Start Here

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0.1 Amazon work sample

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0.2 A. pre-data peeking brainstorm

0.2.1 task description

- Dataset
- Features are attributes ==> need to figure out what they could be, and how to interpret each of them
- Each point is a date/device_id. Need to determine the sparsity in both dimensions, to know which modelisation could make sense.
- Is there a feature bias linked to the time at which maintenance occurs ? (e.g. no more data after a failure) this could build a bias in the data.
- Problem
- Failure detection: two signal axis (which device fails, when does a device fail) to consider. Consider mixing two models ? eg:
- model1 : which device is the most likely to require maintenance.
- model2 : based on past signals, when is a maintenance the most likely to occur.
- Failure detection: positives could be sparse. to be checked. SVD could be worth something This is a precision/recall problem.
- On the other hand, no obvious advantage in detecting a false positive over a false negative.
- Infos
- 3D technologies is electronics, the device sends out telemetry: multiple failure modes (wrong telemetry, bad transmition, etc...) ==> we could be detecting multiple failure modes. ensemble models ?

0.3 The Plan

1. Exploratory Analysis
2. Data shape
3. Labels
4. features
5. Modeling
6. Decide on a model / a list of models
7. Model(s) optimisation process
    1. Dataset building
    2. First model and calibration
    3. Feature optimisation
    4. Test different Models
    5. TPOT
8. Final test on validation set.

1 1. Exploratory Analysis

1.1 A. Data shape

Notebook : here

In general:

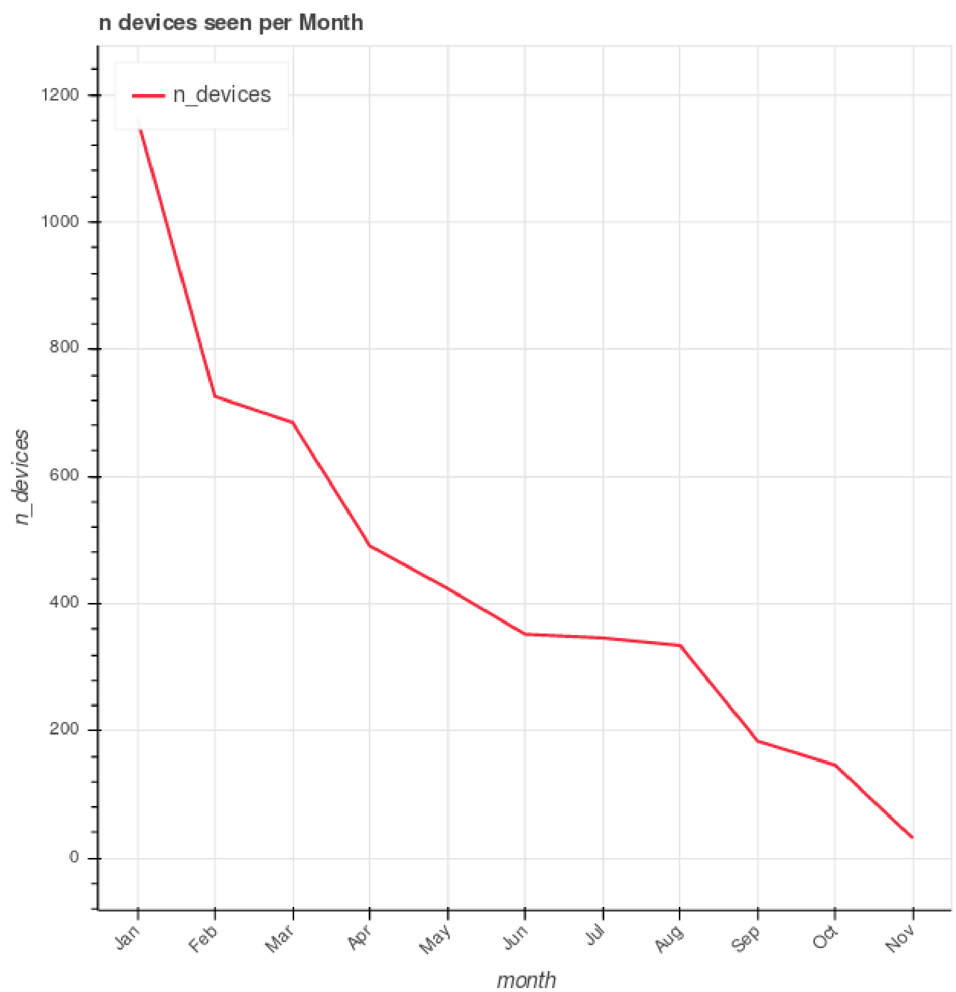
```
- Each line is indexed as a (device, time)
- 9 attributes (features)
- 1168 devices, 106 failing (small data, few positives)
- Date Range: daily timestamps from 2015-01-01 to 2015-11-02
```

Devices are not always on !

```
- Each device is active during a given period, device_period < dataset period
- The device 'start_time' is biased toward the beginning of the dataset. (1163/1168 start the fi
- There are much fewer devices at the end of the measurement period (see graph below)
```

1.2 B. Labels

```
- 1168 devices, 106 failing (small data, few positives)
- failure ratio : 10%, ~1% per month
- inn fact, the % failures varies month to month, from 5% to 0%
```


n devices seen per Month
n_devices
1200
1000
800
600
400
200
0
n_devices
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
month

Alt

Weekly view

```
- Less  failures over the weekend: devices are less strained during the weekend ?
- Warning: fewer failures during weekend could also be explained by maintenance hapening only du
```

weekday	NB failures
0:Monday	27
1:Tuesday	18
2:Wednesday	15
3:Thursday	22
4:Friday	12
5:Saturday	8
6:Sunday	4

Missing data

```
- During device "lifetime", most devices (1077/1168) have a signal per day, without missing days
```

Failure mode

```
- Almost all devices stops measuring after a failure
- Indetified a list of devices, which are still measured after having failed.
```

three hypothesis: - The device is still functionnal after maintenance - The failure was a fluke - The measurement thereafter are false

==> if we cannot distinguish between these hypothesis, need to remove these devices from the dataset

1.3 C. Features

Using the feature analyser notebook over each individual attribute.

- attribute 1: no real influence observed
- attribute 2:
  - Higher values on failures
  - Rising front before failures
- attribute 3:
  - Slightly higher for non-failing that for failing
  - Unclear temporal effect
- attribute 4
  - higher values for failing devices
  - Rising front before failures
  - failing frequency peak
- attribute 5 :
  - no clear impact
  - potential peaks when failing
- attribute 6 :
  - unclear effect onn value or fronts

- on the other hand, signal on frequency distribution

- attribute 7 :
  - unclear effect
- attribute 8 :
  - idem
- attribute 9
  - frequency distribution ?

Conclusion

- Need to check out for attribute values, derivatives and DFT peaks as features

2 2. Modeling

2.1 A. Decide on a model / a list of models

There seems to be some attributes having an effect on the device failing. What we actually want is a model predicting the day devices are failing.

Also, since what we want is to implement a maintenance model, it would be acceptable, if it is more efficient, to predict devices soon to be failing, for example 7 days before the failure.

ccl: we will build two models: - A model predicting which device will fail at some point - A model predicting which device will fail and when, with an acceptable failure window

2.2 B. Models optimisation process

```
1. Dataset building
2. First model and calibration
3. Feature optimisation
4. Test different Models
5. TPOT
```

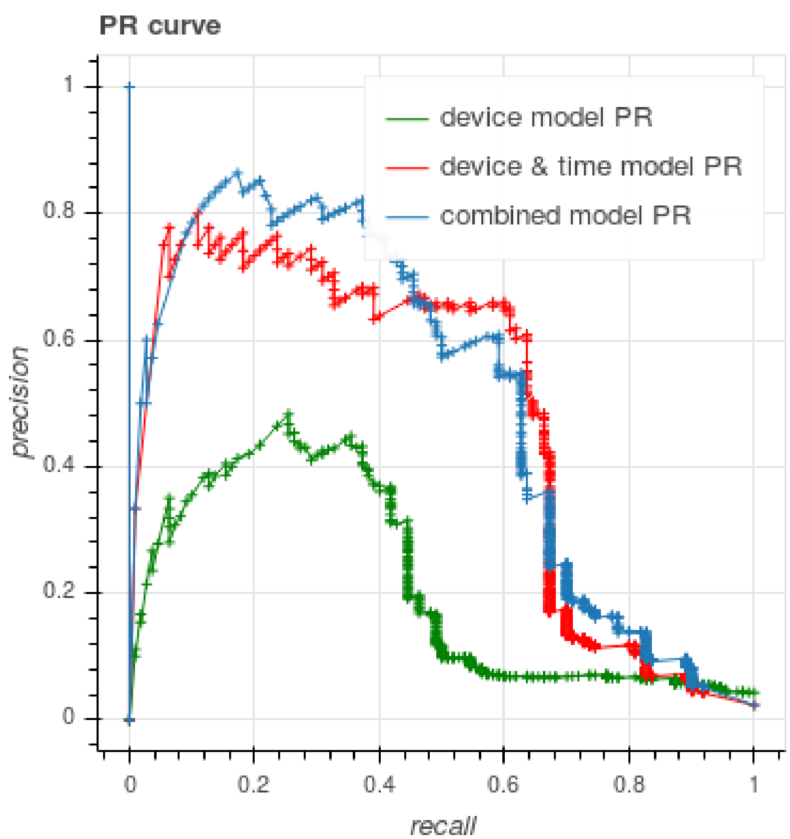
ML decision diary: here
Each models are optimized on different notebooks:

- device base model
- device base model and time

2.3 C. Final Test

Test on a validation set, splitted after the device exploration

```
In [ ]:
```


PR curve
device model PR
device & time model PR
combined model PR
precision
recall
0
0.2
0.4
0.6
0.8
1

Alt