	Paper				
Ontology					
explanationExperience.rdf	**ExplanationExperience**				
	hasDescription	**Description**			
aimodel.rdf		hasAIModel	**AIModel**		
			trained on	**Dataset**	
				hasDataType	**DataType**
					number of features
					number of instances
			solves	**AITask**	
				hasType	**AITaskType**
				hasGoal	**AITaskGoal = Description**
			utilises	**AIMethod**	
				hasType	**AIMethodType**
aimodelevaluation.rdf			annotated by	AIModelAssessmentResult	
				basedOn	**AIModelAssessmentMetric**
				measures	**AIModelAssessmentDimension**
explainer.rdf		needExplainer	**Explainer**		
				hasOutputType	***Explanation***
				hasPortability	**Portability**
				hasConcurrentness	**ExplainerConcurrentness**
				hasPresentation	**InformationContentEntity**
				hasExplanationScope	***Explanation Scope***
				targetType	**Explanation Target**
user.rdf		hasUser	**User**		
			asks	**UserQuestion**	
				hasTarget	**UserQuestionTarget**
				hasType	**QuestionType**
			has intent	**Intent**	
				hasType	IntentType
			has resources	**Technical Facilities**	
				can handle	**ExplanationModality**
			possess	**Domain Knowledge**	
				level of domain knowledge	**KnowledgeLevel**
				level of AI knowledge	**KnowledgeLevel**
behaviour_tree.rdf	hasSolution	**Solution**			
		hasExplainer	**Explainer**		
			utilises	**ExplainabilityTechnique**	
				hasType	**ExplainabilityTechniqueType**
				hasOutputType	**Explanation**
				hasPortability	**Portability**
				hasConcurrentness	**ExplainerConcurrentness**
				hasPresentation	**InformationContentEntity**
				hasExplanationScope	***Explanation Scope***
				targetType	**Explanation Target**
				isCompatiblewithFeatureTypes	**DataType**
				hasComplexity	**ComputationalComplexity**
userevaluation.rdf	hasDone	**UserEvaluation**			
		basedOn	**Metric**		
			measures	**Dimensions**	
Code Availability					

Make it personal: a social explanation system applied to group recommendations	*DisCERN: Discovering Counterfactual Explanations using Relevance Features from Neighbourhoods*
PSIE	***DisCERN***
PsieGroupRecommendationExplanationExperience	LungCancerRiskExplanationExperience
Recommend movies to groups based on social knowledge	predict lung cancer risk given clinical data of patients
HappyMovieRecommenderSystem	LungCancerRiskPredictionModel
HappyMovieDataset	LungCancerRiskDataset
Tabular	Tabular
N/A	12
N/A	427
GroupRecommendation	CancerRiskPrediction
Recommendation	Multi-class Classification
Recommend movies to groups based on social knowledge	predict lung cancer risk given clinical data of patients
SocialGroupRecommender	CancerRiskRandomForest
Knowledge based Recommender	RandomForest
3.86, 3.69, 3.56, 3.89	87.94
Likert scale (5 points - being 5 strongly agree)	Accuracy
Usefulness, Decision process, Reusability, Usability	Performance
Content Based Explanation	Counterfactual Explanation
model-specific	model-agnostic
post-hoc	post-hoc
Any	Computational Entity
local	local
prediction	prediction
Moviegoer	Patient/Clinician
Why does the system recommend movie Y for group X?	How can patient X reduce cancer risk Y to lower
System Recommendation	System Recommendation
Why Question	How/What-if Question
Understand system recommendation	Reducing cancer risk
Trust, Satisfaction	Education, Taking Action
ScreenDisplay	ScreenDisplay
Any	Any
User profile	Any/ Clinical knowledge
high	low/high
low	low
	DisCERNCancerRiskExplainer
PsieRuleBasedTechnique	DisCERN
Knowledge Extraction	Feature Relevance+Example based
ContentBasedExplanation	Counterfactual Explanation
model-specific	model-agnostic
post-hoc	post-hoc
Visual/Textual	Computational Entity
local	local
prediction	prediction
Tabular	Tabular
N/A	N/A
	N/A
Questionnaire	N/A
Usefulness/Helpfulness	N/A
N/A	https://github.com/RGU-Computing/DisCERN-XAI

Evaluating Explainability Methods Intended for Multiple Stakeholders	Directing exploratory search: Reinforcement learning from user interactions with keywords
BTTelecom	***SciNet***
BTTelecomRecommenderExplanationExperience	DocumentSearchExplanationExperience
recommend engineering notes to desk support staff to help on-site engineers	Determine the most related documents given a set of keywords
EngineerNoteRecommender	SciNetSearchEngine
BTEngineeringNotes	WebOfScienceDataset
Text	Documents
300 tf-idf features	7 things, title, abstract, author names, publication year, publication forum, article, keywords
5352	50million
EngineerNoteRecommendation	DocumentRetrieval
Recommendation,classification	InformationRetrieval
Predict next scenario based on description in the engineering notes	Determine the most related documents given a set of keywords
EngineerNoteRecommender	SciNetReinforcementLearning
Content based Recommender, Machine Learning / term frequency, unsupervised	Reinforcement Learning
50.88%, 99.10%(in lab), completeness - 70% (in practice)	0.71
Accuracy with and without (NNR) class, top K Accuracy, confidence score	Kappa
Performance, efficiency of scenario organisation	agreement between expert and system
Neighbourhood Explanation, numerical, textual	Neighbourhood Explanation
model-agnostic	model-specific
post-hoc	ante-hoc
Any	visual
local	local
prediction	prediction
Desk Agent	Scientist
Why task Y is recommended as next task?	Why was this result X retrieved for this query Y?
System Recommendation	System Recommendation
Why question	Why Question
why a recommendation has been made?	Understand system prediction
Transparency, Taking Action, Education	Effectiveness, Satisfaction
ScreenDisplay	ScreenDisplay
Text, Image	Any
BTNetworkPlannerDomainExpert, BTFieldEngineerDomainExpert, BTDeskAgentDomainNovice	Search Domain
high, high, low	high
low	low
BTRecommenderExplainer	
BTContentSimilarityBasedTechnique: confidence score, feature-importance, summarisation of sim/difs	SciNetReinforcementLearning
Knowledge Extraction + Feature Relevance	Knowledge Extraction
Neighbourhood Explanation	Neighbourhood Explanation
model-agnostic	model-specific
post-hoc	ante-hoc
Content + Similarity	Interactive visual
local	local
prediction	prediction
Text	Documents
N/A	N/A
see Notes	
Question to get feedback	Questionnaire
Usefulness/Educatingness/Efficiency	Usability/Quality of user experience
N/A	N/A

Visualizing Recommendations to Support Exploration, Transparency and Controllability	Axiomatic Attribution for Deep Networks	Axiomatic Attribution for Deep Networks
TalkExplorer	***IntGradImage***	***IntGradRetinopathy***
TalkExplorerExplanationExperience	IGImageClassificationExplanationExperience	DiabeticRetinopathyDetectionExplanationExperience
Recommend papers based on content and social connections	predict the category of a given image	predict if a given medical image contains diabetic retinopathy
ConferenceNavigator3RecommenderSystem	IGImageClassificationModel	DiabeticRetinopathyDetectionModel
ConferenceNavigator3Dataset	ILSVRC-2014	EyePACS
Tabular	Image	Image
N/A	89401 pixels	1382400 pixels
N/A	456182	128175
TalkPaperRecommendation	ImageClassification	DiabeticRetinopathyDetection
Recommendation	Multi-class Classification	Binary Classification
Recommend papers based on content and social connections	predict the category of a given image	predict if a given medical image contains diabetic retinopathy
CN3ContentBasedRecommender	GoogleNet	Fine-tubed InceptionV3
Tf-idf + kNN	Convolutional Neural Network	Convolutional Neural Network
N/A	6.67%	90.3%, 98.1%, 99.1%
N/A	top-5 error	FOCP Sensitivity, FOCP Specificity, AUROC for EyePACS
N/A	Performance	Performance
Neighbourhood Explanation	Saliency Map Explanation	Saliency Map Explanation
model-specific	model-specific	model-specific
ante-hoc	post-hoc	post-hoc
Image	Image	Image
local	local	local
prediction	prediction	prediction
Conference atendee	Any User	Clinician, Optomologist
Why does the system recommend paper Y to user X?	Why does the system predict category Y for image X?	Why does the system predict RDR for image X?
System Recommendation	System Recommendation	System Recommendation
Why Question	Why Question	Why Question
Understand system prediction	Understand how system works	Understand how system works
Effectiveness, Transparency, Scruitability	Transparancy, Trust	Transparancy, Trust, Education
ScreenDisplay	ScreenDisplay	ScreenDisplay
Any	Any	Any
Conference Topic Domain	Public Domain	Clinical Knowledge
high	Any	High
low	Any	Low
TalkExplorerKNNTechnique	IntegratedGradientTechnique	IntegratedGradientTechnique
k-nearest Neighbour	IntegratedGradient	IntegratedGradient
Neighbourhood Explanation	Saliency Map Explanation	Saliency Map Explanation
model-specific	model-specific	model-specific
ante-hoc	post-hoc	post-hoc
visual	Annotated Computational Entity	Annotated Computational Entity
local	local	local
prediction	prediction	prediction
Tabular	Image	Image
N/A	N/A	N/A
Questions about explanation visualisation knowledge + tasks with TalkExplorer + Likert Scale questions about their needs	N/A	N/A
Think Aloud + Likert Scale	N/A	N/A
Effectiveness	N/A	N/A
N/A	https://github.com/ankurtaly/Integrated-Gradients	https://github.com/ankurtaly/Integrated-Gradients

Axiomatic Attribution for Deep Networks	Textual Explanations for Self-Driving Vehicles	iBCM: Interactive Bayesian Case Model Empowering Humans via Intuitive Interaction
IntGradTextClassification	***KimEtAlMethod***	***iBCM***
QuestionCategoryExplanationExperience	SelfDrivingExplanationExperience	iBCMGradingExplanationExperience
predict the question category based on question text	make acceleration or change course decisions in a self-driving car based on video	Cluster student assignment submissions to design grading rubric or to compose feedback
KimQuestionCategoryPredictionModel	Self-drivingDecisionMakingModel	iBCMClusteringModel
WikiTableQuestions dataset	BerkeleyDeepDriveDataset	iBCMAssessmentsDataset
text	Video	Code
N/A	40 seconds (frame rate not known)	N/A
22033	6984	N/A
QuestionCategoryPrediction	Self-drivingVehicalControl (acceleration and course)	AssessmentsClustering
Multi-class Classification	Regression	Clustering
predict the question category based on question text	make acceleration or change course decisions in a self-driving car based on video	
KimCNN-multichannel	Deep Neural Networks with Attention	iBCMClusteringMethod
Convolutional Neural Network	NeuralNetwork	BCM
N/A	[2.29, 0.82], [6.06, 0.47]	N/A
N/A	[Mean of absolute error, Mean of distance correlation] of Acceleration and Course	N/A
N/A	self-drivingVehicalControl performance	N/A
Saliency Map Explanation	Introspective Explanation	Prototype Explanation
model-specific	model-agnostic	model-specific
post-hoc	post-hoc	ante-hoc
Text	text	Computational Entity
local	local	cohort
prediction	prediction	prediction
Any User	Driver	Lecturer
Why does the system predict category Y for question text X?	Why does the vehical system make decision X?	Why does the system assign certian assessments in to one cluster? How does the system assign clusters?
System Recommendation	System Recommendation	Model
Why Question	Why Question	Why/How Question
Understand how system works	Understand system decision	Understand system/Understand cohort of predictions
Transparancy, Trust	User acceptance, Trust, Understanding, Effective communication	Education/Transparency
ScreenDisplay	ScreenDisplay	ScreenDisplay
Any	text	Any
Public Domain	Public Domain	Lecturer Knowledge
low	high	High
low	low	Low
IntegratedGradientTechnique	LSTMTextGeneratorExplanationTechnique	iBCMTechnique
IntegratedGradient	Data-driven Explanation Generation	Interactive Bayesian Case Model
Saliency Map Explanation	Introspective Explanation	Prototype Explanation ,Feature Importance Explanation
model-specific	model-agnostic	model-specific
post-hoc	post-hoc	ante-hoc
Annotated Computational Entity	text	Visual, textual
local	local	cohort
prediction	prediction	prediction
Text	Any	Tabular,Image,Text
N/A	N/A	N/A
N/A	N/A	N/A
N/A	N/A	Questionnaire
N/A	N/A	Usefulness/Efficiency
https://github.com/ankurtaly/Integrated-Gradients	https://github.com/pair-code/saliency	N/A

A case-based reasoning system for aiding detection and classification of nosocomial infections	Explaining Models by Propagating Shapley Values	Explaining Models by Propagating Shapley Values
InNoCBR	***DeepSHAPGlobal***	***DeepSHAPLocal***
InnoInfectionExplanationExperience	MortalityPredictionExplanationExperience	MortalityExplanationExperience
Predict patient's infection based on a clinical, laboratory, and medico administrative based data	Predict patient mortality base on clinical, nutritional and behaviorial factors	Predict patient mortality base on clinical, nutritional and behaviorial factors
InnoInfectionDiagnosisModel	MLPMortalityPredictionModel	MLPMortalityPredictionModel
InnHostpitalDataset	NHANESDataset	NHANESDataset
Tabular	Tabular	Tabular
6 tuple {S, B, V, S, C, E}	79	79
5385	14407	14407
InfectionDiagnosis	MortalityPrediction	MortalityPrediction
Multi-class Classification	Binary Classification	Binary Classification
Predict patient's infection based on a clinical, laboratory, and medico administrative based data	Predict patient mortality base on clinical, nutritional and behaviorial factors	Predict patient mortality base on clinical, nutritional and behaviorial factors
InnoHybridMethod	MoralityMLP	MoralityMLP
Rules+PARTRules+NLP(NB)	Neural Network	Neural Network
70.21%, 0.62, 55.75%, 19.18%	82.56%	82.56%
Accuracy, Kappa, false-positive rate (before and after modified data)	Accuracy	Accuracy
performance	Performance	Performance
Reasoning Path Explanation	Feature Importance Explanation	Feature Importance Explanation
model-specific	model-agnostic	model-agnostic
ante-hoc	post-hoc	post-hoc
text	Any	Any
local	global	local
prediction	model	prediction
Spanish NHS Doctor	Clinician	Clinician
Why does the system predict infection Y for patient X?	What/How features contributed to predicting mortality Y for patient X?	What/How features contributed to predicting mortality Y for patient X?
System Recommendation	Model	System Recommendation
Why Question	What/How Question	What/How Question
Validate system prediction	Understand how model make decisions	Understand why model made a decision
Trust/Transparency	Transparency	Transparency/Education
ScreenDisplay	ScreenDisplay	ScreenDisplay
Any	Any	Any
Infection Detection/Prevention Knowledge	Clinical Knowledge	Clinical Knowledge
high	high	high
low	low	low
InnoDecisionPathTechnique	DeepSHAPExplanationTechnique	DeepSHAPExplanationTechnique
Decision tree	SHAP/Game-theory	SHAP/Game-theory
Reasoning Path Explanation	Feature Importance Explanation	Feature Importance Explanation
model-specific	model-agnostic	model-agnostic
anti-hoc	post-hoc	post-hoc
Text	violin plot chart	bar chart
local	global	local
prediction	model	prediction
Tabular	Tabular	Tabular
N/A	N/A	N/A
N/A	N/A	N/A
N/A	N/A	N/A
N/A	N/A	N/A
N/A	https://github.com/lrjball/shap	https://github.com/lrjball/shap