A-proof report

COVID-19 rehabilitation patterns

1. data-mining
2. time-series modeling

November 3, 2021
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Overview

Medical team

- Research Problem
  - medical team : data-mining
- Data statistics
  - Within admission
  - After discharge
  - Tool for data analysis

Machine Learning ADM prediction

- Research Problem
  - AI: time-series modeling
- Feature Engineering
- Modelling and Results
- Discussion and Outlook

For more information please check this Github repository
And this folder on google docs with progress over time

Medical team

Medical team Research questions

- What is the **mean** or **median** level of functioning on the **different ICF** domains at hospital **admission**, at hospital **discharge** and at the 6 weeks and 3 months outpatient visits?
- What is the **mean** course in the **level** of functioning of these domains during hospital stay (from admission to discharge)?
- What is the **frequency of notes per ICF** domain/level?
- What different **patterns** in recovery of functioning can be distinguished?

Filters applied for Data analysis only

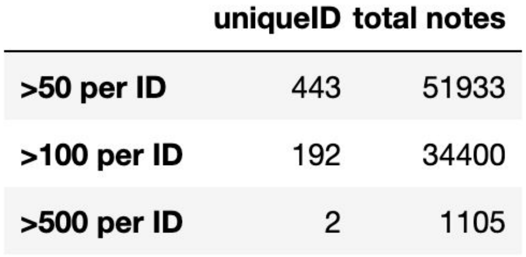
Initial dataset: 110781 instances

- Drop instances with no evaluation for any domain studied: 71287 instances and 1289 unique patients
- Max days difference between note and previous note: 428.0
- Filter considering discharge if more than 2 days with no annotations:58093 instances and still 1289 patients (they all have a day 0)
    - n unique days count: 386
    - min days count: 0
    - mean days count: 199
    - max days count: 429
        - obs: it doesn't mean there are notes every day, it's from the first admission to the last day of note from the patient

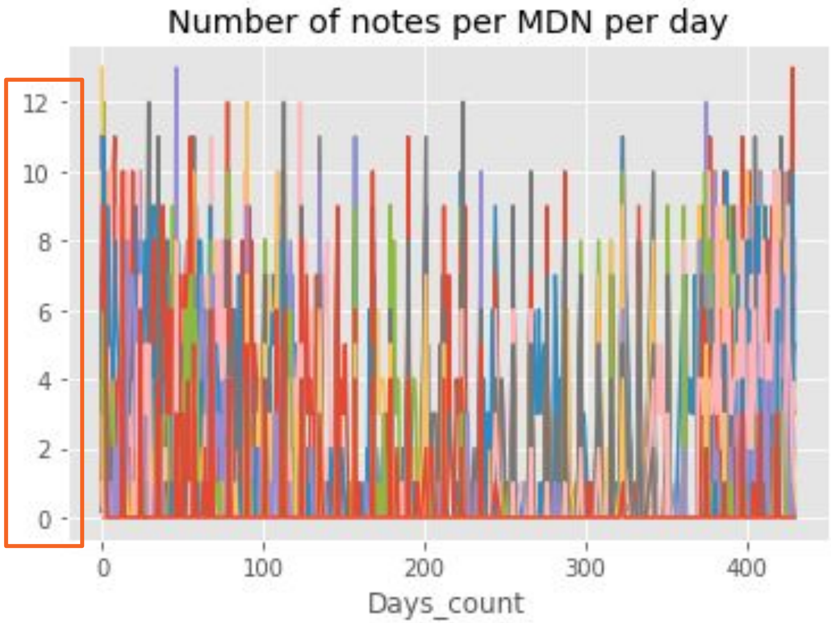
Data statistics

Dataset description

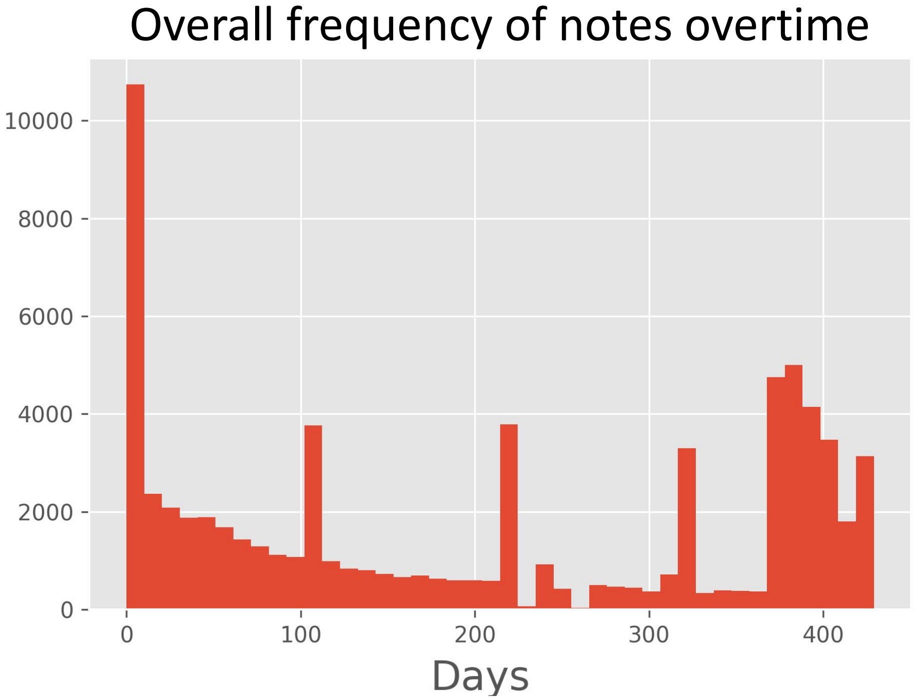
- Dataset from 1/1/2020 until 20/03/2021
- Number of instances with info of at least one domain: 71287
- Initial number of patients: 1289
- Max days difference between note and previous note: 428.0
- N unique days count: 386
- Min days count: 0
- Mean days count: 199 days
- Max days count: 429

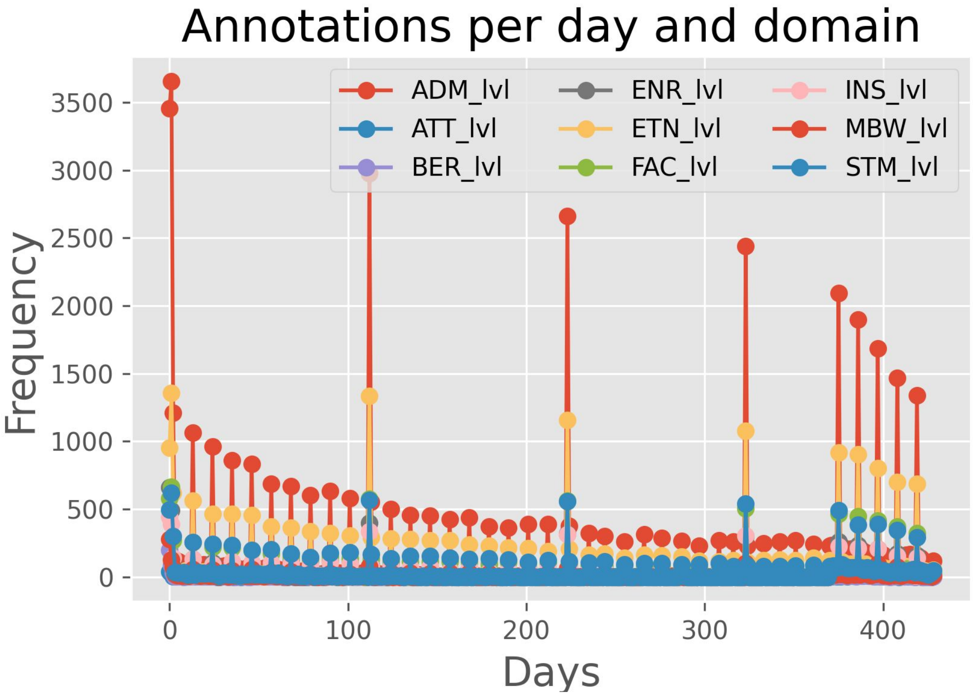


	uniqueID	total notes
>50 per ID	443	51933
>100 per ID	192	34400
>500 per ID	2	1105

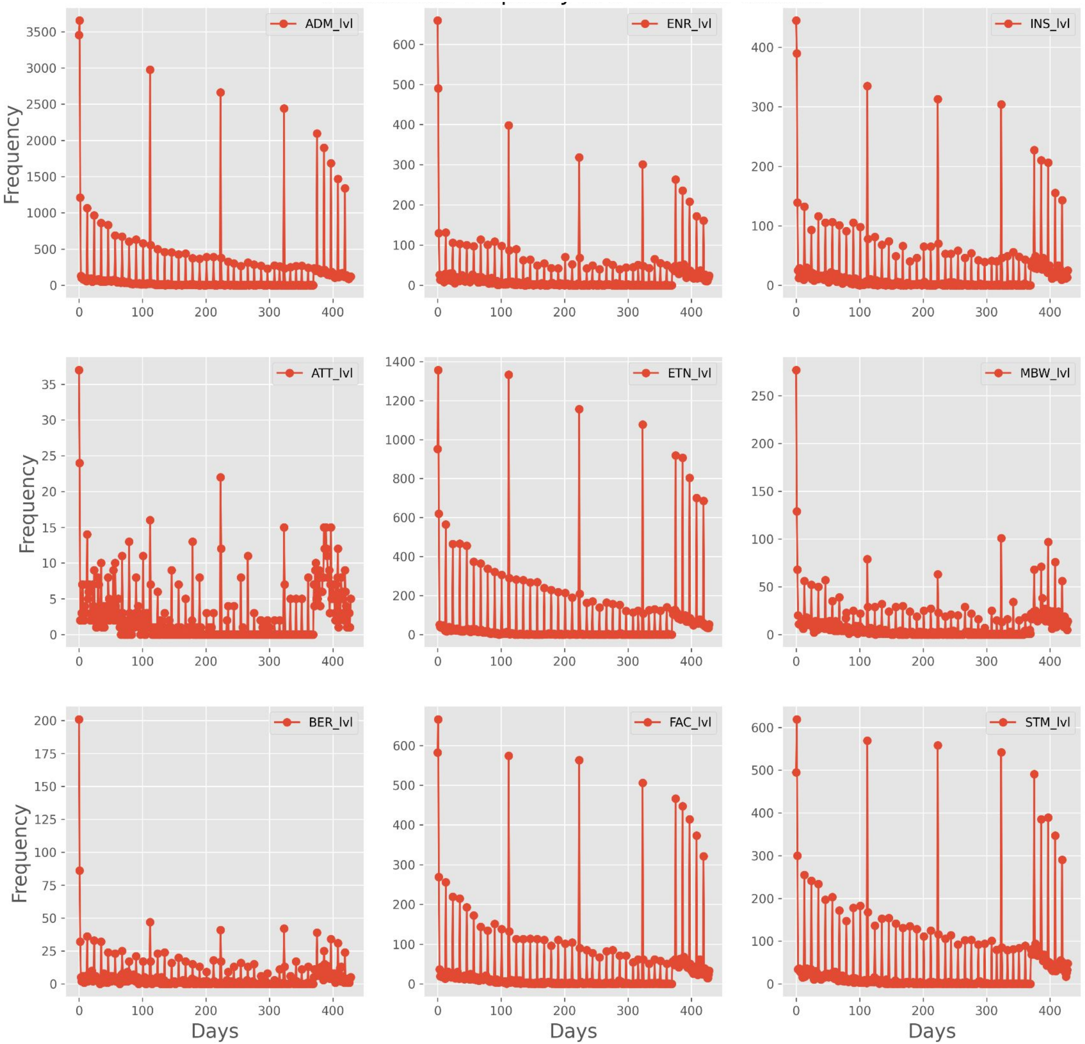


Distribution of frequency of notes over time

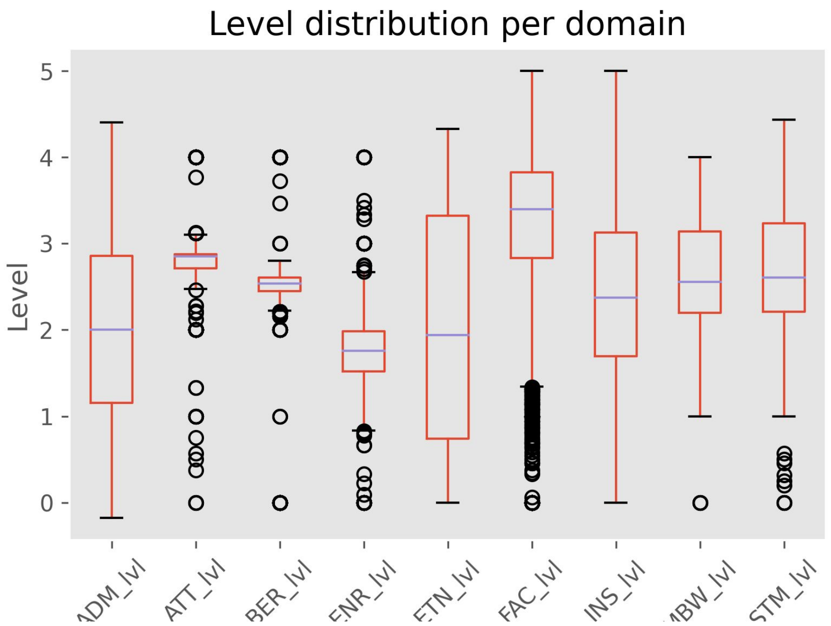




Annotations frequency over time and domain



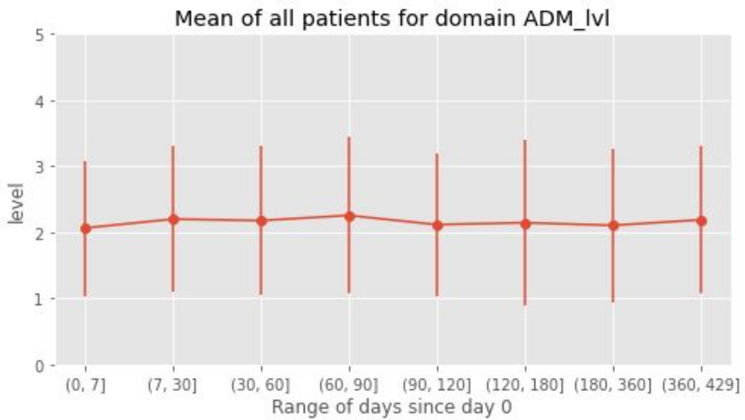
Outliers and missing values

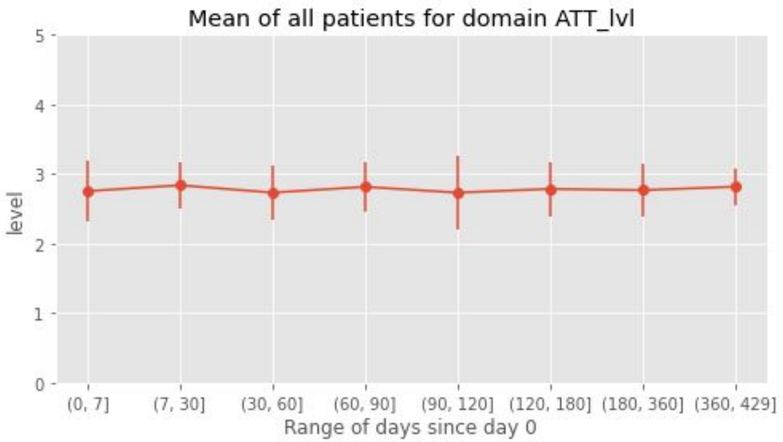


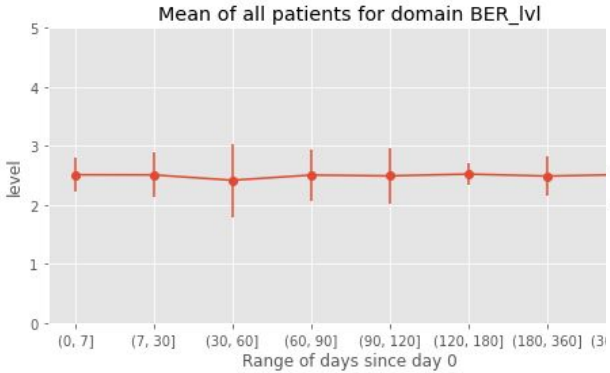
- Missing values
  - Interpolation of ADM_lvl and removal of other domains for modelling

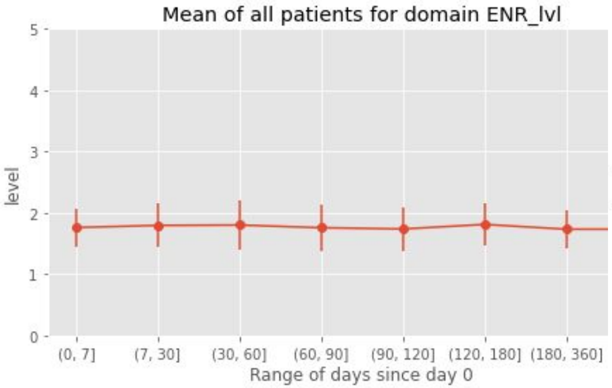
ADM_lvl	4777
ATT_lvl	17746
BER_lvl	17542
ENR_lvl	15966
ETN_lvl	10443
FAC_lvl	15019
INS_lvl	16257
MBW_lvl	17285
STM_lvl	14146

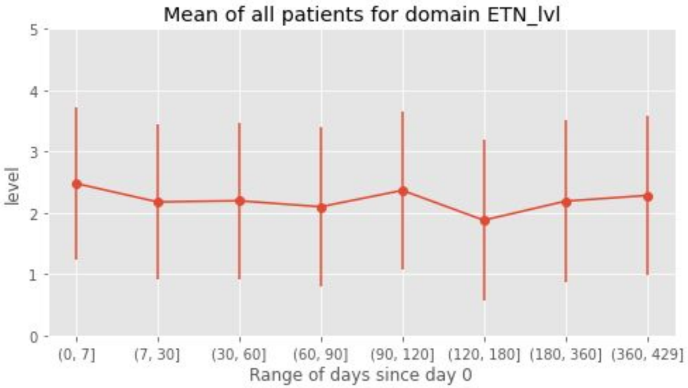
Mean evolution aggregated data for whole period



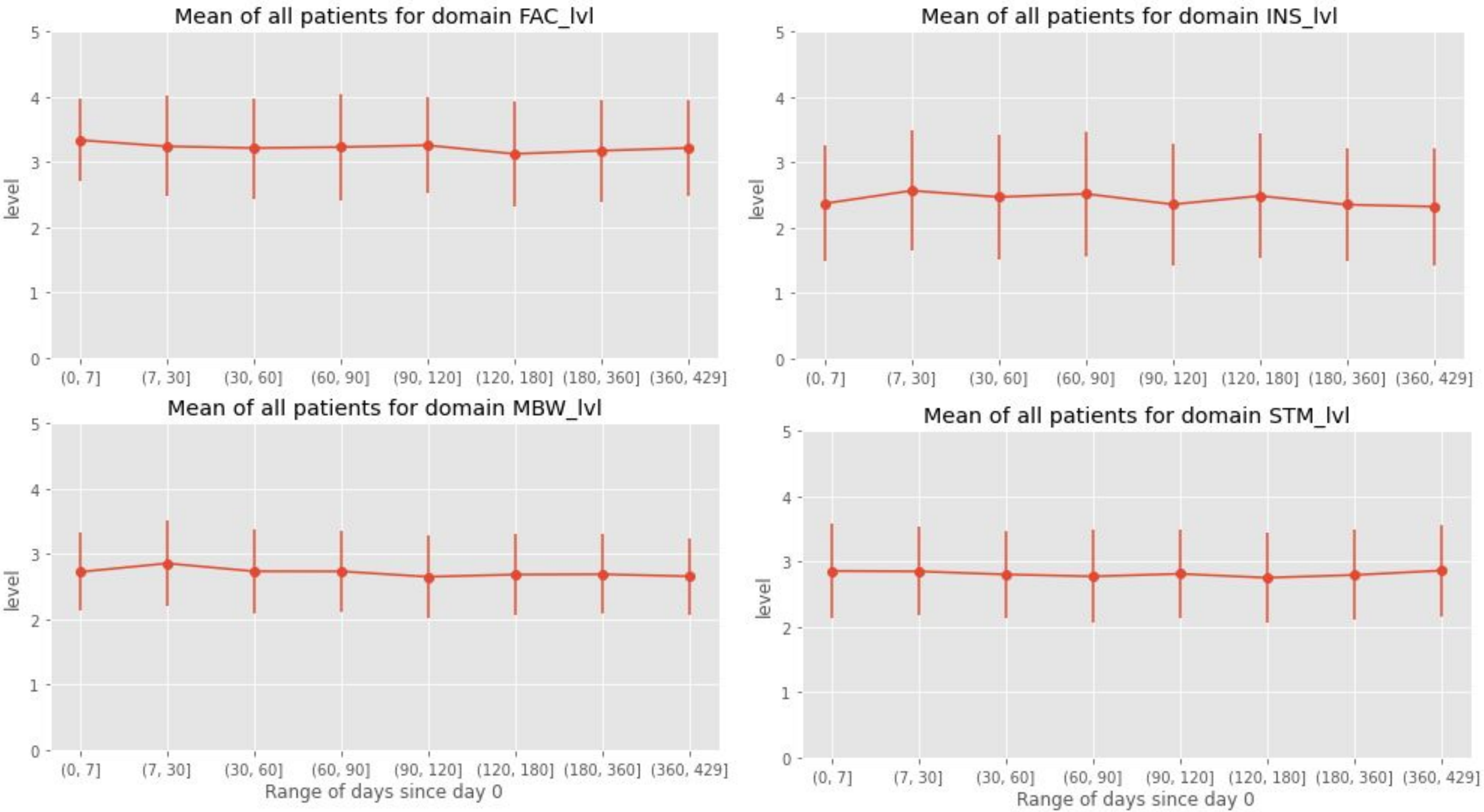






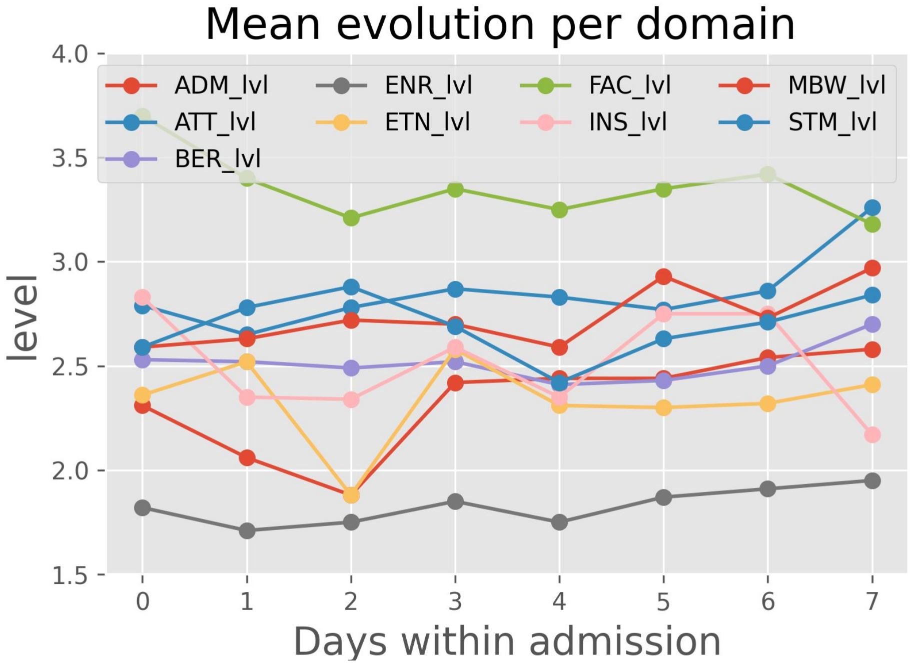


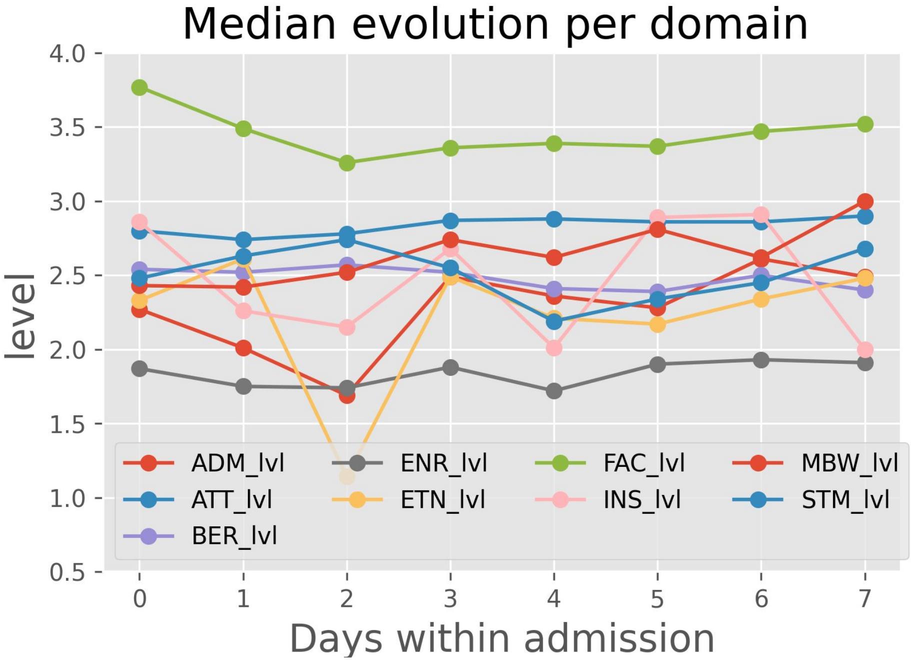
Mean evolution aggregated data for whole period



Within admission

Mean and median daily evolution within admission

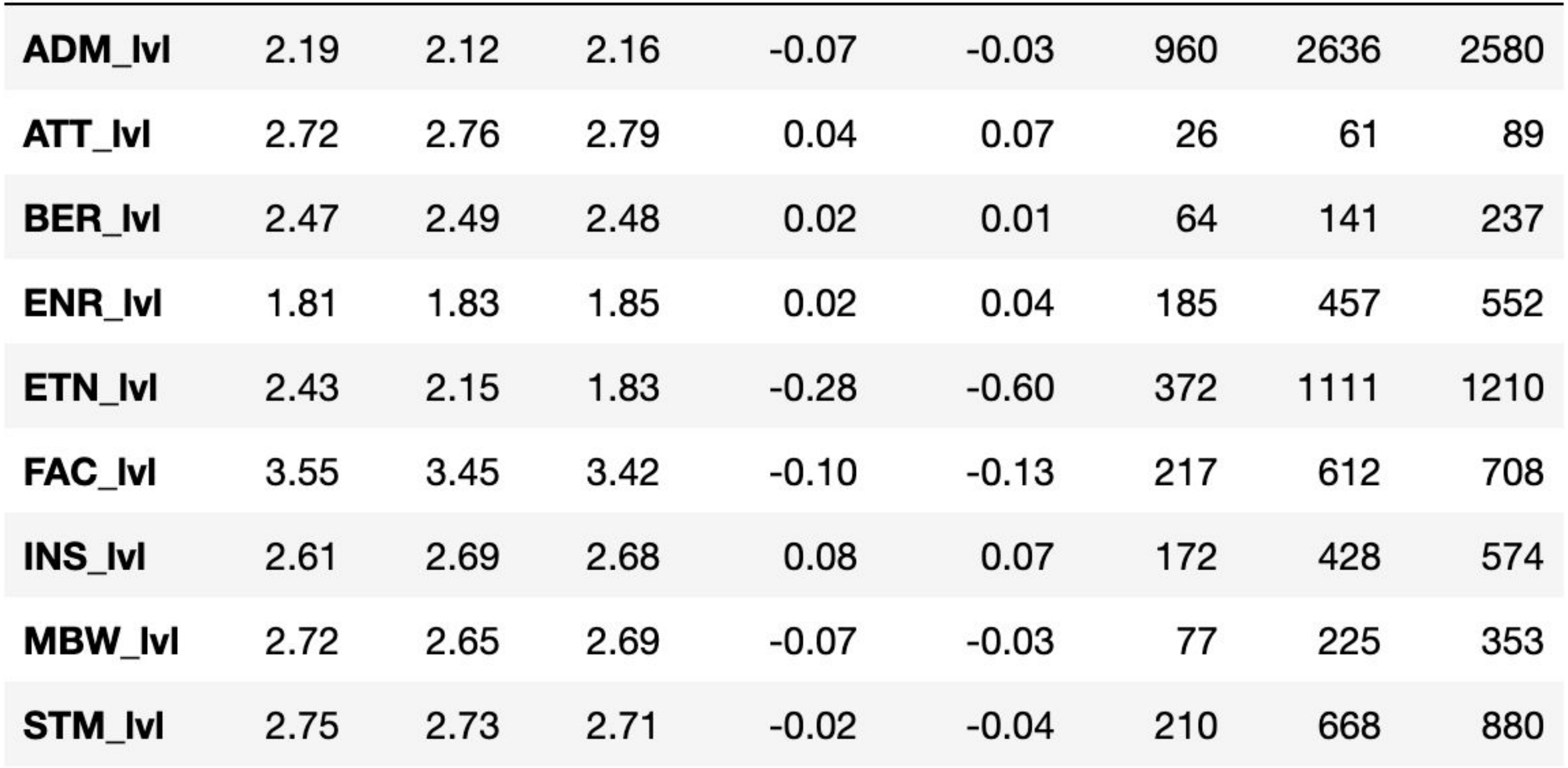




After discharge

- Number of unique patients with discharge information: 1222
- Number of unique patients from discharge to 6w: 1222
- Number of unique patients from 6 weeks discharge to 3 months: 941

Discharge evolution per domain

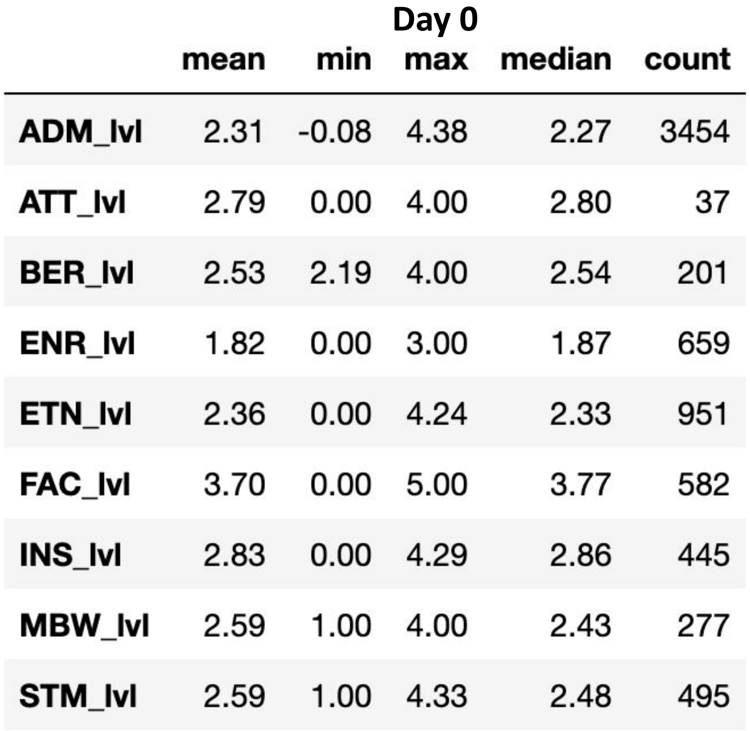


	Mean			Difference		Count		
	day 0 disc	0-6w	6w-3m	date1-0	date2-0	day 0 disc	0-6w	6w-3m
ADM_lvl	2.19	2.12	2.16	-0.07	-0.03	960	2636	2580
ATT_lvl	2.72	2.76	2.79	0.04	0.07	26	61	89
BER_lvl	2.47	2.49	2.48	0.02	0.01	64	141	237
ENR_lvl	1.81	1.83	1.85	0.02	0.04	185	457	552
ETN_lvl	2.43	2.15	1.83	-0.28	-0.60	372	1111	1210
FAC_lvl	3.55	3.45	3.42	-0.10	-0.13	217	612	708
INS_lvl	2.61	2.69	2.68	0.08	0.07	172	428	574
MBW_lvl	2.72	2.65	2.69	-0.07	-0.03	77	225	353
STM_lvl	2.75	2.73	2.71	-0.02	-0.04	210	668	880

Tool for data analysis

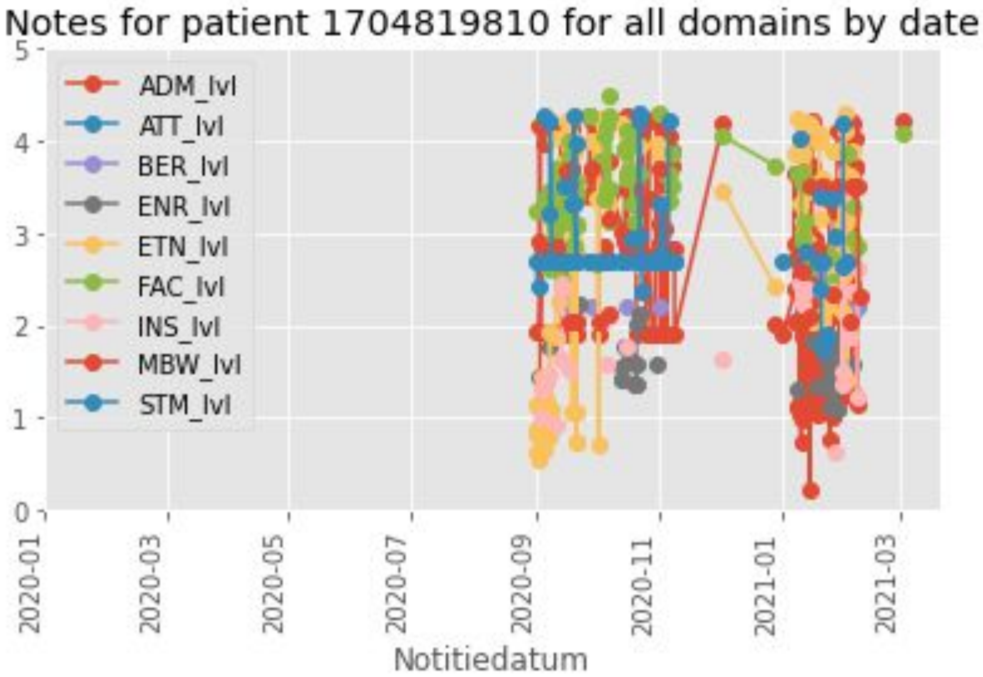
Other analysis that can be done

Statistics from specific day



	Day 0				
	mean	min	max	median	count
ADM_lvl	2.31	-0.08	4.38	2.27	3454
ATT_lvl	2.79	0.00	4.00	2.80	37
BER_lvl	2.53	2.19	4.00	2.54	201
ENR_lvl	1.82	0.00	3.00	1.87	659
ETN_lvl	2.36	0.00	4.24	2.33	951
FAC_lvl	3.70	0.00	5.00	3.77	582
INS_lvl	2.83	0.00	4.29	2.86	445
MBW_lvl	2.59	1.00	4.00	2.43	277
STM_lvl	2.59	1.00	4.33	2.48	495

Case by case analysis of evolution per patient



Machine Learning

ADM prediction

Machine Learning Goal

Goal of project: Build a time series analysis model to predict rehabilitation behavior (levels) for ADM domain for a new patient overtime.

Filters applied for modeling:

- patients with minimum of 100 notes in total;
- and 100 distinct dates;
- with at least 50 notes in the same domain for at least one domain (to analyse the domains in a level layer)

from 1290 unique IDs to 149 when adding restrictions.

frequency over time (up to 12 annotations per ID per date)

Feature Engineering

Creation of time related features:

- Average domains
- Lag of 1, 2 and 3, for ADM feature
- Rolling mean - window sizes 3 and 7
- Rolling min - window sizes 3 and 7
- Rolling max - window sizes 3 and 7
- Expanding window mean

Other changes in dataset:

- Interpolation of ADM to solve missing values
- Discretization of ADM_lvl variable

Modelling and results

Learning setup:

Split of data: divided into 80% of patients in training and 20% of patients in test

- Shapes of DF Train: (13904, 24) | (13904,)
- Shapes of DF Test: (3695, 24) | (3695,)

Hypothesis: Model needs to reflect temporal info!

Models applied to training and test:

F1-macro score on training data per model:

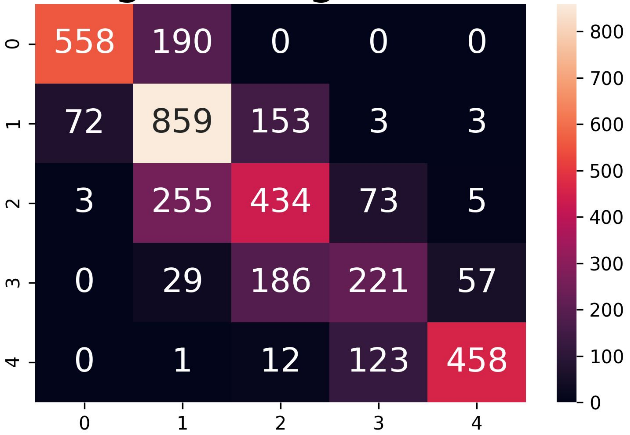
- Log Reg: 0.702
- KNN: 0.766
- Gauss Naive Bayes: 0.616
- Decision Tree: 1.0
- Random Forest: 0.997

F1-macro score for test set per model:

- Log Reg: 0.676
- KNN: 0.617
- Gauss Naive Bayes: 0.625
- Decision Tree: 0.850
- Random Forest: 0.852

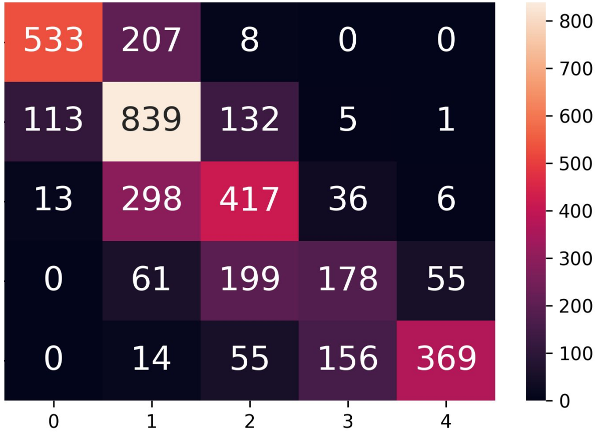
Modeling results - Confusion matrix per model

Logistic Regression



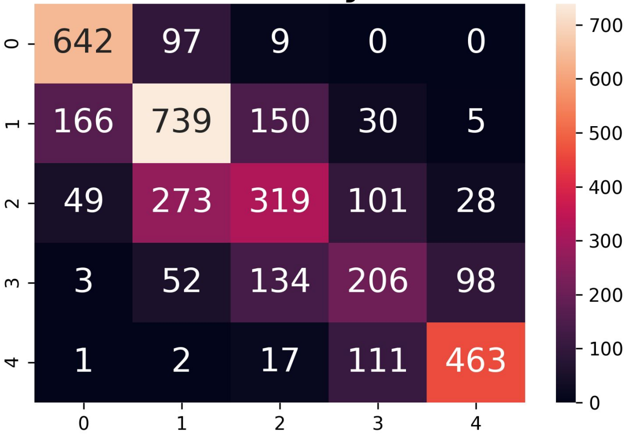
	0	1	2	3	4
0	558	190	0	0	0
1	72	859	153	3	3
2	3	255	434	73	5
3	0	29	186	221	57
4	0	1	12	123	458

KNN



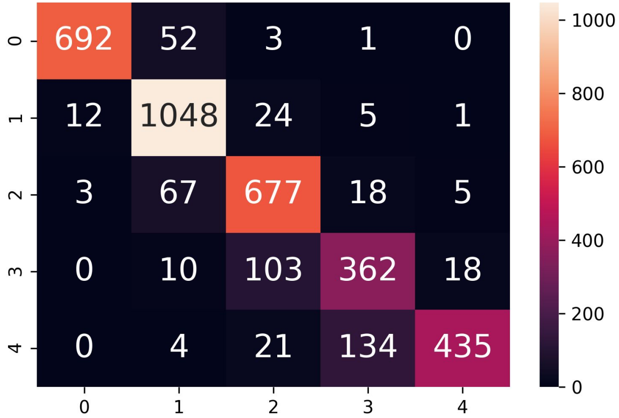
	0	1	2	3	4
0	533	207	8	0	0
1	113	839	132	5	1
2	13	298	417	36	6
3	0	61	199	178	55
4	0	14	55	156	369

Naive Bayes



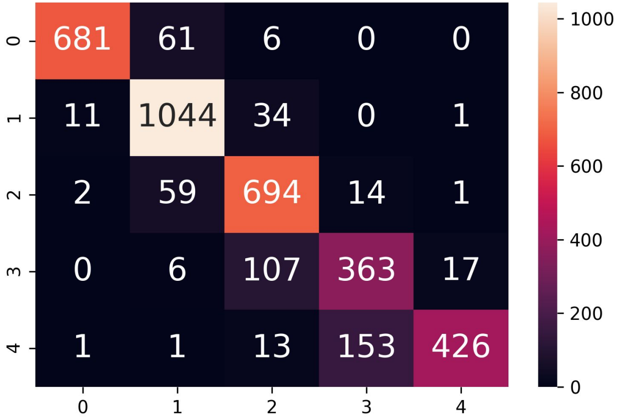
	0	1	2	3	4
0	642	97	9	0	0
1	166	739	150	30	5
2	49	273	319	101	28
3	3	52	134	206	98
4	1	2	17	111	463

Random Forest



	0	1	2	3	4
0	692	52	3	1	0
1	12	1048	24	5	1
2	3	67	677	18	5
3	0	10	103	362	18
4	0	4	21	134	435

Decision Tree



	0	1	2	3	4
0	681	61	6	0	0
1	11	1044	34	0	1
2	2	59	694	14	1
3	0	6	107	363	17
4	1	1	13	153	426

Discussion and Outlook

For ADM feature Random Forest had the best performance in the test set closely followed by Decision Tree

The notebooks created allows a great cross of information to be explored, overall or by patient, domain-wise, frequency-wise and to track evolution

Many possibilities of more sophisticated models and using Predictive modeling with notion of time!