Deep Learning: Predicting hard disks failures using recurrent LSTM network

July 12, 2018 (http://croock.webfactional.com/deep-learning-predicting-hard-disks-failures-using-recurrent-lstm-network/) Lucas KM (http://croock.webfactional.com/author/lukas_km/) Projects (http://croock.webfactional.com/category/projects/)

This time I decided to take the following challenge: predict failures of hard disks in the datacenter. We will check if Neural Network can predict failure patterns based on disks diagnostic (SMART) data.

There are countless number of disks around the world in both on-premise and cloud datacenters.

The (Imaginary) Intro Story

The intro story is fictional, and is here to help you unrderstand potential business context of the problem. I hope you will understand better, why such model can be beneficial.

You are working in the ACME Cloud company as newly joined Data Scientist. You company is a really big player on the market. The competition on this market is fierce and is increasing every year. Customers are demanding lower prices and increased quality of service at the same time.

One of the common problems in datacenter is failing data storage disks. Current business applications transfer large amounts of data and put very big pressure on the disks. Of course, your company has already standard lifecycle management and replacement procedures in place so you do not use disks longer than you should. You also use professional software to manage your datacenter and approaches such as RAID (Redundant Array of Independent Disks) to reduce data loss. But so does your company competition.

ACME Cloud CIO asked you to experiment with datacenter disks diagnostic data and predict disk failures. Your company has been collecting SMART diagnostic data for several years for operational control reasons so data are already there.

Author: sixsixfive at openclipart.org / License: Creative Commons Zero 1.0 Public Domain License

There are a few reasons why such prediction model can be beneficial for ACME Cloud:

1. Prediction will reduce risks related to data loss. Even though you use RAID and perform backups, there is always a risk that more than one disk will fail at the same time, resulting in at least partial data loss. In fact it already happened once and you company lost one big customer.
2. Good prediction model will allow ACME Cloud to extend allowed lifecycle time for one disk. At this moment, you have very conservative approach and you replace disks quite often, even before time suggested by the disk vendor. But that approach increases your costs. If you could lower the replacement rate, your company could save substantial amout of money.
3. You would like also to use older disks as your internal spare backup system. Not all of them, even after passing vendor maximal lifetime, are dead or damaged. But you can do that only if you can know, for at least part of them, whether they will fail or not. That will allow you to transfer data to other disks before the first one will fail.
4. Reasons 2 and 3 will be also beneficial for your modern marketing activities. Your company wants to brand itself as Eco-friendly one, so reducing disk waste can be a good reason to brag about it.

The Solution

In order to solve this problem, you decide to build a Machine Learning model based on recurrent (RNN) Deep Learning network. From all RNN network architectures, LSTM (Long Short Term Memory) network usually delivers best results and you will use it here.

You should be careful while evaluating results of the network. Simple acurracy measure is not good enough so you should use classification report with details about precision and recall.

The Results

I decided to predict disk failure 5 days ahead and also use 5-day samples to feed my LSTM network. The notebook below will give you more details about the solution.

Class 0 represents disks that never failed. Class 1 represents disks that failed.

These are the results I was able to achieve using my LSTM network:
accuracy: 75.27%

Class	Precision	Recall	F1 Score	Support
0	0.68	0.95	0.79	2570
1	0.92	0.56	0.70	2614
Avg / Total	0.80	0.75	0.74	5184

This is interesting result:

- The overall accuracy (75,27%) is good, but not impressive.
- However, results for class 1 (disks that “failed soon” so within our predict_failure_days window) are quite interesting
- Precision equal to 92% means that once our model predicts disk will “fail soon” it is correct roughly in 9 out of 10 cases
- Recall equal to 56% means that we are able to identify more than half of failed disk from the whole pool of failed disks. The other 44% will go undetected.

The results are still fairly acceptable for everyday business use. Even if we can detect only half of failed disks, our model is definitely quite precise in failure prediction. ACME Cloud staff is able to replace majority of failing disks before they actually stop working.

NOTE: Remember this is machine learning (statistical) model. Your results can differ from mine to some extent.

The Notebook

Please review the notebook below for details of the solution.

You can also reviev the Notebook on Github (https://github.com/lukaszkm/machinelearningexp/blob/master/Deep_Learning_Predicting_Hard_Disk_Failures.ipynb).

00. Intro & Goal

Disk Failure Prediction Notebook

- Notebook @author Lukasz Kamieniecki-Mruk, lucas.mlexp@gmail.com, http://machinelearningexp.com (http://machinelearningexp.com)
- Notebook License: Creative Commons CC-BY-SA https://creativecommons.org/licenses/by-sa/4.0/ (https://creativecommons.org/licenses/by-sa/4.0/)
- Dataset source: https://www.backblaze.com/b2/hard-drive-test-data.html (https://www.backblaze.com/b2/hard-drive-test-data.html)
- Dataset license: As per Backblaze statement: “You can download and use this data for free for your own purpose, all we ask is three things 1) you cite Backblaze as the source if you use the data, 2) you accept that you are solely responsible for how you use the data, and 3) you do not sell this data to anyone, it is free.”
- Dataset dates: years 2015 – 2017

Your R&D task is the following:

1. Use Backblaze data for one of the most popular disk model in the dataset to build demo prediction classifier for the disk failure
2. Model should use LSTM Deep Learning networks.
3. Model should be evaluated in details using classification report
4. Model will be successful if it will allow to find faling disk at least 2 days in advance (to ensure safe replacement)

NOTE: This notebook is CPU and memory consuming. You have been warned 🙂

01. Params & imports

In [1]:

```
import os
import gc
import fileinput
import math
import random
from random import shuffle, randrange
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.utils import shuffle
from sklearn import preprocessing
from sklearn.utils import shuffle
from sklearn.metrics import classification_report
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras import regularizers,optimizers
```

```
Using TensorFlow backend.
```

In [2]:

```
# params
data_dir = "./data/"
raw_data_dir = data_dir + 'raw_data'
merged_data_dir = data_dir + 'merged_data'
pretrain_data_dir = data_dir + 'pretrain_data'
train_data_dir = data_dir + 'train_data'
```

02. Data preprocessing

It is very important what Backblaze writes on the data page (quote) : “Reported stats for the same SMART stat can vary in meaning based on the drive manufacturer and the drive model. Make sure you are comparing apples-to-apples as drive manufacturers don’t generally disclose what their specific numbers mean.”
Therefore, we cannot compare different disk types. For this reason, I decided to select one specific model for my analysis. The model I have selected (“ST4000DM000”) is quite popular in the dataset and provides enough data for my analysis. You can try different model if you like; just make sure it provides enough data.

In [3]:

```
chosen_disk_model = 'ST4000DM000'
merged_file_path = merged_data_dir+'/merged_data_2015_2017.csv'
```

First, I have gathered all CSV files in one directory. My “raw_data_dir” has 17,6 GB of data and contains 1096 CSV files. The script belowe will scan all .csv files in raw data files and will keep only first header and then only rows that contain our chosen_disk_model. As a result, we will get single merged CSV file containing only rows for our chosen_disk_model.

In [4]:

```
print ('Files processed',end =": ")
with open(merged_file_path, 'w') as out_file:
    first_line = True
    counter = 0
    for in_file_name in os.listdir(raw_data_dir):
        fcontent = open(os.path.join(raw_data_dir, in_file_name))
        for line in fcontent:
            if (first_line == True) or (('date,serial_number' not in line) and (chosen_disk_model in
line)):
                out_file.write(line)
            first_line = False
        fcontent.close()
        if ((counter%100)==0): print (counter,end =" > ")
        counter += 1
    print ('Completed')
```

```
Files processed: 0 > 100 > 200 > 300 > 400 > 500 > 600 > 700 > 800 > 900 > 1000 > Completed
```

My merged file has around 8,15 GB of data. This is still a lot of data, at least for my machine. I want to create single Pandas dataframe for further processing.
We need to process data in chunks and downcast numerical data to save memory.
I decided also to drop columns with normalized data, I prefer to normalize data later myself.

In [5]:

```
columns_names_text = 'date,serial_number,model,capacity_bytes,failure,smart_1_normalized,smart_1_raw,smart_2_normalized,smart_2_raw,smart_3_normalized,smart_3_raw,smart_4_normalized,smart_4_raw,smart_5_normalized,smart_5_raw,smart_7_normalized,smart_7_raw,smart_8_normalized,smart_8_raw,smart_9_normalized,smart_9_raw,smart_10_normalized,smart_10_raw,smart_11_normalized,smart_11_raw,smart_12_normalized,smart_12_raw,smart_13_normalized,smart_13_raw,smart_15_normalized,smart_15_raw,smart_22_normalized,smart_22_raw,smart_183_normalized,smart_183_raw,smart_184_normalized,smart_184_raw,smart_187_normalized,smart_187_raw,smart_188_normalized,smart_188_raw,smart_189_normalized,smart_189_raw,smart_190_normalized,smart_190_raw,smart_191_normalized,smart_191_raw,smart_192_normalized,smart_192_raw,smart_193_normalized,smart_193_raw,smart_194_normalized,smart_194_raw,smart_195_normalized,smart_195_raw,smart_196_normalized,smart_196_raw,smart_197_normalized,smart_197_raw,smart_198_normalized,smart_198_raw,smart_199_normalized,smart_199_raw,smart_200_normalized,smart_200_raw,smart_201_normalized,smart_201_raw,smart_220_normalized,smart_220_raw,smart_222_normalized,smart_222_raw,smart_223_normalized,smart_223_raw,smart_224_normalized,smart_224_raw,smart_225_normalized,smart_225_raw,smart_226_normalized,smart_226_raw,smart_240_normalized,smart_240_raw,smart_241_normalized,smart_241_raw,smart_242_normalized,smart_242_raw,smart_250_normalized,smart_250_raw,smart_251_normalized,smart_251_raw,smart_252_normalized,smart_252_raw,smart_254_normalized,smart_254_raw,smart_255_normalized,smart_255_raw'
columns_names = columns_names_text.split(',')
columns_to_drop = [col for col in columns_names if '_normalized' in col]
gc.collect()
```

Out[5]:

```
7
```

Be patient, this step can consume a lot of memory and be slow.

In [6]:

```
chunksize = 10 ** 5
chunks_list = list()
print ('Chunks: ',end ="")
for chunk in pd.read_csv(merged_file_path, header = 0 ,names=columns_names, chunksize=chunksize, low_memory=False):
    chunk = chunk.drop(columns_to_drop, axis=1)
    chunk_first_rows = chunk.iloc[:,0:4]
    chunk_num_rows = chunk.iloc[:,4:].fillna(0)
    chunk_num_rows = chunk_num_rows.astype('int64')
    chunk_num_rows = chunk_num_rows.apply(pd.to_numeric,downcast='integer')
    chunk_all = chunk_first_rows.join(chunk_num_rows)
    chunks_list.append(chunk_all)
    if ((len(chunks_list)%50)==0): print (len(chunks_list), end=" > ")
    gc.collect()
print ('Completed')
```

```
Chunks: 50 > 100 > 150 > 200 > 250 > 300 > Completed
```

Now we will a) merge all chunks into one dataframe b) drop columns with empty values c) generate column with weekday and d) save it to pickle file.

In [7]:

```
reduced_df = pd.concat(chunks_list)
reduced_df = reduced_df.dropna(axis=1)
reduced_df['date'] = pd.to_datetime(reduced_df['date'])
reduced_df.insert(1, 'weekday', reduced_df['date'].dt.dayofweek)
reduced_df = reduced_df.sort_values(by=['serial_number','date'],axis=0)
reduced_df = reduced_df.drop(columns=['model'])
reduced_df = reduced_df.reset_index(drop=True)
reduced_df.iloc[0:5,:12]
```

Out[7]:

	date	weekday	serial_number	capacity_bytes	failure	smart_1_raw	smart_2_raw	smart_3_raw	smart_4_raw	smart_5_raw	smart_7_raw	sm
0	2016-09-10	5	S3000A9T	4000787030016	0	14415968	0	0	4	0	97797	0
1	2016-09-11	6	S3000A9T	4000787030016	1	57961664	0	0	4	0	256456	0
2	2017-06-03	5	S3000A9T	4000787030016	0	107687208	0	0	33	0	33158496	0
3	2017-06-04	6	S3000A9T	4000787030016	0	132850464	0	0	33	0	33315265	0
4	2017-06-05	0	S3000A9T	4000787030016	0	176573128	0	0	33	0	33376638	0

In [8]:

```
reduced_df.to_pickle(pretrain_data_dir+'/pretrain_data_01.pkl')
```

Let's clean some memory before further processing

In [9]:

```
del (reduced_df, chunks_list)
gc.collect()
```

Out[9]:

```
80
```

03A. Training data prepration

Let's load prepared data

In [10]:

```
df = pd.read_pickle(pretrain_data_dir+'/pretrain_data_01.pkl')
loaded_shape = df.shape
print ("Data shape: ",loaded_shape)
df = df.sort_values(by=['serial_number','date'],axis=0,ascending=True)
```

```
Data shape:  (31414293, 50)
```

Hm, so we have over 31 million records. That is nice ...

Now we will aggregate data to calculate number of failed and not failed disks. As number of not failed disks is probaby much higher than number of failed disks, we can remove some non-failed disks to reduce dataset size.

In [11]:

```
df_aggregate = (df[['date','serial_number','failure']].groupby('serial_number',as_index = True)
                .agg({'date':'count', 'failure':'sum'})
                .rename(columns={'date': 'date_count', 'failure': 'failure_sum'})
                .sort_values(by=['failure_sum'],axis=0,ascending=False))
df_aggregate.head(5)
```

Out[11]:

	date_count	failure_sum
serial_number		
Z305AQGZ	414	2
Z305PEAL	397	2
S300WEE9	597	2
W3005047	148	1
Z301ZQH4	312	1

As you can see, some disks failed more than once. We have to be careful when processing data.

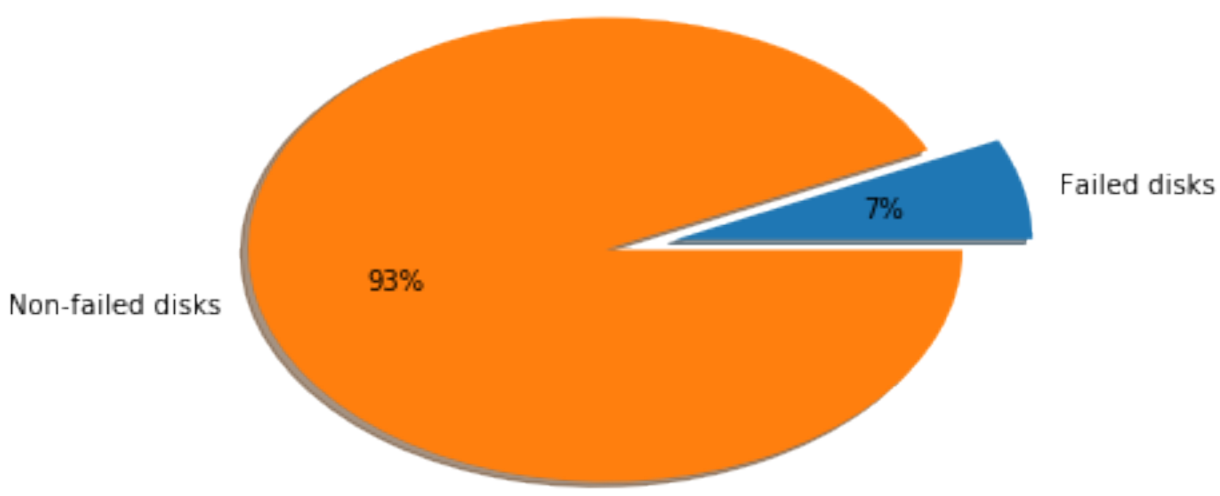
In [12]:

```
all_count = df_aggregate.shape[0]
broken_count = df_aggregate[df_aggregate.iloc[:, 1] >= 1].shape[0]
print ('number of disks : ',all_count)
print ('number of failed disks: ',broken_count)
print ('percentage of broken disks: ',broken_count/all_count*100,'%' )
```

```
number of disks :  36700
number of failed disks:  2587
percentage of broken disks:  7.049046321525886 %
```

In [13]:

```
labels = ['Failed disks','Non-failed disks']
shares = [broken_count,all_count-broken_count]
plt.pie(shares,explode=(0.2,0),labels=labels,autopct='%.0f%%',shadow=True,)
plt.show()
```



Broken disks constitute only ~7% of all disks. In order to balance classes and reduce dataset size, we can decrease number of not failed disks. The parameter num_ok_delta defines how many more not failed individual disks (than failed) we will leave in the dataset as to ensure more variability in this class.
NOTE: This step is not exactly necessary (if you have enough memory on your machine). During further processing I ensure again that number of “not failed” samples corresponds roughly to number of “failed” samples.

In [14]:

```
num_ok_delta = 2000
df_broken = df_aggregate[df_aggregate['failure_sum']>0].index.values
df_ok = df_aggregate[df_aggregate['failure_sum']==0].sample(n=(df_broken.shape[0]+num_ok_delta)).inde
x.values
selected_disks = np.concatenate((df_broken, df_ok), axis=0)
df = df.loc[df.serial_number.isin(selected_disks)]
reduced_shape = df.shape
reduced_shape
```

Out[14]:

```
(5349516, 50)
```

In [15]:

```
print ("dataset size reduction: ",int(100*((loaded_shape[0] - reduced_shape[0])/loaded_shape[0])),"%"
)
```

```
dataset size reduction:  82 %
```

In [16]:

```
del df_aggregate, df_broken, df_ok, selected_disks
gc.collect()
```

Out[16]:

```
1937
```

Now we will add a few empty columns that will help us in further processing.

- fails_soon – this will be our key target column. It tells “the disk will fail in the next N days (N being our parameter)”
- seq_id – sequence is one series of disk history: from the first event in our dataset till: either last recorded event or failure. As we have noticed, some disks failed twice. They will have two different sequence ids then (one for each sequence).
- work_day – consecutive number showing number of days disk is working (for a given sequence). Numbering starts from 1.
- max_work_day – maximal work_day in a sequence. This is a helper parameter for further processing.
- final_failure – information whether disk finally failed (1) or not (0). This is also helper parameter that will help in further processing.

The “helper” parameters, although repeat the same data for a moment, will allow us to keep processing linear and avoid “nested loops/quadratic processing”.

In [17]:

```
df = df.sort_values(by=['serial_number','date'],axis=0,ascending=True)
df.insert(5, 'fails_soon', np.nan)
df.insert(6, 'seq_id', np.nan)
df.insert(7, 'work_day', np.nan)
df.insert(8, 'max_work_day', np.nan)
df.insert(9, 'final_failure', np.nan)
df.iloc[0:5,:12]
```

Out[17]:

	date	weekday	serial_number	capacity_bytes	failure	fails_soon	seq_id	work_day	max_work_day	final_failure	smart_1_raw	smart_2_raw
0	2016-09-10	5	S3000A9T	4000787030016	0	NaN	NaN	NaN	NaN	NaN	14415968	0
1	2016-09-11	6	S3000A9T	4000787030016	1	NaN	NaN	NaN	NaN	NaN	57961664	0
2	2017-06-03	5	S3000A9T	4000787030016	0	NaN	NaN	NaN	NaN	NaN	107687208	0
3	2017-06-04	6	S3000A9T	4000787030016	0	NaN	NaN	NaN	NaN	NaN	132850464	0
4	2017-06-05	0	S3000A9T	4000787030016	0	NaN	NaN	NaN	NaN	NaN	176573128	0

Now we will sort data by disk serial number and date ascending. This is very important step for next processing loop.

In [18]:

```
df = df.sort_values(by=['serial_number','date'],axis=0,ascending=True)
```

The next loop will go through the whole dataset and:

- once encounters new disk, it will set parameters specifically for beginning of a new sequence (see code)
- if continues current sequence, it will just increment current working day and set current sequence id

As a result of this script, two newly added columns will be filled in: seq_id and work_day

In [19]:

```
curr_serial_number = None
prev_failure = 0
observ_seq_id = 0
counter = 0
for idx,data in df.iterrows():
    if (data['serial_number'] != curr_serial_number) or (prev_failure == 1):
        curr_serial_number = data['serial_number']
        curr_work_day = 1
        observ_seq_id += 1
    else:
        curr_work_day += 1
    df.at[idx, 'seq_id'] = observ_seq_id
    df.at[idx, 'work_day'] = curr_work_day
    prev_failure = data['failure']
    # print status every 0.5 million rows processed
    if (counter%500000==0): print (int(counter*100/df.shape[0]),'%',end =" > ")
    counter += 1
print ("completed")
```

```
0 % > 9 % > 18 % > 28 % > 37 % > 46 % > 56 % > 65 % > 74 % > 84 % > 93 % > completed
```

This is our dataset head after first processing loop

In [20]:

```
df.iloc[0:5,:12]
```

Out[20]:

	date	weekday	serial_number	capacity_bytes	failure	fails_soon	seq_id	work_day	max_work_day	final_failure	smart_1_raw	smart_2_raw
0	2016-09-10	5	S3000A9T	4000787030016	0	NaN	1.0	1.0	NaN	NaN	14415968	0
1	2016-09-11	6	S3000A9T	4000787030016	1	NaN	1.0	2.0	NaN	NaN	57961664	0
2	2017-06-03	5	S3000A9T	4000787030016	0	NaN	2.0	1.0	NaN	NaN	107687208	0
3	2017-06-04	6	S3000A9T	4000787030016	0	NaN	2.0	2.0	NaN	NaN	132850464	0
4	2017-06-05	0	S3000A9T	4000787030016	0	NaN	2.0	3.0	NaN	NaN	176573128	0

Cause this step takes a lot of time, we will save result into interim picke file. You will be able to load this interim file and rerun next steps without generating these data again.

In [21]:

```
df.to_pickle(pretrain_data_dir+'/pretrain_data_02.pkl')
```

In [22]:

```
df = pd.read_pickle(pretrain_data_dir+'/pretrain_data_02.pkl')
```

Now we need to sort data again. This time, each sequence will be sorted from last working day to first working day (in descending order). Thanks to that, our next processing script will know what happened with disk at the end – did it fail or not?

In [23]:

```
df = df.sort_values(by=['seq_id','work_day'],axis=0,ascending=[True, False])
```

These two parameters below are one of the key parameters of this excercise:

- sample_days – defines how many days we want to have in each sample (sequence) that we will feed into LSTM network. LSTMs as recurrent networks can learn from sequences and we will take advantage of that. The longer the sequence in a single sample is, the more information about potential trend we provide to the network. But also, days that are more far away from the final failure day have less guidance in SMART parameters whether disk will fail or not, so they may mislead the network.
- predict_failure_days – defines how many days before the failure day we treat as "fails soon "days. So you can think of it

also as a “warning flag” – do you want to be warned about potential failure 3, 5 or 10 days before it happens? The bigger this parameter is, the more samples we can generate for training for “failed” disks. But, the same as for previous parameter, samples more “far away” from the failure day will have less info hidden in SMART parameters about potential trend.

See the image below to understand how we will construct each sample. For LSTM networks, input has 3D structure (num_samples, timesteps, num_featutes). Each star “*” in the sample is one timestep with size of SMART num_features each.

sample_days = 5, predict_failure_days = 5												
working day →	90	91	92	93	94	95	96	97	98	99	100	Sample final target (fails_soon)
failure	0	0	0	0	0	0	0	0	0	0	1	
fails_soon	0	0	0	0	0	0	1	1	1	1	1	
sample n	*	*	*	*	*							0
sample n + 1		*	*	*	*	*						0
sample n + 2			*	*	*	*	*					1
sample n + 3				*	*	*	*	*				1
sample n + 4					*	*	*	*	*			1
sample n + 5						*	*	*	*	*		1
sample n + 6							*	*	*	*	*	1

In [24]:

```
sample_days = 5
predict_failure_days = 5
assert predict_failure_days >= sample_days
```

This script will fill columns: max_work_day, final_failure and fails_soon. It will also remove sequences of data that are smaller (shorter) than sample_days. We cannot use too short sentences to train our network. This also means that we will be able to predict disk failure no sooner than after having sample_days items of data.

In [25]:

```
prev_observ_seq_id = None
counter = 0
remove_list = []
for idx,data in df.iterrows():
    if (prev_observ_seq_id != data['seq_id']):
        max_working_day = data['work_day']
        final_failure = data['failure']
    if max_working_day >= sample_days:
        df.at[idx, 'max_work_day'] = max_working_day
        df.at[idx, 'final_failure'] = final_failure
        if (final_failure == 1) and (data['work_day'] > (max_working_day - predict_failure_days)):
            df.at[idx, 'fails_soon'] = 1
        else:
            df.at[idx, 'fails_soon'] = 0
    else:
        remove_list.append(idx)
    prev_observ_seq_id = data['seq_id']
    if (counter%500000==0): print (int(counter*100/df.shape[0]),'%',end =" > ")
    counter += 1
df = df.drop(remove_list)
df[['fails_soon','seq_id','work_day','max_work_day','final_failure']] = \
df[['fails_soon','seq_id','work_day','max_work_day','final_failure']].astype(int)
print ("completed")
```

```
0 % > 9 % > 18 % > 28 % > 37 % > 46 % > 56 % > 65 % > 74 % > 84 % > 93 % > completed
```

In [26]:

```
df.iloc[0:5,:12]
```

Out[26]:

	date	weekday	serial_number	capacity_bytes	failure	fails_soon	seq_id	work_day	max_work_day	final_failure	smart_1_raw	smart_2_ra
212	2017-12-31	6	S3000A9T	4000787030016	0	0	2	211	211	0	38941024	0
211	2017-12-30	5	S3000A9T	4000787030016	0	0	2	210	211	0	43226920	0
210	2017-	4	S3000A9T	4000787030016	0	0	2	209	211	0	237129448	0

	12-29											
209	2017-12-28	3	S3000A9T	4000787030016	0	0	2	208	211	0	107965856	0
208	2017-12-27	2	S3000A9T	4000787030016	0	0	2	207	211	0	236818080	0

And we save the interim results again.

In [27]:

```
df = df.sort_values(by=['seq_id','work_day'],axis=0,ascending=[True, True])
df.to_pickle(pretrain_data_dir+'/pretrain_data_03.pkl')
```

03B. LSTM Sample selection

In [60]:

```
df = pd.read_pickle(pretrain_data_dir+'/pretrain_data_03.pkl')
df = df.sort_values(by=['seq_id','work_day'],axis=0,ascending=[True, False])
```

In [61]:

```
gc.collect()
```

Out[61]:

```
17066
```

In [62]:

```
df.iloc[0:5,:12]
```

Out[62]:

	date	weekday	serial_number	capacity_bytes	failure	fails_soon	seq_id	work_day	max_work_day	final_failure	smart_1_raw	smart_2_ra
212	2017-12-31	6	S3000A9T	4000787030016	0	0	2	211	211	0	38941024	0
211	2017-12-30	5	S3000A9T	4000787030016	0	0	2	210	211	0	43226920	0
210	2017-12-29	4	S3000A9T	4000787030016	0	0	2	209	211	0	237129448	0
209	2017-12-28	3	S3000A9T	4000787030016	0	0	2	208	211	0	107965856	0
208	2017-12-27	2	S3000A9T	4000787030016	0	0	2	207	211	0	236818080	0

First we will select failed samples, so samples with disks for which we know they finally failed. This is the first step as in the next step we will select samples of disks that did not failed and both classes should be balanced.

In [63]:

```
## Sample data
df_failed_samples = pd.DataFrame()
failed_samples_list = []
counter = 0
for idx,data in df.iterrows():
    if (data['fails_soon'] == 1) and (data['work_day'] >= sample_days):
        int_loc = df.index.get_loc(idx)
        failed_sample = df.iloc[int_loc:int_loc + sample_days]
        failed_samples_list.append(failed_sample)
    if (counter%500000==0): print (int(counter*100/df.shape[0]),'%',end =" > ")
    counter += 1
df_failed_samples = df_failed_samples.append(failed_samples_list)
df_failed_samples = df_failed_samples.reset_index(drop=True)
df_failed_samples = df_failed_samples.sort_index(axis=0,ascending=False)
print ("completed")
```

```
0 % > 9 % > 18 % > 28 % > 37 % > 46 % > 56 % > 65 % > 74 % > 84 % > 93 % > completed
```

In [64]:

```
df_failed_samples.iloc[0:7,:12]
```

Out[64]:

	date	weekday	serial_number	capacity_bytes	failure	fails_soon	seq_id	work_day	max_work_day	final_failure	smart_1_raw	smart_2_
63639	2017-10-17	1	Z306MW5B	4000787030016	0	0	7212	419	427	1	166497128	0
63638	2017-10-18	2	Z306MW5B	4000787030016	0	0	7212	420	427	1	51905616	0
63637	2017-10-19	3	Z306MW5B	4000787030016	0	0	7212	421	427	1	147568504	0
63636	2017-10-20	4	Z306MW5B	4000787030016	0	0	7212	422	427	1	4599640	0
63635	2017-10-21	5	Z306MW5B	4000787030016	0	1	7212	423	427	1	95941328	0
63634	2017-10-18	2	Z306MW5B	4000787030016	0	0	7212	420	427	1	51905616	0
63633	2017-10-19	3	Z306MW5B	4000787030016	0	0	7212	421	427	1	147568504	0

In [65]:

```
len(df_failed_samples)
```

Out[65]:

```
63640
```

Now we will be selecting samples with non-failed disks (the same size as for failed ones). Please note that there are two “types” of non-failed samples 1) samples related to disks that never failed 2) samples related to disks that will fail but “later” that set by our horizon parameter “predict_failure_days”. Such samples are not yet aware that their disk will fail.
Cause here we have much more samples than in failed disks set, we will do the selection randomly to ensure better variability in data.
We also need to ensure that the same disk does not repeat too many times and that our random selection selects different samples, not the same ones. Loop has control structures to ensure that.

In [66]:

```
failed_len = int(df_failed_samples.shape[0]/sample_days)
df_len = df.shape[0]
df_ok_samples = pd.DataFrame()
ok_samples_list = []
counter = 0
used_disks_list = []
used_offset_list = []
max_same_disks = 2
for i in range(failed_len):
    selected_ok = False
    while selected_ok == False:
        ok_offset = random.randint(0, df_len-sample_days)
        check_row = df.iloc[ok_offset]
        if (check_row['fails_soon'] == 0) \
        and (check_row['work_day'] >= sample_days)\
        and (used_disks_list.count(check_row['serial_number']) <= max_same_disks)\
        and (ok_offset not in used_offset_list):
            used_disks_list.append(check_row['serial_number'])
            used_offset_list.append(ok_offset)
            ok_sample = df.iloc[ok_offset:ok_offset+sample_days]
            ok_samples_list.append(ok_sample)
            selected_ok = True
    if (counter%5000==0): print (int(counter*100/failed_len),'%',end =" > ")
    counter += 1
del df
gc.collect()
df_ok_samples = df_ok_samples.append(ok_samples_list)
df_ok_samples = df_ok_samples.reset_index(drop=True)
df_ok_samples = df_ok_samples.sort_index(axis=0,ascending=False)
print ("completed")
```

```
0 % > 39 % > 78 % > completed
```

In [67]:

```
df_ok_samples.iloc[0:7,:12]
```

Out[67]:

	date	weekday	serial_number	capacity_bytes	failure	fails_soon	seq_id	work_day	max_work_day	final_failure	smart_1_raw	smart_2_
63639	2016-05-04	2	Z304K41P	4000787030016	0	0	5641	196	706	0	155674568	0
63638	2016-05-05	3	Z304K41P	4000787030016	0	0	5641	197	706	0	198631672	0
63637	2016-05-06	4	Z304K41P	4000787030016	0	0	5641	198	706	0	69089520	0
63636	2016-05-07	5	Z304K41P	4000787030016	0	0	5641	199	706	0	118052472	0
63635	2016-05-08	6	Z304K41P	4000787030016	0	0	5641	200	706	0	102301768	0
63634	2017-06-01	3	Z305DHVT	4000787030016	0	0	6753	474	686	0	140664320	0
63633	2017-06-02	4	Z305DHVT	4000787030016	0	0	6753	475	686	0	237657416	0

In [68]:

```
df_samples = pd.concat([df_failed_samples, df_ok_samples])
df_samples = df_samples.reset_index(drop=True)
```

In [69]:

```
df_samples.to_pickle(train_data_dir+'/LSTM_train_data.pkl')
```

03C. LSTM Sample preparation

Let’s load our training data again.

In [70]:

```
df = pd.read_pickle(train_data_dir+'/LSTM_train_data.pkl')
df.shape
```

Out[70]:

```
(127280, 55)
```

In [71]:

```
df.iloc[0:5,:12]
```

Out[71]:

	date	weekday	serial_number	capacity_bytes	failure	fails_soon	seq_id	work_day	max_work_day	final_failure	smart_1_raw	smart_2_raw
0	2017-10-17	1	Z306MW5B	4000787030016	0	0	7212	419	427	1	166497128	0
1	2017-10-18	2	Z306MW5B	4000787030016	0	0	7212	420	427	1	51905616	0
2	2017-10-19	3	Z306MW5B	4000787030016	0	0	7212	421	427	1	147568504	0
3	2017-10-20	4	Z306MW5B	4000787030016	0	0	7212	422	427	1	4599640	0
4	2017-10-21	5	Z306MW5B	4000787030016	0	1	7212	423	427	1	95941328	0

We need to choose our train and test data smartly. I decided to do it by disk serial number. Separate individual disks will go to test and train set. This way, we have better guarantee that our LSTM model generalizes well and does not use knowledge from training data to predict test data.
The traditional, alternative approach (select randomly sampes from the dataset) could cause that some samples would overlap and knowledge about future events could leak into test data.

Parameter test_disk_split decides, what percentage of all data should go to test data

In [72]:

```
disks_list = shuffle(df['serial_number'].unique())
test_disk_split = 0.2
split_position = int((1-test_disk_split)*len(disks_list))
train_disks_list = disks_list[:split_position]
test_disks_list = disks_list[split_position:]
print ("no of train disks: ",len(train_disks_list))
print ("no of test disks: ",len(test_disks_list))
```

```
no of train disks:  5373
no of test disks:  1344
```

Now we use train/test disk serial numbers to get separate dataset for test and train data

In [73]:

```
df_train = df[df['serial_number'].isin(train_disks_list)]
df_test = df[df['serial_number'].isin(test_disks_list)]
```

In [74]:

```
# index data will hold disk serial numbers for relevant samples. We do not need serial numbers as tra
ining or testing features
# train index data
IDX_train = df_train.iloc[0:,[0,2]].values
IDX_train = IDX_train[0::sample_days]
# test index data
IDX_test = df_test.iloc[0:,[0,2]].values
IDX_test = IDX_test[0::sample_days]
```

We remove all helper, technical columns and not needed columns and a target column from a features (X) set. As target column fails_soon is not a last column, we cannot easily slice it.

In [75]:

```
drop_columns_list = ['date','serial_number','failure','fails_soon','seq_id','max_work_day','final_fai
lure']
X_train = df_train.drop(columns=drop_columns_list)
X_test = df_test.drop(columns=drop_columns_list)
Y_train = df_train.iloc[:,5]
Y_test = df_test.iloc[:,5]
```

In [76]:

```
X_train.iloc[0:5,:12]
```

Out[76]:

	weekday	capacity_bytes	work_day	smart_1_raw	smart_2_raw	smart_3_raw	smart_4_raw	smart_5_raw	smart_7_raw	smart_8_raw	smart_9_
50	6	4000787030016	131	103879304	0	0	4	0	98228901	0	3135
51	0	4000787030016	132	204068512	0	0	4	0	98925204	0	3159
52	1	4000787030016	133	100851520	0	0	4	0	99568277	0	3183
53	2	4000787030016	134	65844728	0	0	4	0	100275771	0	3207
54	3	4000787030016	135	90875048	0	0	4	0	100893021	0	3231

In [77]:

```
Y_train.iloc[0:5]
```

Out[77]:

```
50    0
51    0
52    0
53    0
54    1
Name: fails_soon, dtype: int32
```

In [78]:

```
X_test.iloc[0:5,:12]
```

Out[78]:

	weekday	capacity_bytes	work_day	smart_1_raw	smart_2_raw	smart_3_raw	smart_4_raw	smart_5_raw	smart_7_raw	smart_8_raw	smart_9_ra
0	1	4000787030016	419	166497128	0	0	4	0	339701174	0	10137
1	2	4000787030016	420	51905616	0	0	4	0	340455664	0	10160
2	3	4000787030016	421	147568504	0	0	4	0	341490395	0	10190
3	4	4000787030016	422	4599640	0	0	4	0	342234422	0	10214
4	5	4000787030016	423	95941328	0	0	4	0	342967290	0	10238

In [79]:

```
Y_test.iloc[0:5]
```

Out[79]:

```
0    0
1    0
2    0
3    0
4    1
Name: fails_soon, dtype: int32
```

First we change Pandas dataframes to Numpy arrays. Then we scale data (train scaler should be used to scale test data too). Finally, we reshape data to get 3D data (num_samples, timesteps, num_featutes) needed to feed LSTM.

In [80]:

```
# X train data
X_train = X_train.values
X_train = X_train.astype(np.float64)
standard_scaler = preprocessing.StandardScaler().fit(X_train)
X_train = standard_scaler.transform(X_train)
X_train = X_train.reshape(int(X_train.shape[0]/sample_days),sample_days,X_train.shape[1])
# X test data
X_test = X_test.values
X_test = X_test.astype(np.float64)
X_test = standard_scaler.transform(X_test)
X_test = X_test.reshape(int(X_test.shape[0]/sample_days),sample_days,X_test.shape[1])
```

In [81]:

```
# Y train daa
Y_train = Y_train.values
Y_train = Y_train[sample_days-1::sample_days]
# Y test data
Y_test = Y_test.values
Y_test = Y_test[sample_days-1::sample_days]
```

In [82]:

```
# shuffle all created datasets together to ensure variability
IDX_train, X_train, Y_train = shuffle(IDX_train, X_train, Y_train)
IDX_test, X_test, Y_test = shuffle(IDX_test, X_test, Y_test)
```

In [83]:

```
gc.collect()
```

Out[83]:

```
136
```

04. Neural Network training and evaluation

Below is the definition of our DNN model. I use multi-layer DNN with three LSTM layers and 3 feed-forward layers. Our network performs classification tasks, predicting whether a given sample belongs to fails_soon class (fails_soon = 1) or not fails_soon class (fails_soon = 0)

In [84]:

```
dp_lvl = 0.2
regularizer_lvl = 0.002
# design network
model = Sequential()
model.add(LSTM(256, input_shape=(X_train.shape[1], X_train.shape[2]),dropout = dp_lvl,recurrent_dropo
ut = dp_lvl, return_sequences =  True ))
model.add(LSTM(256, dropout = dp_lvl,recurrent_dropout = dp_lvl, return_sequences =  True ))
model.add(LSTM(256, dropout = dp_lvl,recurrent_dropout = dp_lvl, return_sequences =  False ))
model.add(Dense(256, activation='sigmoid',activity_regularizer=regularizers.l2(regularizer_lvl)))
model.add(Dense(256, activation='sigmoid',activity_regularizer=regularizers.l2(regularizer_lvl)))
model.add(Dense(1, activation='sigmoid',activity_regularizer=regularizers.l2(regularizer_lvl)))
epochs_num = 10
learning_rate = 0.001
decay_rate = 3 * learning_rate / epochs_num
optimizer = optimizers.Adam(lr=learning_rate, beta_1=0.9, beta_2=0.999, epsilon=None,decay = decay_ra
te)
model.compile(optimizer=optimizer,loss='binary_crossentropy',metrics=['accuracy'])
```

I use quite small validation set for learning control, as the number of samples in training set is not too large. The ultimate test is done via test set anyway.

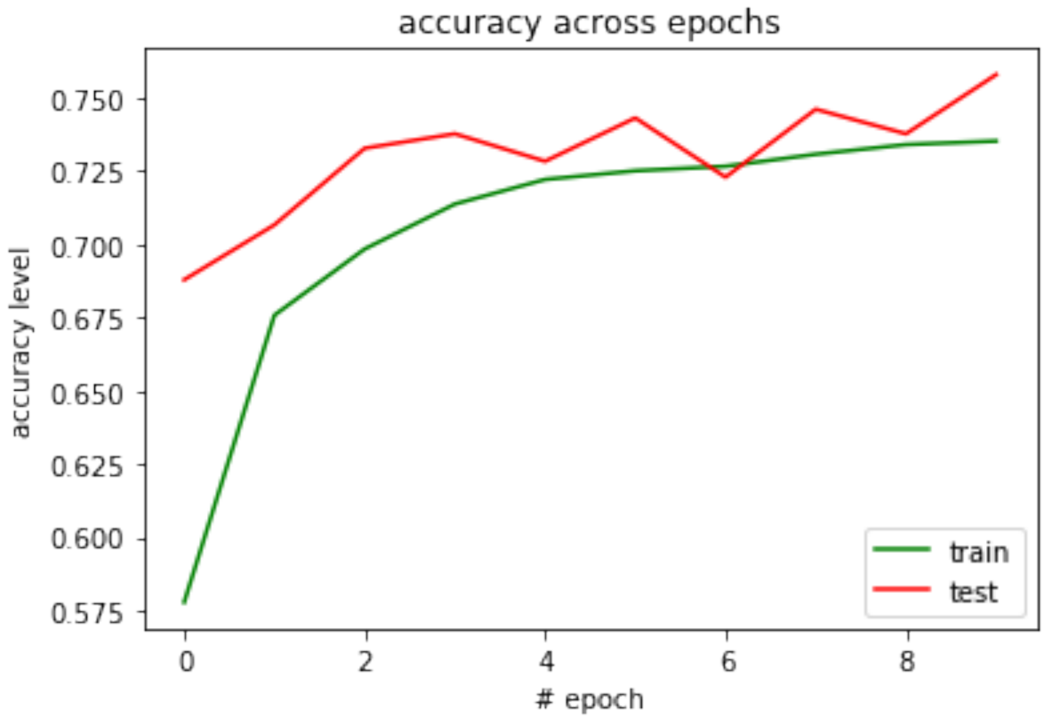
In [85]:

```
# fit network
with tf.device('/gpu:0'):
    history = model.fit(X_train, Y_train, epochs=epochs_num, batch_size=16, validation_split=0.1, ver
bose=1, shuffle=True)
```

```
Train on 18244 samples, validate on 2028 samples
Epoch 1/10
18244/18244 [==============================] - 86s 5ms/step - loss: 0.9430 - acc: 0.5779 - val_loss:
0.7258 - val_acc: 0.6879
Epoch 2/10
18244/18244 [==============================] - 77s 4ms/step - loss: 0.6933 - acc: 0.6758 - val_loss:
0.6423 - val_acc: 0.7066
Epoch 3/10
18244/18244 [==============================] - 78s 4ms/step - loss: 0.6410 - acc: 0.6984 - val_loss:
0.5897 - val_acc: 0.7327
Epoch 4/10
18244/18244 [==============================] - 78s 4ms/step - loss: 0.6091 - acc: 0.7137 - val_loss:
0.5739 - val_acc: 0.7377
Epoch 5/10
18244/18244 [==============================] - 77s 4ms/step - loss: 0.5903 - acc: 0.7221 - val_loss:
0.5761 - val_acc: 0.7283
Epoch 6/10
18244/18244 [==============================] - 84s 5ms/step - loss: 0.5791 - acc: 0.7251 - val_loss:
0.5524 - val_acc: 0.7431
Epoch 7/10
18244/18244 [==============================] - 89s 5ms/step - loss: 0.5695 - acc: 0.7266 - val_loss:
0.5670 - val_acc: 0.7229
Epoch 8/10
18244/18244 [==============================] - 80s 4ms/step - loss: 0.5639 - acc: 0.7307 - val_loss:
0.5473 - val_acc: 0.7461
Epoch 9/10
18244/18244 [==============================] - 79s 4ms/step - loss: 0.5581 - acc: 0.7340 - val_loss:
0.5466 - val_acc: 0.7377
Epoch 10/10
18244/18244 [==============================] - 81s 4ms/step - loss: 0.5542 - acc: 0.7352 - val_loss:
0.5318 - val_acc: 0.7579
```

In [86]:

```
# show plot accuracy changes during training
plt.plot(history.history['acc'],'g')
plt.plot(history.history['val_acc'],'r')
plt.title('accuracy across epochs')
plt.ylabel('accuracy level')
plt.xlabel('# epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.show()
```



In [87]:

```
scores = model.evaluate(X_test, Y_test, verbose=1)
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
Y_pred = model.predict_classes(X_test)
Y_test = Y_test.reshape(Y_test.shape[0],1)
print(classification_report(Y_test, Y_pred))
```

```
5184/5184 [==============================] - 3s 571us/step
acc: 75.27%
             precision    recall  f1-score   support

          0       0.68      0.95      0.79      2570
          1       0.92      0.56      0.70      2614

avg / total       0.80      0.75      0.74      5184
```

This is interesting result:

- The overall accuracy (73,53%) is good, but not impressive.
- However, results for class 1 (disks that “failed soon” so within our predict_failure_days window) are quite interesting
- Precision equal to 91% means that once our model predicts disk will “fail soon” it is correct roughly in 9 out of 10 cases
- Recall equal to 50% means that we are able to identify half of failed disk from the whole pool of failed disks. The other half will go undetected.

The resuls is still fairly acceptable for everyday business use. Even if we can detect only half of failed disks, our model is definitely quite precise in failure prediction.
NOTE: Remember this is machine learning (statistical) model. Your results can differ from mine to some extent.

Now we will play with our network to predict a few individual samples. You can re-run this cell manually as it select random disk from train set.

In [89]:

```
radom_index = randrange(0,X_test.shape[0])
num_samples = 20
print ("Random disks: \n",IDX_test[radom_index:radom_index+num_samples,:])
print ("Y_test (real flags)        ",Y_test[radom_index:radom_index+num_samples,:][:,0])
X_test_sample = X_test[radom_index:radom_index+num_samples,:,:]
Y_pred_sample = model.predict_classes(X_test_sample)[:,0]
print ("Y_predict (predicted flags)",Y_pred_sample)
```

```
Random disks:
 [[Timestamp('2015-12-20 00:00:00') 'Z300K99Q']
 [Timestamp('2015-04-11 00:00:00') 'Z3011WD7']
 [Timestamp('2016-10-03 00:00:00') 'S300Z4EB']
 [Timestamp('2016-07-04 00:00:00') 'Z305CKQX']
 [Timestamp('2015-12-20 00:00:00') 'Z304HS1X']
 [Timestamp('2016-07-25 00:00:00') 'Z3029FA4']
 [Timestamp('2016-01-24 00:00:00') 'Z3025Z3Q']
 [Timestamp('2015-05-17 00:00:00') 'W300R7RG']
 [Timestamp('2015-12-22 00:00:00') 'W3005PYL']
 [Timestamp('2016-01-07 00:00:00') 'Z302FZTY']
 [Timestamp('2017-05-10 00:00:00') 'W300H3HK']
 [Timestamp('2016-09-20 00:00:00') 'Z305D22K']
 [Timestamp('2015-03-11 00:00:00') 'Z302AYP0']
 [Timestamp('2017-05-25 00:00:00') 'Z300XGKG']
 [Timestamp('2017-10-28 00:00:00') 'Z3015CB6']
 [Timestamp('2017-12-04 00:00:00') 'Z305G3NP']
 [Timestamp('2017-02-07 00:00:00') 'Z300ZT4T']
 [Timestamp('2017-10-21 00:00:00') 'Z300JDZC']
 [Timestamp('2017-05-12 00:00:00') 'Z302FDDC']
 [Timestamp('2015-09-30 00:00:00') 'Z3029GYZ']]
Y_test (real flags)         [0 0 0 1 0 1 1 1 0 1 1 0 0 1 0 0 0 1 0 0]
Y_predict (predicted flags) [0 0 0 0 0 1 1 1 0 1 0 0 1 0 1 0 0 0 0 0]
```

Related

Deep Learning: Language identification using Keras & TensorFlow (http://croock.webfactional.com/deep-learning-language-identification-using-keras-tensorflow/)
April 29, 2017
In "Projects"

Machine Learning: Regression of 911 Calls (http://croock.webfactional.com/machine-learning-regression-911-calls/)
February 24, 2017
In "Projects"

Data Science: Performance of Python vs Pandas vs Numpy (http://croock.webfactional.com/data-science-performance-of-python-vs-pandas-vs-numpy/)
July 15, 2017
In "Tips and Tricks"

Deep Neural Networks (http://croock.webfactional.com/tag/deep-neural-networks/) DNN (http://croock.webfactional.com/tag/dnn/) Keras (http://croock.webfactional.com/tag/keras/) Neural Networks (http://croock.webfactional.com/tag/neural-networks/) Numpy (http://croock.webfactional.com/tag/numpy/) Pandas (http://croock.webfactional.com/tag/pandas/) Python (http://croock.webfactional.com/tag/python/)

LUCAS KM (HTTP://CROOCK.WEBFACTIONAL.COM/AUTHOR/LUKAS_KM/)

My name is Lucas and I am an Senior IT Business Anayst with over 10 years of experience in IT system development and integration. I have worked for several large international companies from industries such as: IT, finance, insurance, telecommunications, pharmacy and gambling. I took part in multiple IT projects, ranging from small budgets (hundreds thousands of US dollars) to large (multiple millions of US dollars). A year ago (in 2016), encouraged by a friend, I completed Andrew Ng Machine Learning course on Coursera and I got fascinated by this subject. So I decided to master it. Feel free to contact me via my Email address: lucas.mlexp@gmail.com / Linkedin profile: https://www.linkedin.com/in/lukaszmruk / Twitter account: https://twitter.com/ml_exp

< Data Science: Performance of Python vs Pandas vs Numpy (http://croock.webfactional.com/data-science-performance-of-python-vs-pandas-vs-numpy/)