.000000e+00	0.000000e+00	1.000000e+00	1.000000e+00	8.115800e+04	4.000000e-03	-6.560303e+00	-1.888258e+00
25%	1.000000e+00	1.290000e+02	2.000000e+00	9.000000e+00	1.113170e+05	2.056000e+00	-3.696310e-01	-2.201461e-02
50%	2.000000e+00	2.590000e+02	4.000000e+00	1.800000e+01	1.348180e+05	4.104000e+00	-1.187128e-01	6.456900e-04
75%	3.000000e+00	3.890000e+02	8.000000e+00	2.300000e+01	1.618270e+05	6.152000e+00	2.546913e-01	2.380830e-02
max	8.000000e+00	5.180000e+02	1.200000e+01	3.100000e+01	2.232490e+05	8.199999e+00	3.856873e+00	2.021531e+00

- The data is neither normalized nor standardized

Missing Values

Let's check for missing values in the columns related to sensor readings

In [4]:
```
data.isnull().any()
```

Out[4]:
```
mode                                                  False
segment                                               False
smonth                                                False
sday                                                  False
stime                                                 False
timestamp                                             False
pCut::Motor_Torque                                    False
pCut::CTRL_Position_controller::Lag_error             False
pCut::CTRL_Position_controller::Actual_position       False
pCut::CTRL_Position_controller::Actual_speed          False
pSvolFilm::CTRL_Position_controller::Actual_position  False
pSvolFilm::CTRL_Position_controller::Actual_speed     False
pSvolFilm::CTRL_Position_controller::Lag_error        False
pSpintor::VAX_speed                                   False
dtype: bool
```

No missing value in the dataset

Acquisition Windows

And let's check the length of each segment

In [5]:
```
data.groupby('segment')['mode'].count().describe()
```

Out[5]:
```
count     519.0
mean     2048.0
std         0.0
min      2048.0
25%      2048.0
50%      2048.0
75%      2048.0
max      2048.0
Name: mode, dtype: float64
```

- There are 519 segments overall
- ...Each with 2048 samples

Input Columns

Let's have a look at all non-time related columns

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```

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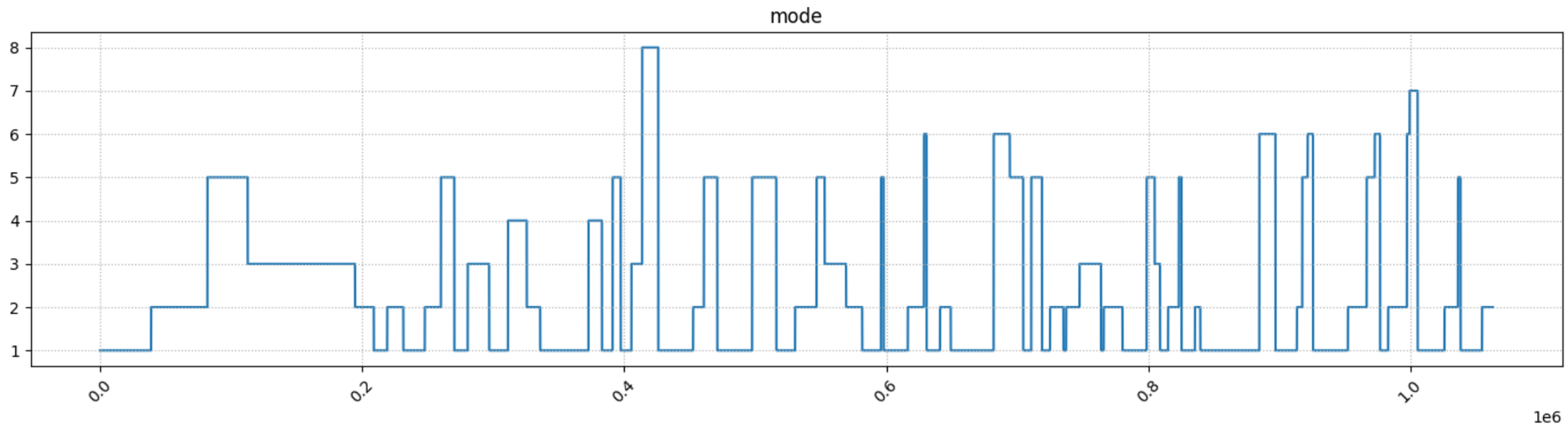
Input Columns

Let's have a look at all non-time related columns

Input Columns

Column 0 corresponds to an operating mode

In [7]:
```
util.plot_series(data2[data2.columns[0]], figsize=figsize, title=data2.columns[0])
```

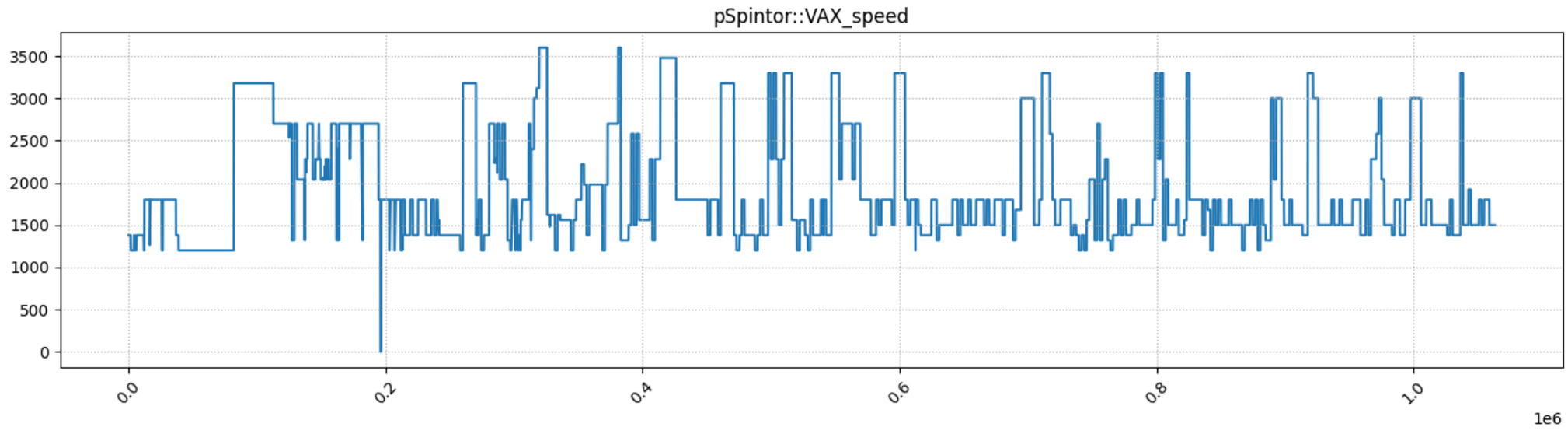


- The mode is a controlled parameter and does not change in the middle of a segment
- Intuitively, the mode has an impact on the machine behavior

Input Columns

Column 8 is also a fixed over long periods of time

In [8]:
```
util.plot_series(data2[data2.columns[8]], figsize=figsize, title=data2.columns[8])
```

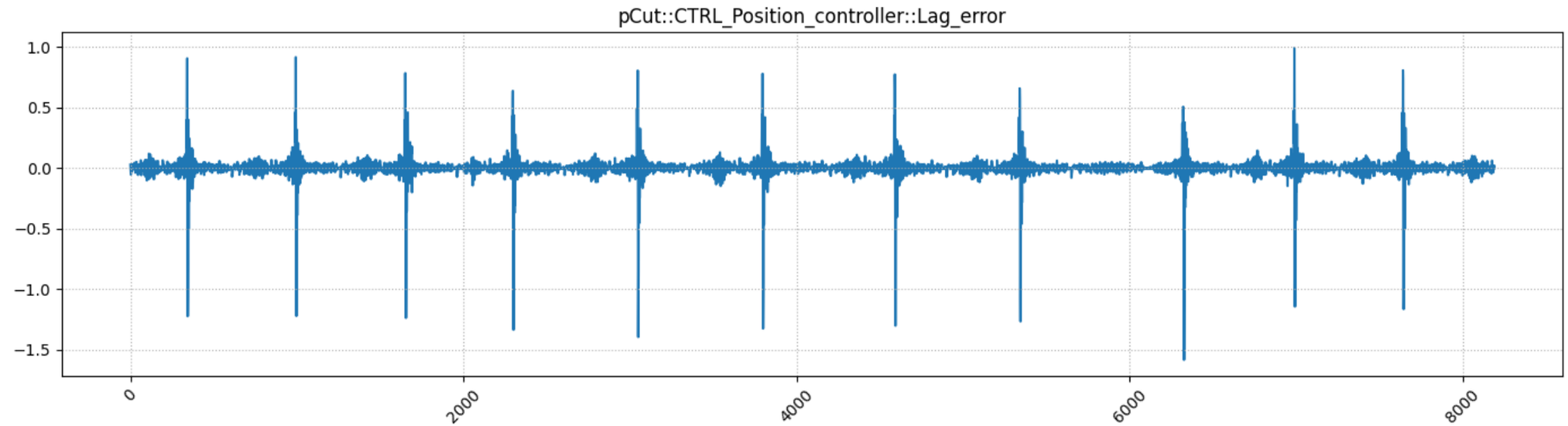


- This is likely a controlled parameter
- Ideally, we would speak with the customer (but in this excercise we can't)

Input Columns

Column 2 peaks repeatedly over short time periods

In [9]:
```
util.plot_series(data2[data2.columns[2]].iloc[:2048*4], figsize=figsize, title=data2.columns[2])
```

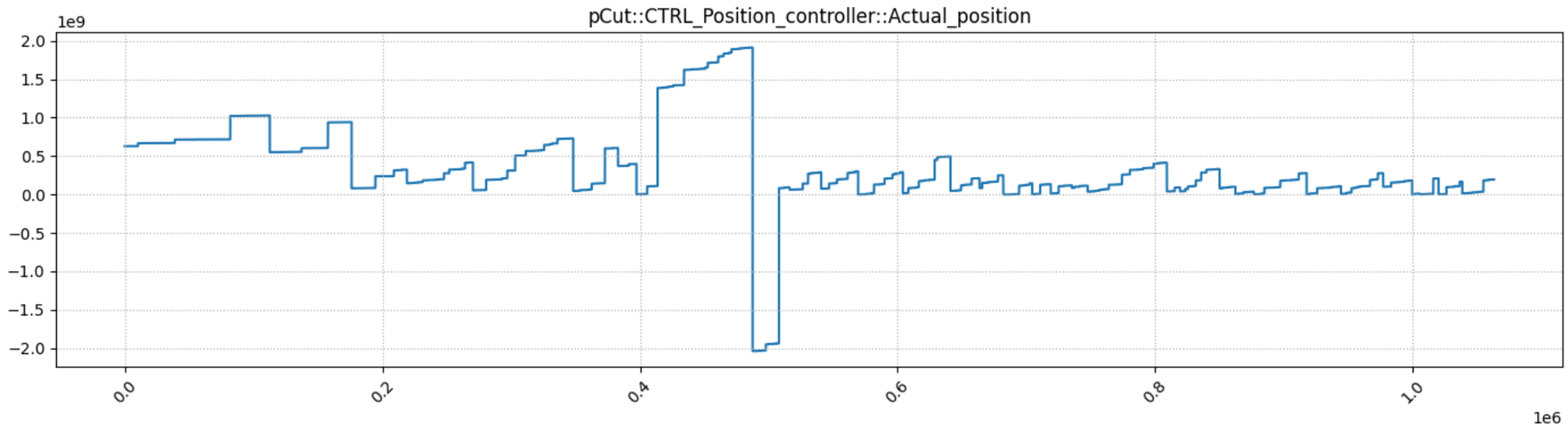


- There is nothing really wrong with this
- ...And it explains the mostly white row in our previous plot

Input Columns

Column 3 contains an odd, localized, deviation

In [10]:
```
util.plot_series(data2[data2.columns[3]], figsize=figsize, title=data2.columns[3])
```

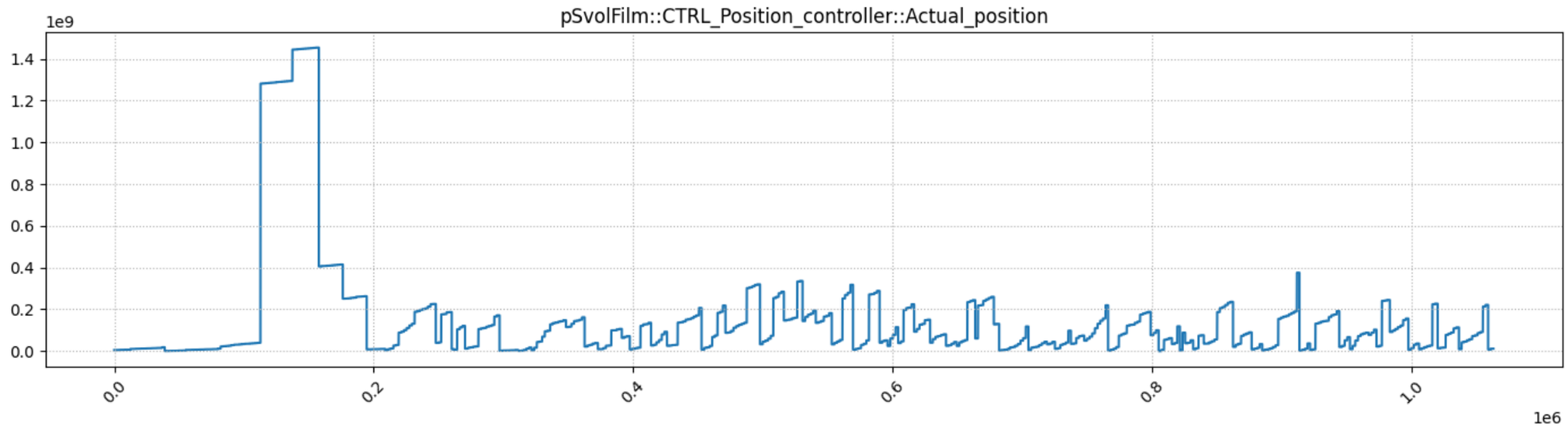


- This is likely the result of manual adjustment
- We'd better keep this column off

Input Columns

...And the same holds for column 5

In [11]:
```
util.plot_series(data2[data2.columns[5]], figsize=figsize, title=data2.columns[5])
```



- Again, this is probably the a mistake, or due to human intervention
- We'd better keep this column off

Data Preparation

Binning

This dataset contain high-frequency data (4ms sampling period)

- In this situation, feeding the raw data to a model does not usually make sense
- So we will use subsampling

A binning approach typically works as follows:

We apply a sliding window, but so that its consecutive applications do not overlap

- Each window application is called a bin
- ...From which we extract one or more features
- ...By applying different aggregation functions

The result is series that contains a smaller number of samples

...But typically a larger number of features

Binning

We will apply binning to all columns not related to time

...Except for the two we chose to discard

In [12]:
```
feat_in_r = data2.columns[[0, 1, 2, 4, 6, 7, 8]]
print(list(feat_in_r))
```

```
['mode', 'pCut::Motor_Torque', 'pCut::CTRL_Position_controller::Lag_error', 'pCut::CTRL_Positi
on_controller::Actual_speed', 'pSvolFilm::CTRL_Position_controller::Actual_speed', 'pSvolFil
m::CTRL_Position_controller::Lag_error', 'pSpintor::VAX_speed']
```

First, we define which aggregation function to apply to each field

In [13]:
```
aggmap = {a: ['mean', 'std', 'skew'] for a in feat_in_r}
aggmap['mode'] = 'first'
aggmap['pSpintor::VAX_speed'] = 'first'
```

- For the features that are fixed over a segment, we pick the first value


Binning

Then we build out bins

In [14]:
```
binsize = 512 # 2 seconds of measurements
bins = []
for sname, sdata in data.groupby('segment'):
    sdata['bin'] = sdata.index // binsize # Build the bin numbers
    tmp = sdata.groupby('bin').agg(aggmap) # Apply the aggregation functions
    bins.append(tmp)
data_b = pd.concat(bins)
```

- We process each segment individually
- ...So that we are sure that no bin overlaps two segments

We chose our bin size based on:

- Having enough data to compensate noise
- Capture regular patterns (e.g. our spiking signal)

Binning

Let's inspect the result

In [15]:
```
data_b
```

Out[15]:

	mode	pCut::Motor_Torque			pCut::CTRL_Position_controller::Lag_error			pCut::CTRL_Position_controller::Actual_speed			p
	first	mean	std	skew	mean	std	skew	mean	std	skew	m
bin											
0	1	-0.125718	0.544329	-2.488922	-0.000167	0.110956	-3.746651	1599.917513	3999.045185	-0.209394	3
1	1	-0.072671	0.540906	-2.635165	-0.000567	0.103435	-3.336454	844.540436	3862.165458	0.309415	3
2	1	0.014070	0.354287	0.152579	0.000724	0.031961	0.032216	60.570994	2816.788446	-0.245380	3
3	1	-0.207667	0.455206	-3.803152	-0.000150	0.103125	-4.496910	2670.353585	2474.506197	0.155697	2
4	1	-0.289142	0.434465	-4.372388	-0.000275	0.106193	-5.242337	2579.037789	2626.919219	-0.502959	3
...	...	...	...	...	...	...	...	...	...	...	...
2071	2	-0.184381	0.781750	-3.758458	0.000508	0.116385	-1.459755	1819.838542	4007.857890	-0.029032	3
2072	2	-0.207829	0.791797	-3.968010	-0.000285	0.115259	-1.482473	1936.977300	3932.533837	-0.082154	3
2073	2	-0.146367	0.846064	-3.683229	-0.001013	0.116217	-1.488226	1556.298091	4088.929784	0.137784	3
2074	2	-0.125521	0.800829	-3.798401	-0.001139	0.117804	-1.245373	1148.293884	3980.947227	0.422832	3
2075	2	0.032077	0.349737	-0.137235	-0.000274	0.034452	-0.078601	493.331985	3127.137947	0.204754	3

2076 rows × 17 columns

- We have much fewer rows, and more columns