Bridging Medical Data Inference to Achilles Tendon Rupture Rehabilitation

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Abstract

Imputing incomplete medical tests and predicting patient outcomes are crucial for guiding the decision making for therapy, such as after an Achilles Tendon Rupture (ATR). We formulate the problem of data imputation and prediction for ATR relevant medical measurements into a recommender system framework. By applying MatchBox, which is a collaborative filtering approach, on a real dataset collected from 374 ATR patients, we aim at offering personalized medical data imputation and prediction. In this work, we show the feasibility of this approach and discuss potential research directions by conducting initial qualitative evaluations.

1 Introduction

Despite advancements in treatment methods, recovery after musculoskeletal injuries, such as Achilles Tendon Rupture (ATR), is still a prolonged process with an unknown wide variation and often unsatisfactory outcome [1]. Current meta-analyses of the outcome after ATR have mainly focused on operative versus non-operative treatment, lately demonstrating no superiority of one over the other when early mobilization is applied [2]. However, when it comes to other factors and variables affecting the outcomes of ATR, there is currently a lack of knowledge. A recent study investigated how patient characteristics affected outcomes in male ATR patients. For example, it was found that increased age was a strong predictor of reduced function [3]. In an earlier work, factors such as pain and physical activities during rehabilitation were shown to be important for functional outcomes. However, the under-representation of female ATR patients has made it difficult to investigate the importance of gender on outcome [4]. Furthermore, the reason for the variability in outcome at least one year after ATR, however, still remains unknown. Hence, using machine learning tools to aid the study of ATR rehabilitation is desired.

Prediction of ATR rehabilitation is extremely challenging for both medical experts and machines due to numerous noisy measurements with large amount of missing data. Medical tests and outcome measurements for ATR, including the aforementioned ones, involve a large variety of metrics, and the total number of those metrics is on the magnitude of hundreds. Although many tests can be applied to patients to monitor the rehabilitation processes, the correlations between various measurements and patient characteristics are still under-explored. Thus, the test results are not fully informative to the clinicians. Moreover, some seemingly more reliable tests are expensive to perform, time consuming or uncomfortable for patients. Leveraged on the predictive power of data-driven approaches, it would be of great interest to find out whether we can use simple tests to predict possible results of those more reliable tests and potential outcomes for new patients.

Therefore, the task is to predict missing measurements and rehabilitation outcomes using existing noisy measurements. Since the rehabilitation out comes are a subset of measurements, we formulate the research question as data imputation thus we do not differ rehabilitation measures from other measurements. To this end, by formulating the data imputation and prediction of ATR relevant medical measurements into a recommender system framework, we apply MatchBox, which is a collaborative filtering approach [5], to 1) predict possible rehabilitation outcomes for patients; and 2)

impute untested measurements for patients based on partially tested data. Our initial evaluation results show that the proposed method can predict a large set of medical measurements with high accuracy, while some measurements could not be well predicted due to reasons such as insufficient amount of training data, or weak medical relevance between the measurements and ATR rehabilitation etc.

2 Problem Statement

A dataset of ATR relevant medical measurements and rehabilitation outcomes have been collected at the Department of Orthopedics, Karolinska Institute Hospital, Solna, Sweden. The dataset composes medical records from 374 ATR patients involved in prospective randomized trials with 216 measurements, including routine medical tests, validated subjective outcome measurements and objective outcome measurements. Subjective outcomes are evaluated from the patient-reported questionnaires conducted at one year post operation, higher scores in those outcomes indicate better recovering. Objective outcomes are measured by ATR relevant medical examination conducted at one year post operation. Figure 1 illustrates the format of the employed dataset.

	DVT_2w	inf_6w	...	Total_work_l	Height_max_l	...	ATRS_12m	FAOS_3_pain	...
patient_1	1	X	...	X	9.4	...	74	X	...
patient_2	0	0	...	3811.7	X	...	X	X	...
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
patient_n	X	X	...	4425.0	13.1	...	X	97	...

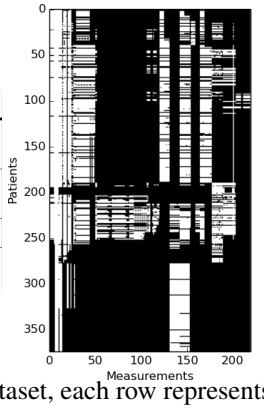


Figure 1: Left: a snapshot of the ATR relevant medical measurement dataset, each row represents a medical record of a patient including both routine tests and outcomes, and each column represents a measurement. The description for the entries is detailed in Appendix A. Right: an image showing the dataset by marking missing entries in black and the known entries in white.

In this dataset, however, 57205 measurement and outcome entries (as depicted in Figure 1), which account for 70% of the total number of entries in the dataset, are left untested due to health situations of patients, expensive medical cost or long time consumption required by the tests. Incomplete medical data record downgrades the effectiveness and accuracy for clinicians in analyzing patients' health status and rehabilitation progress, and then in turn affects making decisions for treatments.

Therefore, it is desired to enable the prediction of missing data, which can compensate for the unavailable information needed by clinicians, while not requiring extra resources to be committed by clinicians and patients. Referring to the dataset shown in Figure 1, this boils down to the widely addressed matrix completion problem. Methods such as mean imputation and last value carried forward have been investigated in simple scenarios [6]. When the matrix is of low rank, a convex optimization method was shown to produce exact result [7]. In cases of high rank matrices, [8] has shown good performance under the assumption that the columns of the matrix belong to a union of multiple low-rank subspaces. In the research line of recommender systems, Poisson factorization [9] and collaborative topic modeling [10, 11] have shown promising results, however, due to the underlying assumption of discrete rating space, they are not feasible for completing missing data that lies in continuous space.

In this work, we aim at offering personalized data prediction for patients, and the data amount is relatively small. Therefore, we employ a probabilistic graphical model based collaborative filtering framework, i.e. MatchBox [5] which is flexible on data type and does not require large amount of training data, for the imputation of missing tests and the prediction of rehabilitation outcomes. In this context, as both data imputation and prediction are conducted in the same framework, we will not distinguish between them in the presentation hereafter.

3 Methodology

Given a dataset of medical records with large amount of missing entries(Figure 1), we address the data prediciton problem using a recommender system framework that regards each patient as a user

while regarding each of various medical records as an item rating. As such, the prediction of missing entries in the dataset is converted to the problem of predicting the ratings of items for a patient.

We adopt MatchBox [5], which is a generative model designed for personalized recommendation [5], for predicting the missing data in our dataset. Built upon collaborative filtering utilizing matrix factorization, MatchBox defines the low dimensional latent space as traits to encode latent properties of the data, and offers personalized predictions for individual users. Concretely, denoted by $A \in \mathbb{R}^{N \times M}$ the affinity matrix that represents patients' test results composed of N patients and M medical measurements, the prediction of an user $u's$ i-th medical test result is obtained by:

$$A_{u,i} = P_u R_i + B_u^P + B_i^R \tag{1}$$

where P_u denotes the u-th row in the patient trait matrix $P \in \mathbb{R}^{N \times T}$ and R_i is i-th column of the medical measurement trait matrix $R \in \mathbb{R}^{T \times M}$, T indicates the number of traits selected. Additionally, B_u^P is the u-th entry of the patient bias vector $B^P \in \mathbb{R}^N$, and B_i^R represents the i-th entry of the medical measurement bias vector $B^R \in \mathbb{R}^M$. All elements in the aforementioned matrices are generated from independent Gaussian distributions, for which the means and variances need to be inferred. Thus, the priors are set as hyperparameters.

Note that MatchBox provides additionally content-based filtering to offer a hybrid system to encode user and item features for coping with also the cold-start problem. As an initial attempt in the ATR data prediction and given that we have many data points available for the majority of patients, we in this work adopt collaborative filtering only.

Importantly, our goal is to predict missing medical measurements that mostly lie in continuous space, which is different from the discrete rating system that thresholds the probabilistic outputs to produce a finite set of ratings. We thus adapted the implementation from Infer.NET [12] to model the measurement values directly, and omit the thresholding procedure to produce continuous outputs.

4 Evaluations

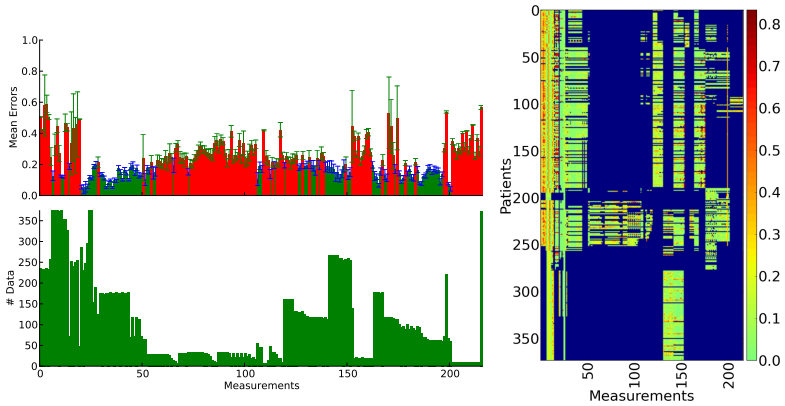
In this section, we evaluate the introduced problem formulation by applying collaborative filtering on the dataset collected from Achilles Tendon Rupture (ATR) patients. Prior to applying the prediction to the real dataset, we have tested the inference by latent parameter recovering using synthetic data as in [13]. The aim is to evaluate the inference performance since the latent variables are unknown to the model. The synthetic data was generated following the generative process of the model described in Section 3 with given priors. We were able to recover all the latent parameters in the model which indicate that the inference performs well.

As listed in Appendix A, the employed dataset composes ATR relevant medical test result for 216 measurements from 374 patients. Therefore, there are in total 80784 entries in the dataset, of which 57205 entries are missing.

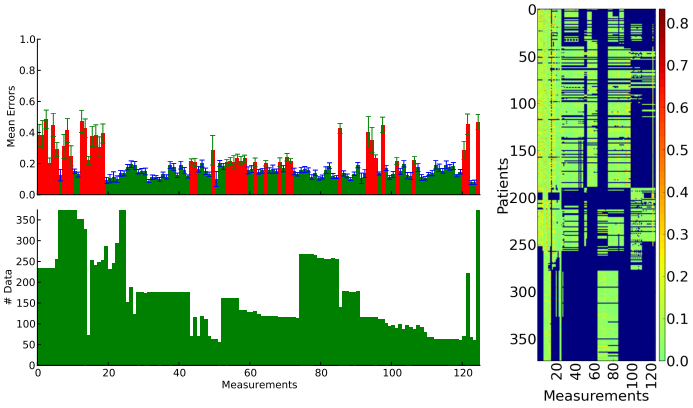
Before inputting our dataset into the collaborative filter, we normalize the entry values to lie within $[0, 1]$ on a per measurement basis in terms of available data. Moreover, we have observed that the prior means and prior variances assigned to the patient trait matrix P, medical measurement trait matrix R, patient bias and medical measurement bias matrices B^P and B^R greatly affect the final prediction accuracy. As we do not have good knowledge for those priors, we fix the prior variances to be 0.5, and then apply grid search for the prior means for each matrix. The grid search was conducted in the range of $[0.05, 0.95]$ with a fixed step size of 0.05.

Results For the experiment, we conducted a 5-fold cross validation for the whole dataset composed by 374 patients and 216 measurements. For evaluating the performance of our approach, in the 5-fold cross validation we predict the measurement values of every test set, which we have the true values of, and compare the results against the ground truth. The mean errors of our predictions are reported in Figure 2a. We can see that almost half of the measurements can be predicted with mean errors smaller than 0.2, which is relatively small to be able to indicate the real test results. Furthermore, we also observe that the majority of inaccurate predictions were associated with the measurements which have very little amount of known data. This is expected since the model was not able to generalize over different values for those measurements with insufficient training data.

In order to evaluate the method without being affected by the insufficiency of data, we conducted the same experiments for the 125 measurements, each of which has more than 50 known data for training and testing. As reported in Figure 2b, we can see an enhancement in prediction mean errors



(a) Results for 216 measurements. Mean error over all measurements: 0.2478.



(b) Results for 125 measurements. Mean error over all measurements: 0.2010.

Figure 2: In both (a) and (b), left side shows prediction mean errors for each measurement (upper), we color the measurement in green if the prediction for it was relatively small (mean error ≤ 0.2) and in red otherwise. The number of known data points per measurement (lower) is also shown. The right side shows the prediction mean errors for each data point with colors indicating the magnitudes, the blue areas are the missing data points without available ground truth.

which decreased from 0.2478 to 0.2010. However, it is worthwhile to note that there are still some measurements (red bars) that can not be well predicted, although the amount of known data for them is large. By taking a closer look at the data, as listed in Appendix A, we have observed that those inaccurate predictions were made mostly for either medically irrelevant measurements, e.g., date of test, or the measurements that have binary outputs, which were not well predicted as our framework models measurements in continuous space and is not capable of handling those measurements.

5 Conclusion

Because some of the medical tests of interest are expensive to perform, time consuming or uncomfortable for patients, the amount of missing data is unavoidably large. As desired by clinicians, more medical test results will be helpful in medical diagnosis and making decisions for treatments. Therefore, we in this work investigated the possibility of formulating the medical data prediction problem into a recommender system framework. By modeling the patients as users and medical test results as item ratings, we show that it is feasible to predict missing medical data using collaborative filtering, and the evaluation results indicated that we could achieve good prediction accuracy for many medical measurements.

As a potential future work, we would like to separate the measurement data types, e.g., continuous or discrete values, to decide whether a thresholding is needed for output to improve the prediction accuracy. Furthermore, rather than pure collaborative filtering, it would be interesting to adopt the hybrid system provided by MatchBox to investigate further improvements. For better evaluation of the performance, we plan to compare our method with other matrix completion approaches, as well as tracking the rehabilitation results of patients to justify the usefulness of our method.

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Appendix A List of Medical Measurements in the Achilles Tendon Rupture Patients' Dataset

	Measurements	Description
1	Complication	Signs in journal documentation of any complication?
2	Paratenon	Closed the paratenon?
3	Fascia	Closed the fasica cruris?
4	PDS	Used 2 PDS sutures?
5	Surg_comp	Surgeon catogorized as compliant to op-schedule?
6	Treatment_Group	Treatment Group For all studies
7	Plast_foot	A - Plastercast + Foot-IPC
8	Ort_B	B - Calf IPC
9	Plast	A, B, D plastercast
10	Vacoped	B, C, D - Vacoped
11	Time_to_op	Time to Operation
12	Op_time	Operation Time
13	Op_time_dic	Dicomisation of op. time
14	EXP	Specialist Y/N
15	Compliant	Compliant
16	DVT_2	Deep venous thrombosis after two weeks?
17	DVT_6w	DVT after 6 weeks?
18	DVT_2w_and_6w	DVT at both 2 and 6 weeks?
19	DVT_2w_or_6w	Total DVT after 2 and 6 weeks?
20	DVT_8w	Only for GBG Studies
21	Inf_2w	Infection at 2 weeks post.op?
22	Inf_6w	Infection at 6 weeks post.op?
23	Any_inf	Infection at either 2 or 6 weeks postop?
24	Rerupture	Rerupture?
25	Pump_pat_reg	Patient registered pump time (hh:mm:ss)
26	Pump_reg	Device registered pump time (hh:mm:ss)
27	Preinjury	Degree of activity preinjury
28	Post_op	Degree of activity one year post operation
29	D_PAS	Delta PAS = Pre-Post
30	Con_Power_I	Concentric power (Watt) - Injured side
31	Con_Power_U	Concentric power (Watt) - Uninjured side
32	LSI_Con_Power	Limb Symmetry Index - Concentric power
33	Total_work_I	Total concentric work (Joule) - Injured side
34	Total_work_U	Total concentric work (Joule) - Uninjured side
35	LSI_Total_work	Limb Symmetry Index - Total work
36	Repetition_I	Number of heel-rises - Injured side
37	Repetition_U	Number of heel-rises - Uninjured side
38	LSI_Repetitions	Limb Symmetry Index - Repetitions
39	Height_Max_I	Maximum height of heel-rise (Centimeter) - Injured side
40	Height_Max_U	Maximum height of heel-rise (Centimeter) - Uninjured side
41	LSI_Height	Limb Symmetry Index - Height
42	Height_A_I	Average height of heel-rise (Centimeter) - Injured side
43	Height_A_U	Average height of heel-rise (Centimeter) - Uninjured side
44	LSI_Height_Ave	Limb Symmetry Index ? Height_Average
45	Ecc_Power_I	Eccentric power (Watt) - Injured side
46	Height_Min_I	Mimimum height of heel-rise (Centimeter) - Injured side
47	Ecc_Power_U	Eccentric power (Watt) - Uninjured side
48	Height_Min_U	Mimimum height of heel-rise (Centimeter) - Uninjured side
49	LSI_Height_Min	Limb Symmetry Index - Height_Min
50	LSI_Ecc_Power	Limb Symmetry Index - Eccentric power
51	Muscle_vein_thrombosis_2	Muscle vein thrombosis 2 weeks follow-up

52	Thompson_2	Thompson 2 weeks follow-up
53	Podometer_day1	Podometer day 1
54	Podometer_day2	Podometer day 2
55	Podometer_day3	Podometer day 3
56	Podometer_day4	Podometer day 4
57	Podometer_day5	Podometer day 5
58	Podometer_day6	Podometer day 6
59	Podometer_day7	Podometer day 7
60	Podometer_day8	Podometer day 8
61	Podometer_day9	Podometer day 9
62	Podometer_day10	Podometer day 10
63	Podometer_day11	Podometer day 11
64	Podometer_day12	Podometer day 12
65	Podometer_day13	Podometer day 13
66	Podometer_day14	Podometer day 14
67	Podometer_day15	Podometer day 15
68	Podometer_day16	Podometer day 16
69	Podometer_on_day_of_microdialysis	Podometer on day of microdialysis
70	Podometer_on_day_minus_1	Podometer on day before microdialysis
71	Podometer_on_day_minus_2	Podometer two days before microdialysis
72	Subjective_load_day1	Subjective load day 1
73	Subjective_load_day2	Subjective load day 2
74	Subjective_load_day3	Subjective load day 3
75	Subjective_load_day4	Subjective load day 4
76	Subjective_load_day5	Subjective load day 5
77	Subjective_load_day6	Subjective load day 6
78	Subjective_load_day7	Subjective load day 7
79	Subjective_load_day8	Subjective load day 8
80	Subjective_load_day9	Subjective load day 9
81	Subjective_load_day10	Subjective load day 10
82	Subjective_load_day11	Subjective load day 11
83	Subjective_load_day12	Subjective load day 12
84	Subjective_load_day13	Subjective load day 13
85	Subjective_load_day14	Subjective load day 14
86	Subjective_load_day15	Subjective load day 15
87	Subjective_load_day16	Subjective load day 16
88	Days_until_microdialysis	Days postsurgery until microdialysis
89	Load_on_day_of_microdialysis	LOAD
90	Load_on_day_minus_1	LOAD_Minus1
91	Load_on_day_minus_2	LOAS_Minus2
92	Number_of_days_with_load	Load_Days
93	VAS_day1_act	VAS day 1, active
94	VAS_day1_pas	VAS day 1, passive
95	VAS_day2_act	VAS day 2, active
96	VAS_day2_pas	VAS day 2, passive
97	VAS_day3_act	VAS day 3, active
98	VAS_day3_pas	VAS day 3, passive
99	VAS_day4_act	VAS day 4, active
100	VAS_day4_pas	VAS day 4, passive
101	VAS_day5_act	VAS day 5, active
102	VAS_day5_pas	VAS day 5, passive
103	VAS_day6_act	VAS day 6, active
104	VAS_day6_pas	VAS day 6, passive
105	VAS_day7_act	VAS day 7, active
106	VAS_day7_pas	VAS day 7, passive
107	VAS_injured_2weeks	VAS injured, 2 weeks
108	Calf_circumference_injured_mean	Calf circumference -injured tendon, mean value, week 2
109	Calf_circumference_control_mean	Calf circumference -control tendon, mean value, week 2
110	Plantar_flexion_injured_mean	Plantar flexion -injured tendon, mean value, week 2
111	Plantar_flexion_control_mean	Plantar flexion -control tendon, mean value, week 2

112	Dorsal_flexion_injured_mean	Dorsal flexion -injured tendon, mean value, week 2
113	Dorsal_flexion_control_mean	Dorsal flexion -control tendon, mean value, week 2
114	Heel_rise_average_height_injured_6mo	heel raise injured 6 months
115	Heel_rise_average_height_control_6mo	heel raise uninjured 6 months
116	difference_heel_raise_6mo	difference heel raise 6 months
117	Heel_rise_average_height_injured_1yr	heel raise injured 1 year
118	Heel_rise_average_height_control_1yr	heel raise uninjured 1 year
119	difference_heel_raise_1yr	difference heel raise 1 year
120	ATRS_3_Strenght	Achilles Tendon Rupture score 3 months - Limited strength in the calf/tendon/foot?
121	ATRS_3_tired	Achilles Tendon Rupture score 3 months - Tired in the calf/tendon/foot?
122	ATRS_3_stiff	Achilles Tendon Rupture score 3 months - Stiffness in the calf/tendon/foot?
123	ATRS_3_pain	Achilles Tendon Rupture score 3 months - Pain in the calf/tendon/foot?
124	ATRS_3_ADL	Achilles Tendon Rupture score 3 months - limited ADL?
125	ATRS_3_Surface	Achilles Tendon Rupture score 3 months - limited on uneven surface?
126	ATRS_3_stairs	Achilles Tendon Rupture score 3 months - limited in stairs/hills?
127	ATRS_3_run	Achilles Tendon Rupture score 3 months - limited when running?
128	ATRS_3_jump	Achilles Tendon Rupture score 3 months - limited when jumping?
129	ATRS_3_phys	Achilles Tendon Rupture score 3 months - limited in physical work?
130	ATRS_3_Sum	Achilles Tendon Rupture score 3 months - total sum
131	ATRS_item1_6month	ATRS 6month - Limited strength in the calf/tendon/foot?
132	ATRS_item2_6month	ATRS 6month - Tired in the calf/tendon/foot?
133	ATRS_item3_6month	ATRS 6month - Stiffness in the calf/tendon/foot?
134	ATRS_item4_6month	ATRS 6month - Pain in the calf/tendon/foot?
135	ATRS_item5_6month	ATRS 6month - limited ADL?
136	ATRS_item6_6month	ATRS 6month - limited on uneven surface?
137	ATRS_item7_6month	ATRS 6month - limited in stairs/hills?
138	ATRS_item8_6month	ATRS 6month - limited when running?
139	ATRS_item9_6month	ATRS 6month - limited when jumping?
140	ATRS_item10_6month	ATRS 6month - limited in physical work
141	ATRS_total_score_6month	ATRS total score 6month
142	ATRS_12_strength	Achilles Tendon Rupture score 12 months - Limited strength in the calf/tendon/foot?
143	ATRS_12_tired	Achilles Tendon Rupture score 12 months - Tired in the calf/tendon/foot?
144	ATRS_12_stiff	Achilles Tendon Rupture score 12 months - Stiffness in the calf/tendon/foot?
145	ATRS_12_pain	Achilles Tendon Rupture score 12 months - Pain in the calf/tendon/foot?
146	ATRS_12_ADL	Achilles Tendon Rupture score 12 months - limited ADL?
147	ATRS_12_Surface	Achilles Tendon Rupture score 12 months - limited on uneven surface?
148	ATRS_12_stairs	Achilles Tendon Rupture score 12 months - limited in stairs/hills?
149	ATRS_12_run	Achilles Tendon Rupture score 12 months - limited when running?
150	ATRS_12_jump	Achilles Tendon Rupture score 12 months - limited when jumping?
151	ATRS_12_phys	Achilles Tendon Rupture score 12 months - limited in physical work?

152	ATRS_12m	Achilles Tendon Rupture Score, 12 month control
153	ATRS_2cl	ATRS> 80.0?
154	FAOS_3_Pain	FAOS Pain 3 months
155	FAOS_3_Symptom	FAOS Symptom 3 months
156	FAOS_3_ADL	FAOS ADL 3 month
157	FAOS_3_sport_rec	FAOS sport and recreation 3 months
158	FAOS_3_QOL	FAOS QOL 3 months
159	FAOS_6_Symptom	FAOS Symptom 6month
160	FAOS_6_Pain	FAOS Pain 6month
161	FAOS_6_ADL	FAOS ADL 6month
162	FAOS_6_Sport_Rec	FAOS Function 6month
163	FAOS_6_QOL	FAOS QOL 6month
164	FAOS_12_Pain	FAOS 1 year Pain - 100=No pain
165	FAOS_12_Symptom	FAOS 1 year Symptom - 100=No symtoms
166	FAOS_12_ADL	FAOS 1 year Activity of daily living - 100=Full ADL
167	FAOS_12_Sport_Rec	FAOS 1 year Function in sport and recreation - 100=No problems
168	FAOS_12_QOL	FAOS 1 year Foot and ankle-related Quality of Life - 100=full QoL
169	Q1	Q1(mobility)
170	Q3	Q3(activities)
171	Q4	Q4(pain)
172	Q5	Q5(depression)
173	EQ5D_ix	EQ5D index
174	VAS	EuroQoL Visual Analogue Scale
175	VAS_2	Dichotomized EQ VAS
176	GLUC_injured_mean	Glucose - Injured tendon, mean value, week 2
177	GLUC_control_mean	Glucose - Control tendon, mean value, week 2
178	LAC_injured_mean	Lactate - Injured tendon, mean value, week 2
179	LAC_control_mean	Lactate - Control tendon, mean value, week 2
180	PYR_injured_mean	Pyruvate - Injured tendon, mean value, week 2
181	PYR_control_mean	Pyruvate - Control tendon, mean value, week 2
182	GLY_injured_mean	Glycerol - Injured tendon, mean value, week 2
183	GLY_control_mean	Glycerol - Control tendon, mean value, week 2
184	GLUT_injured_mean	Glutamate - Injured tendon, mean value, week 2
185	GLUT_control_mean	Glutamate - Control tendon, mean value, week 2
186	LAC2_PYR2_ratio_injured_mean	Lactate-Pyruvate ratio -Injured tendon, mean value, week 2
187	LAC2_PYR2_ratio_control_mean	Lactate-Pyruvate ratio -Control tendon, mean value, week 2
188	PINP_injured	Collagen I marker (pg/ml) - injured leg
189	PIIINP_injured	Collagen III marker (pg/ml) - injured leg
190	Bradford_injured	Protein concentration in injured leg (ug/ml)
191	PINP_normalized_Injured	Collagen I marker normalized to protein conc. (pg/ul) - injured leg
192	PIIINP_normalized_injured	Collagen III marker normalized to protein conc. (pg/ul) - injured leg
193	PINP_uninjured	Collagen I marker (pg/ml) - uninjured leg
194	PIIINP_uninjured	Collagen III marker (pg/ml) - uninjured leg
195	Bradford_uninjured	Protein concentration in uninjured leg (ug/ml)
196	PINP_normalized_Uninjured	Collagen I marker normalized to protein conc. (pg/ul) - uninjured leg
197	PIIINP_normalized_uninjured	Collagen III marker normalized to protein conc. (pg/ul) - uninjured leg
198	Collagen	Collagen Analysis
199	Glut_2_inj_values	Complete Glut_2_inj values?

200	P_ratio_inj	PINP/PIIINP ratio injured
201	P_ratio_uninj	PINP/PIIINP ratio uninjured leg
202	RF_injured	INJURED - Resting flux: the median flux value obtained during baseline
203	RF_uninjured	uninjured - Resting flux: the median flux value obtained during baseline
204	BZ_injured	INJURED - Biological zero: the median flux value obtained during occlusion
205	BZ_uninjured	uninjured - Biological zero: the median flux value obtained during occlusion
206	MF_injured	INJURED - Maximum flux: the highest flux value obtained during PORH
207	MF_uninjured	uninjured - Maximum flux: the highest flux value obtained during PORH
208	T_RF_injured	INJURED - Time to resting flux. the time from t0 until RF is reached
209	T_RF_uninjured	uninjured - Time to resting flux. the time from t0 until RF is reached
210	T_MF_injured	INJURED - Time to maximum flux: the time from t0 until MF is reached
211	T_MF_uninjured	uninjured - Time to maximum flux: the time from t0 until MF is reached
212	T_HR_injured	INJURED - Time to half recovery: the time from t0 after tMF until MF + RF is reached
213	T_HR_uninjured	uninjured - Time to half recovery: the time from t0 after tMF until MF + RF is reached
214	Ratio_MF_RF_injured	INJURED - Ratio of maximum flux and resting flux
215	Ratio_MF_RF_uninjured	uninjured - Ratio of maximum flux and resting flux
216	B1_D66	B1-150, C3,4,6,7,17-25, D2-D66