Process mining to identify bottlenecks and identify improvements in elective pathways

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THINK OF A PATHWAY THROUGH A&E...

WHAT STAGES DID THAT GO THROUGH?
WHAT WAS THE TIME BETWEEN?

WHO WAS RESPONSIBLE FOR EACH STAGE?





What is Process Mining?

Process mining is an analytics technique that provides insights into how processes are managed.

It analyses events along a process, using the dates and times inputted into your NHS systems when a patient has activity, to visualise actual workflow to discover, monitor, and improve the way services are delivered and resources are utilised.

Think of it as X-ray vision for business operations, revealing the bottlenecks, constraints and unwarranted variations.

DATA PROCESS PROCESS NANAGEMENT

Large volumes of data already collected

Understanding & optimising processes – think process mapping, analysing how long each step of the journey is taking, modelling what the standardised process should be.

Helping to define the reality of a process

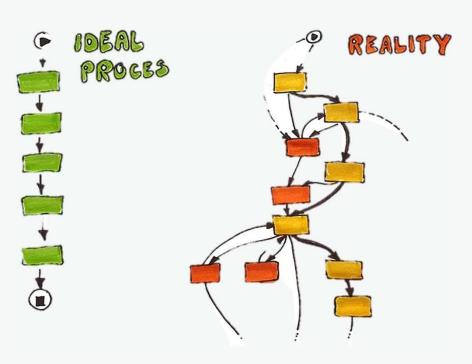
Humans by nature will find different routes to get the end of a process.

Think of this like a desire path, illustrated in this picture. The circular concrete path could illustrate the protocol you've established that you believe everyone is following. What you find after establishing a concrete path, is that humans have created their own desired path – usually the shortest route, or the most navigated route between an origin and a destination.

Now think of that in terms of healthcare – how many desired paths have been built around a structured defined path? Process mining aims to highlight **any** pathways that exist and show you the reality.



Process Mining in Health and Social Care

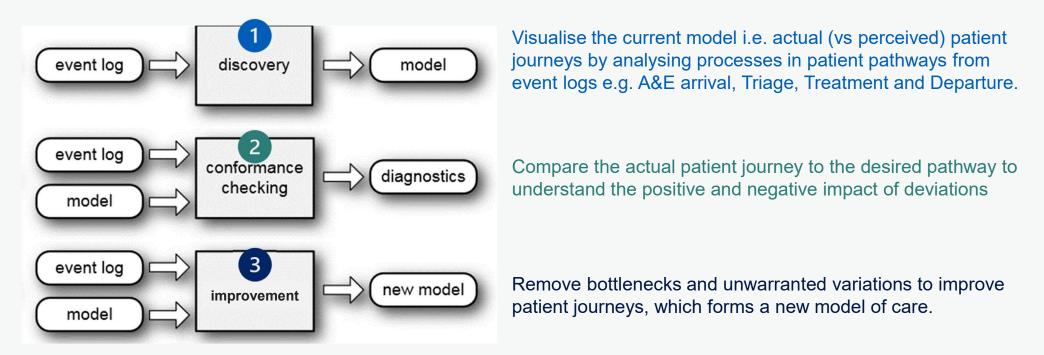


In health and social care, workflows are often complex and involve multiple stakeholders, systems, and steps. From a visit to a GP to treatment in a hospital, every step generates data that can be mined to uncover inefficiencies, bottlenecks, and areas for improvement. If you were to process map 100 different patient journeys, how many post-it notes & how long would that take you?

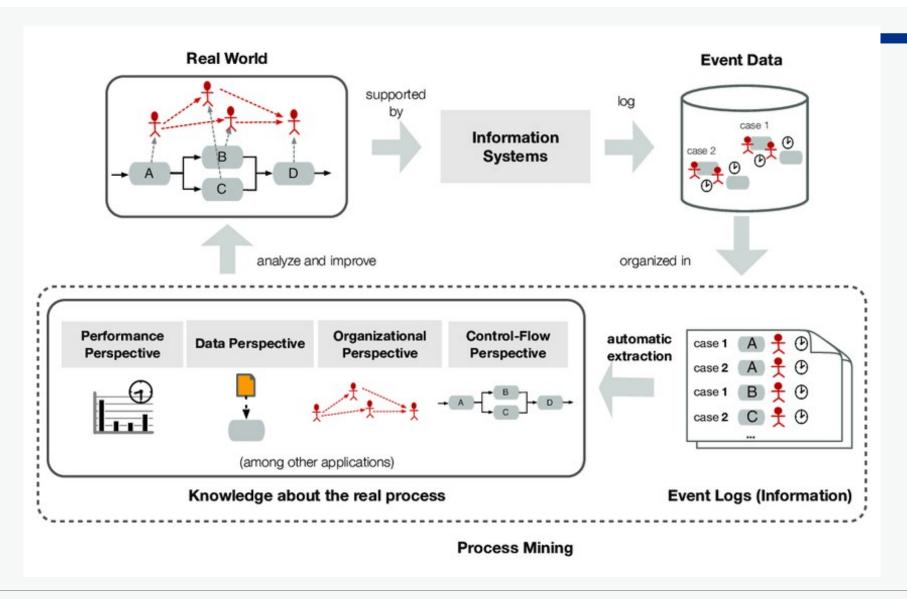
Process mining helps visualise these processes, in very little time, to enable teams to deliver better care and allocate resources efficiently.

How Does Process Mining Work?

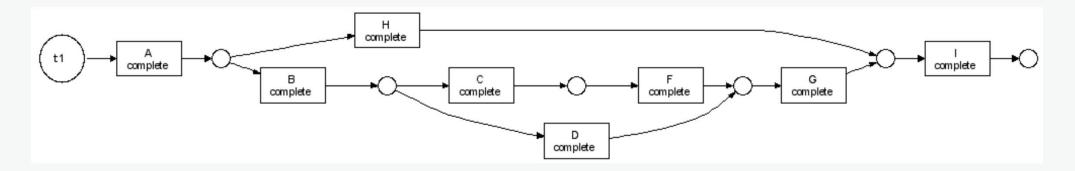
The three basic types of insights for healthcare are:

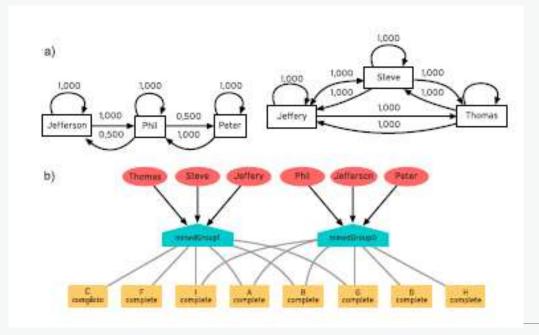


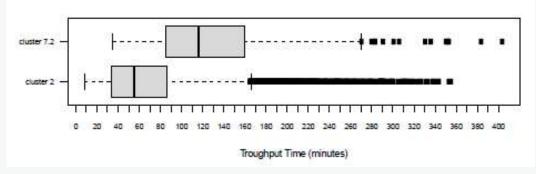
Users can understand the current state, make relevant improvements and redesign a future state without the cost of piloting it in real life to assess the impacts.



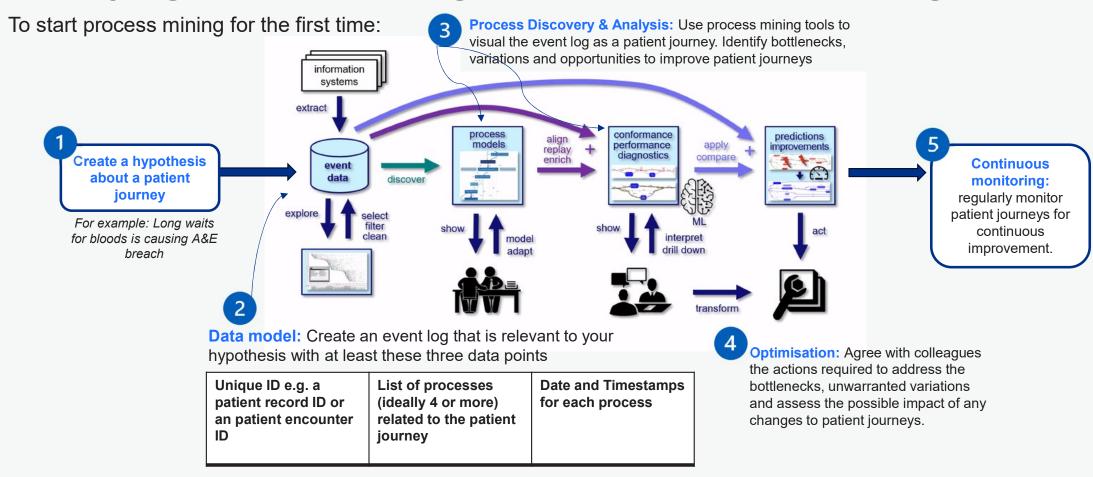
Perspectives







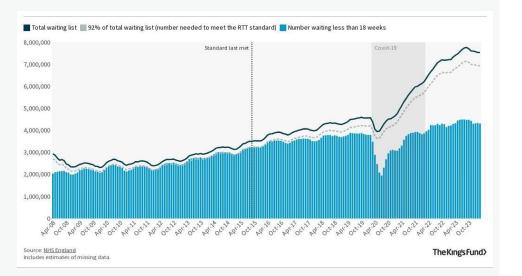
Applying Process Mining in Health and Care Settings



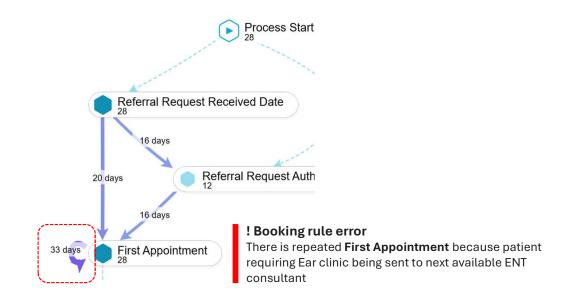
Most appropriate tool?



Demand is within plan and all clinics are utilised but wait times have gone up..

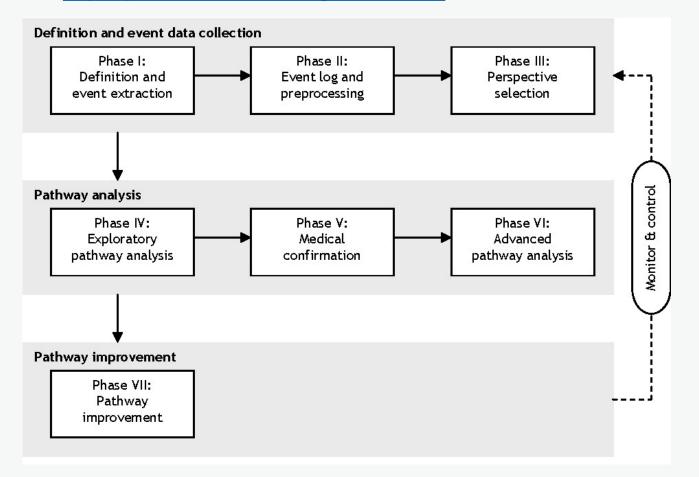


Using process mining insights to uncover the activities within each patient journey using the NWL minimum datasets



Roadmap example

Source: https://pubmed.ncbi.nlm.nih.gov/27010685/



Key Terminology:

Events = activities that happen on a patient pathway eg A&E Attendance, Outpatient Attendance, Diagnostic

Responsibilities:

Phase I: Project Team
Phase II – IV: Data Analyst

Phase V: Operational & Medical Teams with

Data Analyst

Phase VI: Data Analyst

Phase VII: Operational & Medical Teams with

Data Analyst

Roadmap example

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Phase VI: Data Analyst

Phase VII: Operational & Medical Teams with Data Analyst

Project definition & event log extraction Define pathway scope definition Identify event sources Select event log attribute Construct event log Event log preprocessing Select log format and transform event log Deal with log divergence Event log specific operations, e.g. (re)grouping of activities, scrambling personal information, etc. Perspective selection Identify interesting perspective (patient, treatment, diagnosis, department or drug) ≡ Perform necessary log filtering operations Identify and describe potential information losses, provide a solution to deal with the information Exploratory pathway analysis Functional analysis Process analysis Organisational Data analysis analysis Existence/absence Workflow discovery Social network Data-driven of activities analysis (teams, conditions Process variant hand-overs, Activity coanalysis Correlations data existence Additional analyses interactions) and pathway Task allocation structure Additional analyses Additional analyses Additional analyses Medical confirmation Review by medical expert(s) of results Comparison with medical guidelines Determine whether the results represent local conditions Externalisation of knowledge Advanced pathway analysis Efficiency analysis Quality and conformance analysis Rule-based pathway analysis Bottleneck analysis Humber & duration of diagnosis & Conformance & delta analysis treatment cycles Analysis of adverse events Performance analysis and comparison Root-cause analysis for variation Additional analyses Additional analyses Improvement of pathway Phase VII Adapt clinical pathway models according to new insights Reinforce existing to-be models

FIGURE 3: CPAM ROAD MAP BY CARON ET AL.

Benefits of Process Mining in Health and Social Care*

Enhance your improvement programme

Can be used as part of your improvement toolkit to support GIRFT, NHS IMPACT, Further Faster and Quality Improvement Programmes. Identifies and eliminates actual bottlenecks, reduces duplication, unwarranted variation and improves resource utilisation.

Enhance Patient Care

Avoid 'lost' patients with the ability to visualise every patient journey and deliver timely and consistent care delivery

Cost Reduction

Remove waste, optimise use of resource by improving workload and workflow.

Compliance and Transparency

Measures and monitor adherence to best practice, protocols and regulations.

Data-Driven Decisions

Provides consistent and tailored insights to address a wide range of needs including strategy, operations, clinical, improvement etc.

^{*}Benefits found using enterprise process mining solutions with enhanced functionality compared to open-source solutions

Case Study 1

Urology Cancer Case Study – Imperial College

Link to paper - https://core.ac.uk/outputs/189834099/?source=2 (Author: Bushra Siddiqi)

Overview of case study



This work aims to analyse prostate cancer patient treatment pathways within the west and south of London in order to identify delays, bottlenecks and deviations from a known standard pathway (i.e. the pathway suggested by the London Cancer Alliance).

These deviations will aid in capacity planning and eventually the development of a technique or model to highlight the nonconformities and gaps in care.

Data Sources for project

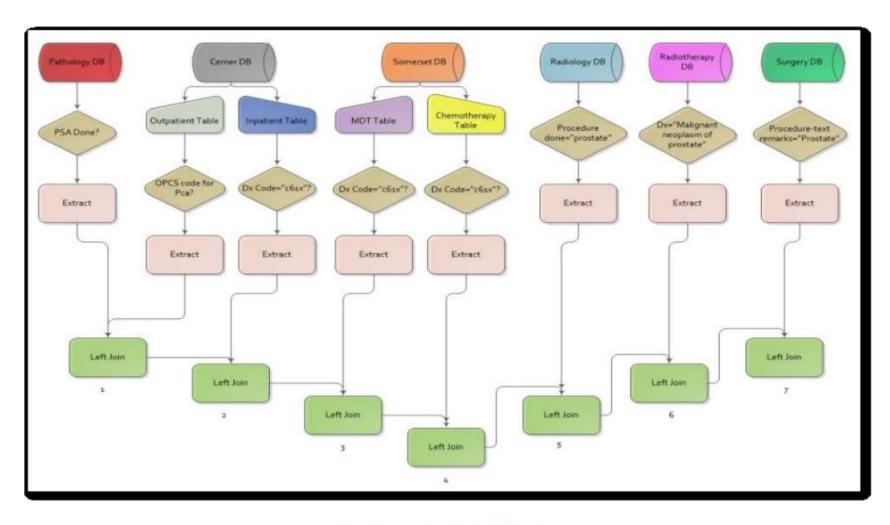


TABLE 16: EVENT LOG INFORMATION IN EACH TABLE

Table Name (Patient activity)	Case ID	Timestamp	Resource ID	Other important variables
Outpatient Appointments	NHSNumber	Date_of_Appointment	OPCS code	DateRaisedByGP, OriginalGPReferralDate, ReferralRequestReceivedDate, ClinicName1, ConsultantName, ReferringGP, ReferralConsultant, ReferringSourceNational, GPUrgentFlag, AttendedFlag, AttendedOrDidNotAttendNational, DateOutcomeRecorded, OutcomeCodeLocalDescription, ReasonForAppointmentDescription, AppointmentTypeLocal, AppointmentPriorityLocal, HospitalCodeDescription, SiteCode, MainSpecialityCodeLocal, DateOfBirth, AgeAtStartOfSpell, DateOfDeath, SexCodeLocal, EthnicCodeLocal, MaritalStatus, ReligionLocal, RegisteredGP, RTTStartDate, RTTEndDate
PSA	NHSNumber	Collection_date	Result	LabDept, OrderCode, OrderName, ordercomment, TestCode, TestName, Result, ResultUnits
Biopsy	NHSNumber	Collection_date_bio	Result_bio	LabDept, OrderCode, OrderName, ordercomment, TestCode, TestName, Result_bio, ResultUnits
Radiology	NHSNumber	Appointment_date	Rad_Procedure_code	-none-
MDT	NHSNumber	MDT_date	-none-	-none-
Radiotherapy	NHSNumber	Course_start	Procedure_code_rtherapy	PatientType, Diagnosis, Intent, CourseEnd, ActivityCode_Rtherapy, ProcedureComment, ProcedureDateTime, ActivityCategoryCode
Inpatient (Admissions)	NHSNumber	Procedure_date	Inp_Procedure	AdmissionDate, WhoAdmitted, WhereAdmitted, DateDecidedToAdmit, HospitalCode, IntendedManagementNational, SourceOfAdmissionNational, PointOfDelivery, DischargeMethodNational, DischargeDestinationNational, DischargeDate, WhereDischarged, WhoDischarged, DIAG1
Surgery	NHSNumber	Surgery_date	Surgery_Procedure_text	PrimarySurgeonCode, AdmissionType, OperationType, Theatre
Chemotherapy	NHSNumber	Chemo date	Therapy_type	Drug_regimen

TABLE 17: DATA EXTRACTION RESULTS

Table Name	Records filtered	
Total no. of instances (events)	148,898	
No. of distinct patients	27,419	
No. of distinct activities (processes)	9	

TABLE 18: SNAPSHOT OF PATIENT-BY-PATIENT FLAT FILE

Trial -1 DATE_PROC	I DATE_PROCZ	PROCESS -	TimeOfAppointment	 DateRaisedByGP 	 OriginalGPReferralDate 	 ReferralRequestRe 	eceivedDate 💌 ClinicName1
1 30039-08-08	200,01-00-04	OUTPATIENT APPOINTMENT	\$1/07/2406 Rt 30:00	2013-09-25		2013-09-02	STONE CLANC 3
1 2003 00 00	20123-127-29	OUTPATIENT APPOINTMENT	\$1,403,10400 to 90.00			2010 h LOT-208	NUMBER OF THE PROPERTY OF THE
1 2004-00-08	200 H ID- GA	OUTPATIENT APPOINTMENT	81/101/1000 08:40:00			2013-11-05	BEN UNDLOST CLIN
1 2000 00-00	2014-03-14	LABS PSA				2013-11-05	
2 200	20129-02-12	OUTPATIENT APPOINTMENT	\$1,751,1986 (0.00.00			2013 1413 168	AMPID ACCESS PRO
2	20019-60-08	LABS PSA				2015-00-06	
3 200	20023-00-04	IMAGING				2013-07-02	
3 2013 66 66	20123-049-06	IMAGING				2610-67-62	
3 2011-08-08	2012-05-25	LABS PSA				2013-07-02	

ConsultantName	ReferringGP	ReferralConsultant	ReferringSourceNational	▼ GPUrgentFlag	AttendedFlag	AttendedOrDidNotAttendNational	DateOutcomeRecorde
ph 4 pages. Phys.	A05		referral from a GP	Υ	Υ	Arrived late but seen	20-49-4200
SER IS HEROLESIA	100	40390	other - initiated by the CONSULTANT	N	Υ	Arrived late but seen	
DE NO. N. I NAMEDA	400		other - initiated by the CONSULTANT	N	Y	Arrived late but seen	
						Arrived late but seen	
MED HEDLER	40.000		referral from a GP	N	Y	Attended on time	
						Attended on time	
						Arrived late but seen	
						Arrived late but seen	
						Arrived late but seen	

OutcomeCodeLocalDescription -	ReasonForAppointmentDescription 💌 AppointmentTy	ypeLocal 💌 AppointmentPi	riorityLocal 💌 HospitalCodeDescriptic 💌 SiteC	ode 💌 MainSpecialityCodeLocal 🕙
Paradi or control of	F	U	Charing Cross Hospital RYJO	2 Urology
	R	R	Charing Cross Hospital RYJ03	Urology
Person douburged	R	R	Charing Cross Hospital RYJO	2 Urology
			Charing Cross Hospital RYJ03	2
Network shadharged	F	T	Charing Cross Hospital RYJO	2 Urology
			Charing Cross Hospital RYJO	2
			Charing Cross Hospital RYJO	2
			Charing Cross Hospital RYJ02	2
			Charing Cross Hospital RYJO	2

DISCUSSION

The construction of this process model went through various data integration, extraction and preparation steps to achieve the required event log necessary for the process mining stage.

- The initial steps of understanding the prostate cancer domain included a thorough understanding of a generic cancer pathway and from that focusing on the prostate cancer pathway as a case study. To make sense out of the pathway, met with clinicians and operational staff.
- Established a minimum required dataset and identified the databases that can provide those variables.
- The linkage process was a lengthy, reiterative process that involved linkage and testing to see if the cohort of patients was representative and covered all patients potentially having prostate cancer.
- Included all patients having a PSA done in the years between June 2009 until June 2015.
- Identified the parameters to be applied to each dataset to identify Urology Cancer patients.

MAIN CHALLENGES (APPLICABLE)

• Working with large datasets (length of time to execute queries and store data)

LIMITATIONS

- Data availability
- Limited accuracy of timestamps (eg no ending timestamp)
- Blank values

These deviations helped aid in capacity planning and highlighting the nonconformities and gaps in care and suggest pathway improvements to facilitate treatment.

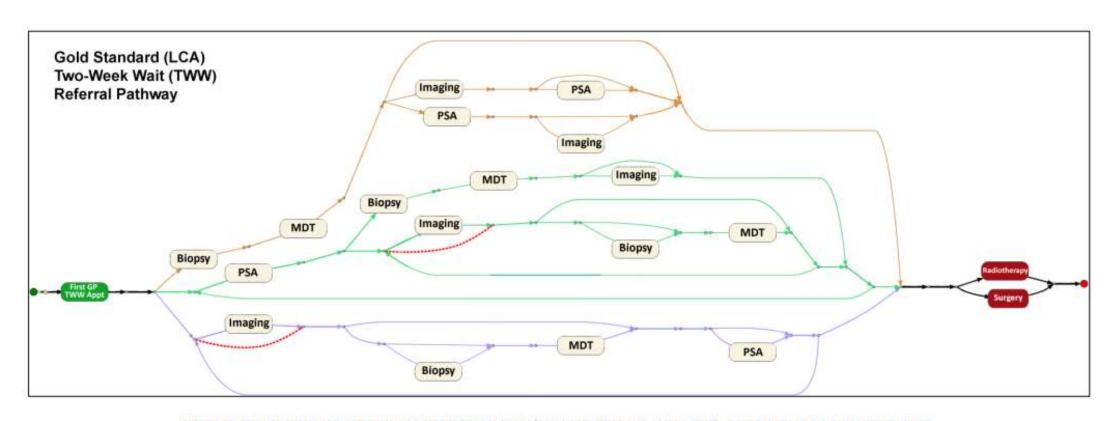


FIGURE 73: THE LCA STANDARD PATHWAY PROCESS FLOW DIAGRAM (100% ACTIVITIES AND 100% PATHS) - MADE WITH PROM 6 INDUCTIVE MINER

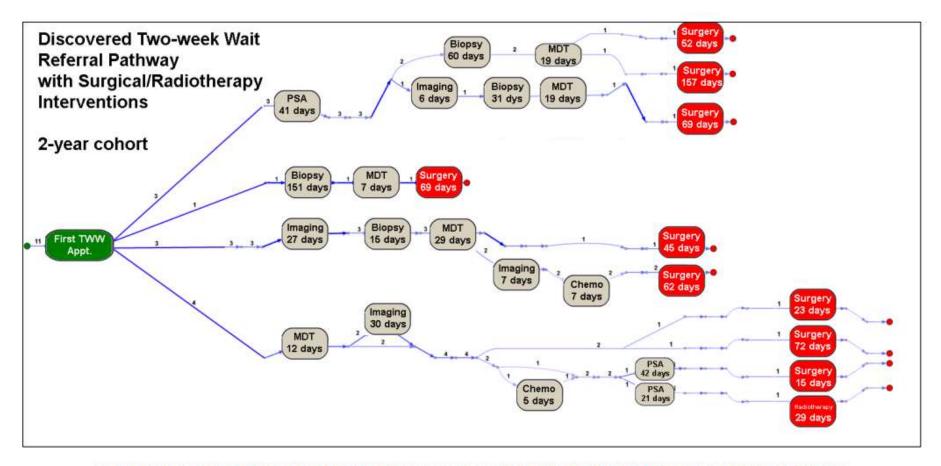


FIGURE 76: 2-YEAR COHORT TWW REFERRAL CLUSTER PROCESS FLOW DIAGRAM (100% ACTIVITIES AND 100% PATHS) SHOWING FREQUENCY OF PATIENTS AND SOJOURN TIMES

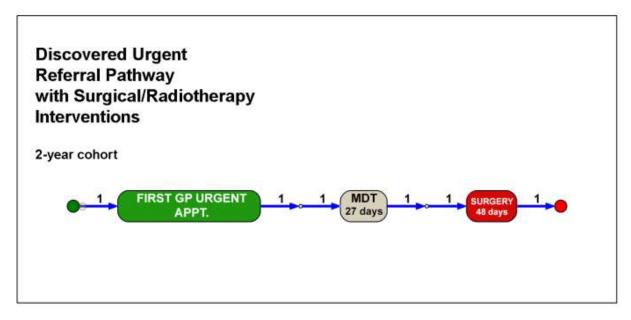
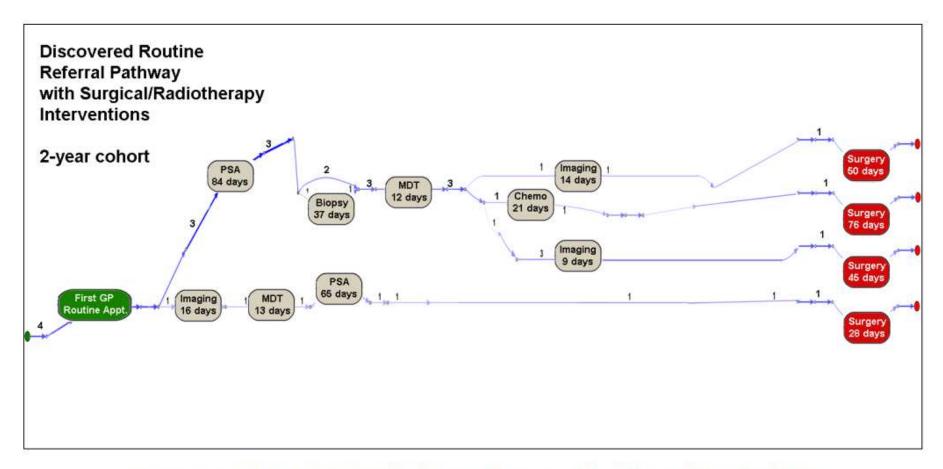


FIGURE 78: 2-YEAR COHORT URGENT REFERRAL CLUSTER PROCESS FLOW DIAGRAM (100% ACTIVITIES AND 100% PATHS) - MADE WITH PROM 6 INDUCTIVE MINER



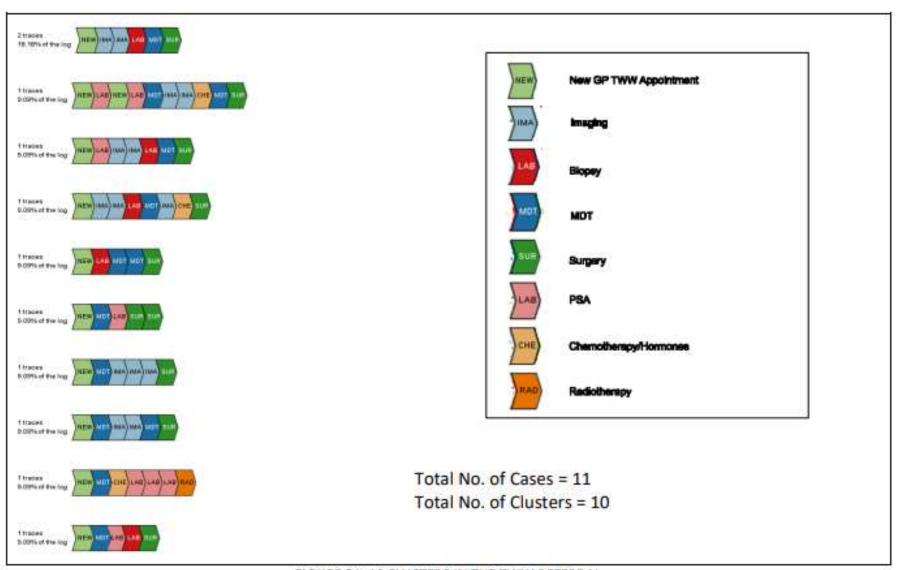


FIGURE 81: 10 CLUSTERS IN THE TWW REFERRAL

TABLE 34: BOTTLENECKS IN THE TWW REFERRAL

Trace #	Path	Total Duration (days)	No. of Bottlenecks in Path	Percentage of path that has bottlenecks	Delays in handover from	Ref.
1	GP-TWW-Appt.→PSA→Biopsy→MDT→Surgery	172	4	100%	 GP-TWW-Appt.→PSA PSA→Biopsy Biopsy→MDT MDT→Surgery 	Figure 84
2	GP-TWW-Appt.→PSA→Biopsy→Surgery	248	3	100%	GP-TWW-Appt.→PSA PSA→Biopsy Biopsy→Surgery	Figure 84
3	GP-TWW-Appt.→PSA→Imaging→Biopsy→MDT→Surgery	166	4	80%	 GP-TWW-Appt.→PSA Imaging→Biopsy Biopsy→MDT MDT→Surgery 	Figure 84
4	GP-TWW-Appt.→Biopsy→MDT→Surgery	227	2	50%	 GP-TWW-Appt.→Biopsy MDT→Surgery 	Figure 85
5	GP-TWW-Appt.→MDT→Imaging→Surgery	65	2	67%	MDT→Imaging Imaging→Surgery	Figure 86
6	GP-TWW-Appt.→MDT→Surgery	90	1	50%	MDT→Surgery	Figure 86
7	GP-TWW-Appt.→MDT→Chemo→PSA→Radiotherapy	67	1	25%	PSA→Radiotherapy	Figure 86
8	GP-TWW-Appt.→MDT→PSA→Surgery	69	1	33%	MDT→PSA	Figure 86
9	GP-TWW-Appt.→Imaging→Biopsy→MDT→Surgery	116	4	100%	GP-TWW-Appt.→Imaging Imaging→Biopsy Biopsy→MDT MDT→Surgery	Figure 87
10	GP-TWW-Appt.→ Imaging→ Biopsy→MDT→Imaging→Chemo→Surgery	147	4	67%	GP-TWW-Appt.→Imaging Imaging→Biopsy Biopsy→MDT Chemo→Surgery	Figure 87

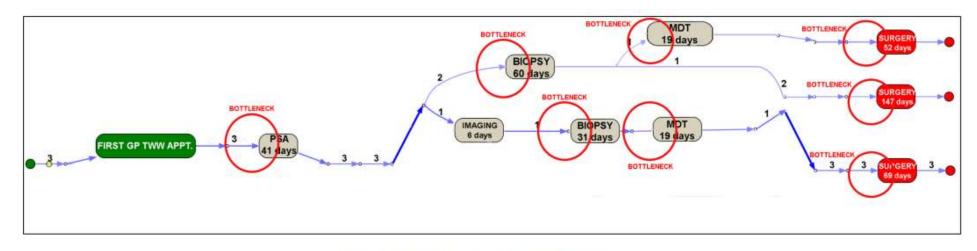


FIGURE 84: BOTTLENECKS IN TRACES 1, 2, 3 OF TWW REFERRAL

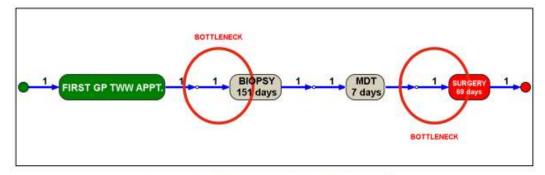


FIGURE 85: BOTTLENECKS IN TRACE 4 OF TWW REFERRAL

TABLE 39: METRIC AND COMPLIANCE TABLE WITH CANCER WAITING TIMES

No.	Metric	What are we measuring?	Data Item (s)	Cases on Target (N=1184)	Percentage on target	Target to reach
1	First 2ww appointment for prostate cancer patients	Date from referral to first appointment is to be < 14 days	2ww appointment date – 2ww referral date	11/11	100%	93%
2	62 day first treatment	Date from referral to first treatment <63 days	First treatment date – 2ww referral date	1/11	9%	85%
3	Biopsy	Date from referral to biopsy < 14 days	Sample collection date – 2ww referral date	0/7	0%	Not yet set by operational standards
4	MRI	Date from referral to MRI < 10 days	Procedure date (if imaging modality = MRI scan) – 2ww referral date	0/8	0%	Not yet set by operational standards
5	Pre Biopsy MRI	Date of MRI to be before date of biopsy	Sample collection date – Procedure date (if imaging modality = MRI scan)	4/4 MRI before Bx	100%	Not yet set by operational standards

Case Study 2

Reviewing elective processes

Overview of case study

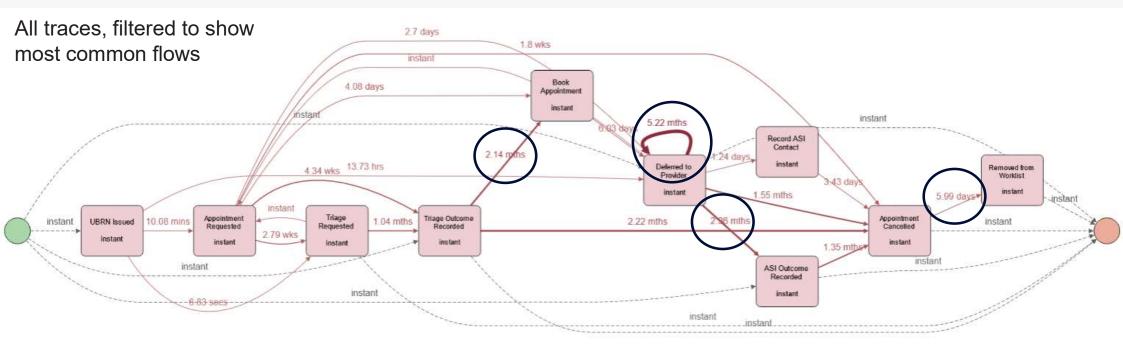
As an analyst working in elective care, a lot of the emphasis is on pathway improvement. I therefore started to explore different analytical methods I could use to analyse pathways.

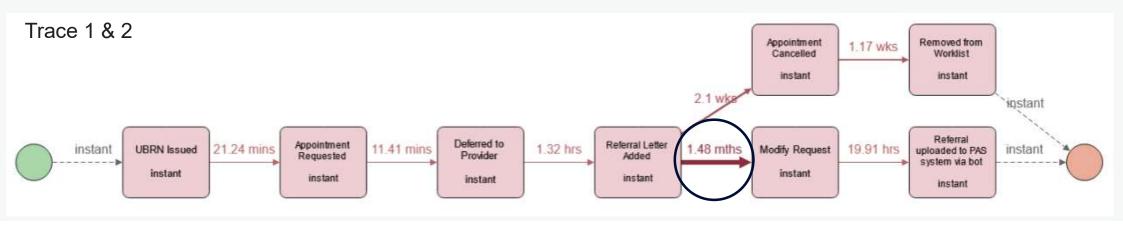
So far we have explored using;

- RTT data
- E-Referral data

And we are due to explore a full pathway for a sample of patients.

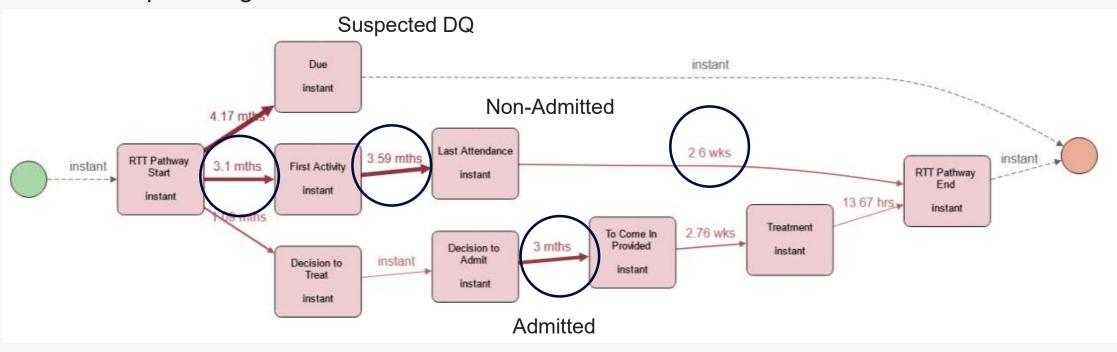
E-referral Data





RTT Data

MSK sample of regional data



Local focus – identification and management of long-term conditions

It is estimated that:

- Around 10% of operations are cancelled on the day of surgery,
- A national audit is currently reviewing the number of patients postponed in the run up to surgery by POA services, but a local audit suggests 20% of contacts results in a postponement
- A significant proportion of postponements and cancellations are currently referred to primary care for health optimisation.
- Removing Red Tape Improving the primarysecondary interface will be a key regional and national focus in 2024/25⁵

Dr Al Hughes (System Clinical Lead) and Fiona Sommerville (Regional Non-Medical Lead), will lead the outlined work programme, will support from NHSE East of England Elective Improvement Team.

The aim of this workplan is to:

- Understand the current patient pathway for highrisk patients and highlight blocks, wastage and gaps in quality
- Test a new way of working that makes best use of available patient data as early in the pathway as possible
- 3. Test ways for primary care and secondary care to work together to optimise patients for surgery, therefore mitigating the risk that a patient has their procedure cancelled and is referred to primary care late in the pathway.
- 4. Coproduce best practice and guidance to improve both patient care and communication between primary and secondary care.

Work packages

1 - Current "As Is" Model

- Map high risk patients with time stamps from referral to discharge and highlight any referrals back to primary care (Data mining.)
- Understand current pathway issues for high-risk patients.
- Clinical notes review to add qualitative input regarding what could be improved at each stage.

2 – Test a Potential "To Be" Model

- Pilot an automated referral form at point of referral (data pulled automatically from GP systems).
- Understand what data is routinely missing in conjunction with primary care.
- Identify key information fields required in secondary care to identify POA risks at time of referral.
- Test pathways in secondary care to use referral information to optimise patients early.
- Work with primary care to develop a list of examples that a require interface with primary care.
- Understand where communication with primary care is required to aid shared decision making.

3 – Developing Guidance and Best Practice

- Recommendations on metrics included in referral and the process and pathways required in secondary care.
- Triggers that cause interface between secondary and primary care.
- Triggers where primary care information is required to aid shared decision making with patient.
- Recommendations for RTT policy, pathway development and primary/secondary care interface.

Plan for work package 1: "As Is" mapping.

Output:

Produce a process map showing the patient journey of 27 high risk patients. All patients were assessed by MSE POA teams over the last 12 months and had an HBA1C reading of >100 at time of assessment.

Outcome:

Understand the blocks in flow and within the current process.

Benefit:

Baseline time from referral to cancelation, rereferrals from primary care and impact on procedure date and recovery.

Process:

- Step 1: Dr Al Hughes to engage with MSE data team and supply them with the NHS No of all the patients within the study, with support from ruby.nicholls@nhs.net
- Step 2: Data team to upload all time stamped data fields in table 1A against individual NHS No and then NHS No is anonymised as patient 001, 002...etc. Time frame to cover from the date of initial referral to Procedure date/discharge/30-day readmission. If the patient does not receive a procedure, then the data will cover all fields in table 1a up to 1st Dec 2024 (including rereferrals) (see table 1B)
- Step 3: Data team to produce an excel sheet of all time stamped events logged against each individual anonymised no and send to ruby.nicholls@nhs.net
- Step 4: Ruby to produce a process map highlighting the patient pathway for all patients and Dr Al Hughes to do a notes review to understand what data was available at each step of the process and gaps in provision.
- Step 5: Tina Yarnton to work with Dr Hughes and Ruby Nicholls to produce an As Is process review document

1A: Data fields

Event	Source	Additional Caveats	Link to Data Dictionary Date Field
Referral Date	Outpatient SUS		https://www.datadictionary.nhs.uk/data_elements/referral_request_received_date.html
RTT Clock Start Date	WL MDS		https://www.datadictionary.nhs.uk/data_elements/referral_to_treatment_period_start_dat
			<u>e.html</u>
Outpatient First Attendance Date	Outpatient SUS	Where First Attendance code in (1,)3	https://www.datadictionary.nhs.uk/data_elements/appointment_date.html
Outpatient Follow Up Attendance	Outpatient SUS	Where First Attendance code in (2,4) and HRG like WF%	https://www.datadictionary.nhs.uk/data_elements/appointment_date.html
Date			
Outpatient Procedure Date	Outpatient SUS	Where HRG does not start with WF%	https://www.datadictionary.nhs.uk/data_elements/appointment_date.html
Outpatient DNA Date	Outpatient SUS	Where Attended or Did Not Attend is code in (3,7)	https://www.datadictionary.nhs.uk/data_elements/appointment_date.html
Outpatient Cancellation Date	Outpatient SUS		https://www.datadictionary.nhs.uk/data_elements/appointment_date.html
Decision To Admit Date			https://www.datadictionary.nhs.uk/attributes/decided_to_admit_date.html
Pre-Assessment Date	Outpatient SUS	Use local definition of pre-assessment clinic e.g. identify	https://www.datadictionary.nhs.uk/data_elements/appointment_date.html
		an outpatient appointment as pre-assessment by clinic	
		code.	
Elective Inpatient Admission	Inpatient SUS	Start of Inpatient Spell linked to referral where admission	https://www.datadictionary.nhs.uk/data_elements/start_datehospital_provider_spellht
Date		method like '1%'	<u>ml</u>
Elective Inpatient Primary	Inpatient SUS	Date the primary procedure within the inpatient spell	
Procedure Date		was performed.	
Elective Inpatient Discharge Date	Inpatient SUS	End of Inpatient Spell linked to referral where admission	https://www.datadictionary.nhs.uk/data_elements/discharge_datehospital_provider_spel
		method like '1%'	<u>Lhtml</u>
RTT Clock Stop Date	WL MDS		https://www.datadictionary.nhs.uk/data_elements/referral_to_treatment_period_end_date.
			<u>html</u>
Referral End Date	Internal Referral Data	Date patient is discharged back to GP	Internal date that captures when the referral was ended. This could either be the RTT end
			date, or if activity is occurring on the same referral post-RTT end date, the date the referral
			was ended and patient discharged back to care of GP.
NEL Inpatient Admission Date	Inpatient SUS	An emergency admission that occurs within the referral,	https://www.datadictionary.nhs.uk/data_elements/start_datehospital_provider_spellht
		not necessarily linked to the elective referral, but will	<u>ml</u>
		give an indication of a patient contact whilst patient is	
		waiting.	
		Defined as admission method beginning with '2%'.	
30 Day Re-admission Date	Inpatient SUS	If patient has been discharged from an inpatient spell,	https://www.datadictionary.nhs.uk/data_elements/start_datehospital_provider_spellht
		date of any non-elective admissions that have occurred	<u>ml</u>
		30 days post-discharge of elective spell within same	
		specialty.	

1B: Patient ID

Event_ID	Timestamp	Event
001	DD/MM/YYYY HH:MM	Referral Received

How would you use process mining?

ANALYTICAL THINKING

Analytical thinking refers to the process of breaking down complex information into components and understanding how they are interconnected.

DEFINITION

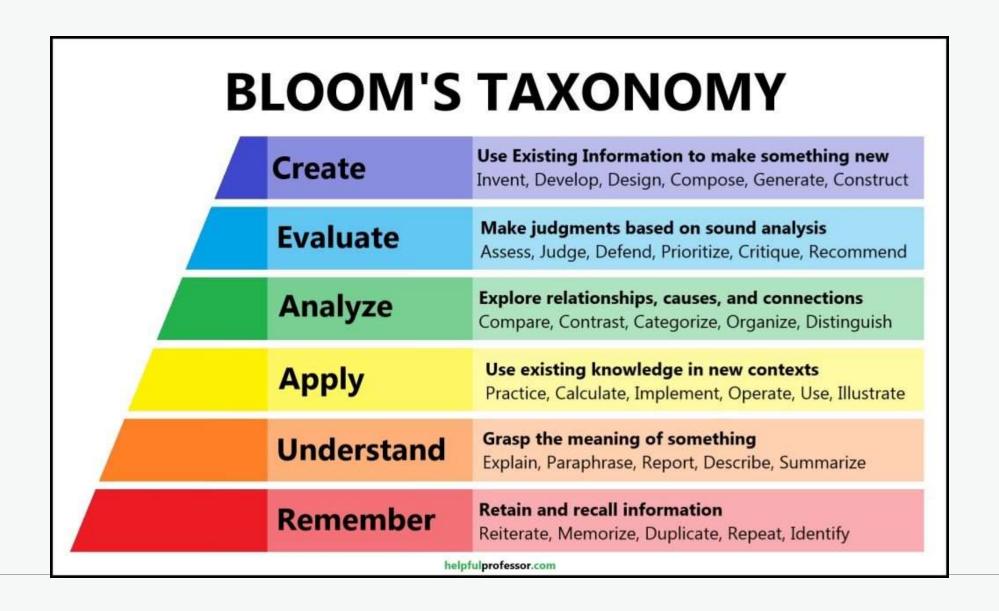
Spaska et al. (2021) identify the key components of analytical thinking as "in-depth search, data analysis and evaluation, problem-solving, and decision-making," which are essential to "reasoning, planning and conducting a learning inquiry process, interpreting the yielded data and findings followed by drawing conclusions" (p. 880).

EXAMPLES

Identifying patterns: Analytical thinkers excel at identifying patterns in data to predict future trends.

Problem decomposition:

Breaking down complex problems into smaller, manageable components is a key analytical thinking skill.





How can you get involved?

Software available

Open-Source Software

- •PM4PY: A process mining library written in Python, offering basic process mining components and advanced features.
- •**ProM:** A process mining framework focused on academic improvement, implemented in Java.
- •bupaR: An open-source package for handling and analysing business process data in R.

Figure 1: Magic Quadrant for Process Mining



For more information

AnalystX – Process Mining Centre of Excellence:

https://future.nhs.uk/connect.ti/DataAnalytics/view? objectId=34562160

Contains resources available, points of contact, list of current projects, etc.

Our blog post on using process mining to improve elective recovery:

https://processmining.analystx.uk/Elective Recovery with Patient Flow Analytics

R code on Github recently shared that uses a sample dataset to explore the types of visualisations available in the bupaverse package:

https://github.com/RubyNixx/Process Mining R Hea Ithcare

What resources are already available?



Training Courses



On this course you will explore how process mining can help turn this data into valuable insights by looking at different areas of process mining and seeing how it has been applied. You will even get the chance to apply process mining on real life healthcare data.

Duration: 4 Weeks

FutureLearn - Introduction to Process Mining

Learn how to use the free, open source process mining framework (ProM) to analyse, visualise, and improve processes based on data

Duration: 4 Weeks



Process Mining Book

This book will teach you what you need to know about the practical application of process mining, so that you don't make the mistakes that others have made before you.

Coursera - Process Mining: Data science in



Open Source Libraries

Libraries with free or partially free editions

- . ProM framework that supports a wide variety of process mining techniques in the form of plug-ins
- . Apromore collaborative business process analytics platform, free community edition
- . BupaR handling and analysis of business process data with R
- . PM4Py Python library that contains process mining alorithms for
- . pmlab interactive programming environment for (exploratory) process
- . RapidProM Process Mining as an extension for the data science framework RapidMiner

Single implementations of certain process mining alorithms, that could help in certain fields of application:

- · pyalpha Python tool that generates a Petri net using the Alpha Algorithm from event logs
- . csv2xes python tool converting .csv file to .xes



Process Mining Tools