

Explaining the Road Not Taken

Hua Shen, Ting-Hao (Kenneth) Huang

The Pennsylvania State University

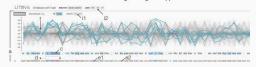




NLP XAI Studies are Growing Rapidly

LSTMVis: A Tool for Visual Analysis of Hidden State Dynamics in Recurrent Neural Networks

Hendrik Strobelt, Sebastian Gehrmann, Hanspeter Pfister, and Alexander M. Rush - Harvard School of Engineering and Applied Sciences -



Visualizing and Understanding Neural Models in NLP

Jiwei Li1, Xinlei Chen2, Eduard Hovy2 and Dan Jurafsky1

¹Computer Science Department, Stanford University, Stanford, CA 94305, USA ²Language Technology Institute, Carnegie Mellon University, Pittsburgh, PA 15213, USA {iiweil.jurafsky}@stanford.edu {xinleic.ehovy}@andrew.cmu.edu

Abstract

While neural networks have been successfully applied to many NLP tasks the resulting vectorbased models are very difficult to interpret. deep learning models deal with composition, implementing functions like negation or intensification, or combining meaning from different parts of the sentence, filtering away the informational chaff from the wheat, to build sentence meaning.

Attention is not Explanation

Sarthak Jain

Northeastern University jain.sar@husky.neu.edu

Abstract

Attention mechanisms have seen wide adoption in neural NLP models. In addition to improving predictive performance, these are often touted as affording transparency: models equipped with attention provide a distribu-

Byron C. Wallace

Northeastern University

b.wallace@northeastern.edu

after 15 minutes watching the movie i was asking myself what to do leave the theater sleep or try to keep watching the movie to see if there was anything worth i finally watched the movie what a waste of time maybe i am not a 5 original or

 $f(x|\alpha, \theta) = 0.01$

adversarial $\tilde{\alpha}$ $f(x|\tilde{\alpha}, \theta) = 0.01$

after 15 minutes watching the movie i was asking myself what to do leave the theater sleep or try to keep watching the movie to see if there was anything worth i finally watched the movie what a waste of time maybe i am not a 5

Analysis Methods in Neural Language Processing: A Survey

Yonatan Belinkov¹² and James Glass¹

¹MIT Computer Science and Artificial Intelligence Laboratory ²Harvard School of Engineering and Applied Sciences Cambridge, MA, USA

{belinkov, glass}@mit.edu

BERT Rediscovers the Classical NLP Pipeline

Dipanjan Das¹ Ellie Pavlick^{1,2} Google Research 2Brown University {iftenney, dipanjand, epavlick}@google.com

Abstract

ed text encoders have rapidly adhe state of the art on many NLP le focus on one such model. BERT. to quantify where linguistic informaaptured within the network. We find nodel represents the steps of the tra-NLP pipeline in an interpretable and le way, and that the regions responeach step appear in the expected se-POS tagging, parsing, NER, semantic en coreference. Qualitative analysis nat the model can and often does adpipeline dynamically, revising lowerisions on the basis of disambiguating on from higher level representation

of the network dir exist localizable re types of linguistic duced evidence tha code a range of sy tion (e.g. Shi et al ney et al., 2019), ar 2018).

We build on thi on the BERT mode a suite of probing

HOTPOTOA: A Dataset for Diverse, Explainable **Multi-hop Ouestion Answering**

Zhilin Yang** Peng Oi*♥ Saizheng Zhang** Yoshua Bengio William W. Cohen Ruslan Salakhutdinov[♠] Christopher D. Manning[♡]

negie Mellon University 🤝 Stanford University 🜲 Mila, Université de Montréal ♦ CIFAR Senior Fellow † Google AI

ny, rsalakhu}@cs.cmu.edu, {penggi, manning}@cs.stanford.edu zhang@umontreal.ca, yoshua.bengio@gmail.com, wcohen@google.com

Abstract

answering (QA) datasets fail ms to perform complex reade explanations for answers. TPOTOA, a new dataset with pased question-answer pairs itures: (1) the questions rereasoning over multiple supts to answer; (2) the ques-

Paragraph A, Return to Olympus:

[1] Return to Olympus is the only album by the alternative rock band Malfunkshun. [2] It was released after the band had broken up and after lead singer Andrew Wood (later of Mother Love Bone) had died of a drug overdose in 1990. [3] Stone Gossard, of Pearl Jam, had compiled the songs and released the album on his label, Loosegroove Records.

Paragraph B. Mother Love Bone:

[4] Mother Love Bone was an American rock band that formed in Seattle, Washington in 1987. [5] The band was active from 1987 to 1990. [6] Frontman Andrew

Rationalizing Neural Predictions

Tao Lei, Regina Barzilay and Tommi Jaakkola

Computer Science and Artificial Intelligence Laboratory Massachusetts Institute of Technology {taolei, regina, tommi}@csail.mit.edu

Abstract

Prediction without justification has limited apare represented hie plicability. As a remedy, we learn to extract of the model (Pete pieces of input text as justifications - rationales - that are tailored to be short and coherent, yet sufficient for making the same prediction. Our approach combines two modular components, generator and encoder, which are trained to operate well together. The genrived from the tradi erator specifies a distribution over text fragments as candidate rationales and these are

the beer was n't what i expected, and i'm not sure it's "true to style", but i thought it was delicious. a very pleasant ruby red-amber color with a relatively brilliant finish, but a limited amount of carbonation, from the look of it, aroma is what i think an amber ale should be - a nice blend of caramel and happiness bound together.

Look: 5 stars Smell: 4 stars

Figure 1: An example of a review with ranking in two categories. The rationale for Look prediction is shown in bold.

XAI Question Bank Shows Practical User Needs

Input	 What kind of data does the system learn from? What is the source of the data? How were the labels/ground-truth produced? * What is the sample size? * What data is the system NOT using? * What are the limitations/biases of the data? * How much data [like this] is the system trained on? 	Why Why not	 Why/how is this instance given this prediction? What feature(s) of this instance leads to the system's prediction? Why are [instance A and B] given the same prediction? Why/how is this instance NOT predicted? Why is this instance predicted P instead of Q? Why are [instance A and B] given different predictions?
Output	 What kind of output does the system give? What does the system output mean? How can I best utilize the output of the system? * What is the scope of the system's capability? Can it do? 	What If	 What would the system predict if this instance changes to? What would the system predict if this feature of the instance changes to? What would the system predict for [a different instance]? How should this instance change to get a different prediction?
Performance	 * How is the output used for other system component(s)? How accurate/precise/reliable are the predictions? How often does the system make mistakes? In what situations is the system likely to be correct/incorrect? * What are the limitations of the system? * What kind of mistakes is the system likely to make? * Is the system's performance good enough for 	How to be that How to still be this	How should this feature change for this instance to get a different
How (global)	 How does the system make predictions? What features does the system consider? * Is [feature X] used or not used for the predictions? What is the system's overall logic? How does it weigh different features? What rules does it use? How does [feature X] impact its predictions? * What are the top rules/features it uses? * What kind of algorithm is used? * How are the parameters set? 	Others	 What is the necessary feature(s) present or absent to guarantee this prediction? What kind of instance gets this prediction? * How/what/why will the system change/adapt/improve/drift over time? (change) * How to improve the system? (change) * Why using or not using this feature/rule/data? (follow-up) * What does [ML terminology] mean? (terminological) * What are the results of other people using the system? (social)

How Well Can Existing NLP XAI Research Respond to these Questions that Users Care About?

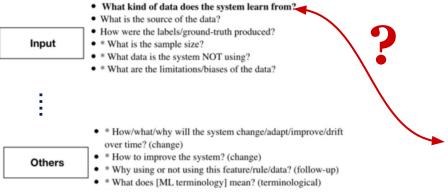
We surveyed 200+ XAI Papers in NLP

Title	Vear	Venue	Paper URL	Title	Year	Venue	Paper URL	ID Title Yea	r Venue	Paper URL
"Why should I trust you?" Explaining the predictions of a		KUD	https://arxiv.org/pdf/1602.04938.pdf	74 FIND: - an-in-the-Loop Debugging Deep Text Classifiers	2020	EMNI P	https://www.aclweb.org/anthology/2020.emnlp-r	147 Multimodal language analysis in the wild: Cmu-mosei dataset and interpretat 2018		https://www.aclaush.org/anthology/D18
causal framework for explaining the predictions of blac		FMNI P	https://arxiv.org/pdf/1707.01943.pdf	75 Fine-grained analy of sentence embeddings using auxiliary pre		ICLR		148 Multimodal Routing: Improving Local and Global Interpretability of Multimoda 2020		https://www.acardo.org.ac.de/coopyr-10
A Diagnostic Study of Explainability Techniques for Text 6		EMNLP	https://arxiv.org/pdi/2009.13295.pdf	76 Generating Fact Checking Co., Senations	2020	ACL.	https://anxiv.org/pdf/1608.04207.pdf https://anxiv.org/pdf/2004.05773.pdf	149 Natural Language Rationales with Full-Stack Visual Reasoning: From Pixels 2020		https://arxiv.org/pdf/2004.14198.pdf https://arxiv.org/pdf/2010.07526.pdf
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A Shalled Attention Mechanism for Interpretation of Neuro		ACL	https://arxiv.org/pdi/2002.1232/.pdf	78 Generating loken-Level Explanations for Natural College Interes 79 GEval: Tool for Debugoing NLP Datasets and Models	2019 2019	BlackboxNLP		151 No Explainability without Accountability: An Empirical Study of Explanations (2020) 152 Obtaining Faithful Interpretations from Compositional Neural Networks 2020		
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A structural probe for finding syntax in word representation		NAACL	https://www.aclweb.org/anthology/N19-1419.pdf	80 Slobal model interpretation via recursive partitioning	2018	DSS	https://arxiv.org/pdf/1802.04253.pdf	153 Open Sesame: Getting Inside BERT's Linguistic Knowledge 2019		https://www.aclweb.org/anthology/W19
A Survey the State of Explainable Al for Natural Langu		AACL-IJCNLP	https://arxiv.org/pdf/2010.00711.pdf	81 GLUC-SE: GeneraLized and COntextualized Story Explanations		EMNLP	https://anxiv.org/pdf/2009.07758.pdf	154 OpenDialKG: Explainable Conversational Reasoning with Attention-based W 2019		https://www.aclweb.org/anthology/P19
Allennip into pret: A framework for explaining predictions		EMNLP	https://www.aclweb.org/anthology/D19-3002.pdf	82 Guiding the Parking of Semantics: Interpretable Video Captioning		Elme	https://pdfs.semanticscholar.org/7ad5/4b109a05	155 Pathologies of Neural Models Make Interpretations Difficult 2018		https://arxiv.org/pdf/1804.07781.pdf
An Information Bottleneck Approach for Controlling Conc		EMNLP	https://arxiv.org/pdf/2005.00652.pdf	83 HEIDL: Learning Ling listic Expressions with Deep Learning and I		ACL	https://www.aclweb.org/anthology/P19-3023.pdf	156 Perturbed Masking: Parameter-free Probing for Analyzing and Interpreting BI 2020		https://arxiv.org/pdf/2004.14786.pdf
n Interpretable Knowledge Transfer Model for Knowledge		ACL	https://www.aclweb.org/anthology/P17-1088.pdf	84 HotpotQA: A Dataset for Diverse, Explainable Multi-hop Question	Answering 2018	EMNLP	https://www.aclweb.org/anthology/D18-1259.pdl	157 Predicting and interpreting embeddings for out of vocabulary words in downs 2018	BlackboxNLP	https://www.aclweb.org/anthology/W1
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Matching 200+ Papers with XAI Question Bank?

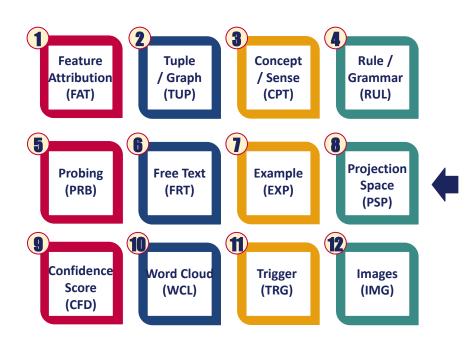
43 User Questions

218 NLP XAI Papers



ID	Title	Year	Venue	Paper URL
1	" Why should I trust you?" Explaining the predictions of any classifier	2016	KDD	https://arxiv.org/pdf/1602.04938
2	Visualizing and Understanding Neural Models in NLP	2016	NAACL	https://www.aclweb.org/antholo
3	Rationalizing Neural Predictions	2016	EMNLP	https://people.csail.mit.edu/taol
4	BERT Rediscovers the Classical NLP Pipeline	2019	ACL	https://www.aclweb.org/antholo
5	Attention is not Explanation	2019	NAACL	https://arxiv.org/pdf/1902.10186
214	How much should you ask? On the question structure in QA systems	2018	BlackboxNLP	https://arxiv.org/pdf/1809.03734
214 215		2018 2020	BlackboxNLP EMNLP	https://arxiv.org/pdf/1809.03734 https://arxiv.org/pdf/2011.06854.
215	How much should you ask? On the question structure in QA systems	2020		
	How much should you ask? On the question structure in QA systems Interpretable Multi-dataset Evaluation for Named Entity Recognition	2020	EMNLP	https://arxiv.org/pdf/2011.06854.

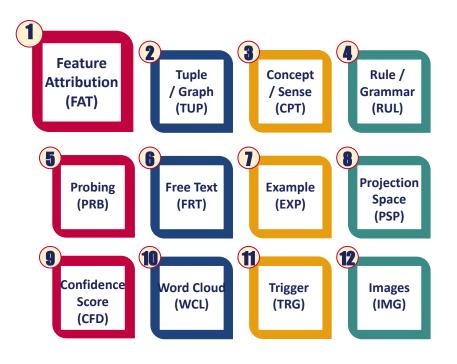
A Collection of XAI Forms



218 NLP XAI Papers

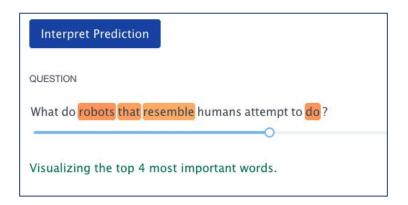
ID	Title	Year	Venue	Paper URL
1	" Why should I trust you?" Explaining the predictions of any classifier	2016	KDD	https://arxiv.org/pdf/1602.04938
2	Visualizing and Understanding Neural Models in NLP	2016	NAACL	https://www.aclweb.org/antholog
3	Rationalizing Neural Predictions	2016	EMNLP	https://people.csail.mit.edu/taole
4	BERT Rediscovers the Classical NLP Pipeline	2019	ACL	https://www.aclweb.org/antholog
5	Attention is not Explanation	2019	NAACL	https://arxiv.org/pdf/1902.10186.
	.			
214	How much should you ask? On the question structure in QA systems	2018	BlackboxNLP	https://arxiv.org/pdf/1809.03734.
214 215	How much should you ask? On the question structure in QA systems Interpretable Multi-dataset Evaluation for Named Entity Recognition	2018 2020	EMNLP	https://arxiv.org/pdf/2011.06854.j
	0.044.00.00000000000000000000000000000	2020		
215	Interpretable Multi-dataset Evaluation for Named Entity Recognition	2020	EMNLP	https://arxiv.org/pdf/2011.06854.j

A Collection of XAI Forms



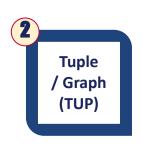
1 - Feature Attribution (FAT)

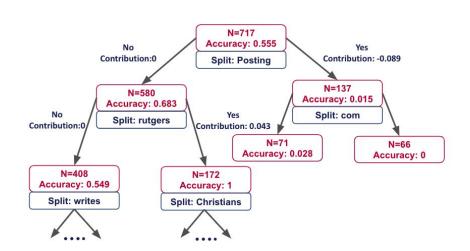
- Definition: highlight the subsequence in input texts
- Typical User Question: "How can we attribute the Al systems' predictions to input features?"



XAI Question Bank

XAI Question Bank





XAI Question Bank



XAI Question Bank

How (global) Q19 - How does the system make predictions?



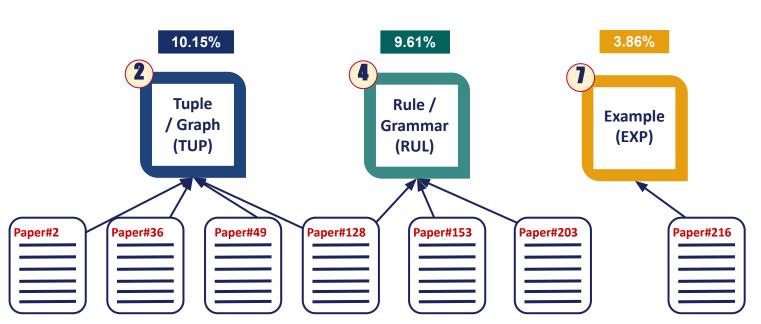
Positive Training Examples:

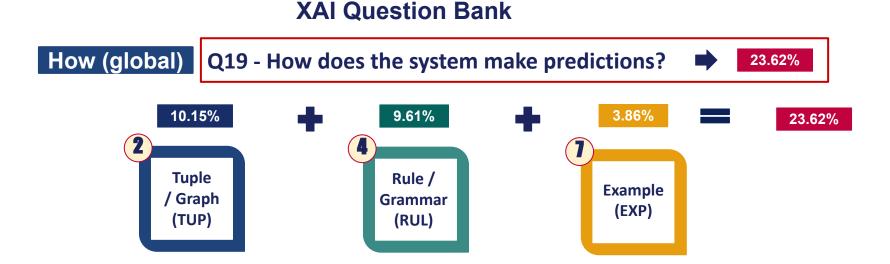
- This gem for gore lovers is extremely underrated. It's pure delight and fun!
- Project A II is a classic Jackie Chan movie with all the kung fu, crazy stunts and slapstick humor you expect......

Negative Training Examples:

- Believe it or not, this was at one time the worst movie I had ever seen. ...
- Great story and great lead actors (Quaid and Ryan) but the movie suffers from bad directing, bad screenplay and bad script......

XAI Question Bank





Findings

	1-What kind of data does the system learn from?	EXP	3.86%		23-Why/how is this instance given this prediction?	L/TUP/FAT/FRT/EXP	74.70%
	2-What is the source of the data?		*		24-What instance feature leads to the system's prediction?	FAT	43.99%
	3-How were the labels/ground-truth produced?		*	Why /		L/TUP/FAT/FRT/EXP	74.70%
Input/Data	4-What is the sample size?		*	Why not	26-Why/how is this instance NOT predicted?	TRG	0.93%
(0.55%)	5-What data is the system NOT using?		_	(45.14%)	27-Why is the instance predicted P instead of Q?	TRG	0.93%
	6-What are the limitations/biases of the data?		•		· · · · · · · · · · · · · · · · · · ·	RUL/TUP/FAT/FRT/EXP	75.62%
	7-How much data [like this] is the system trained on?		-		29-What would the system predict if this instance changes to		
			*				
	8-What kind of output does the system give?	EXP	3.86%		30-What would system predict if this instance feature changes to?	CFD/FAT/TRG	_
	9-What does the system output mean?		*		31-What would the system predict for [a different instance]? CFD/TRG	2.11%
Output (0.77%)	10-How can I best utilize the output of the system?		•		32-How should this instance change to get a different prediction?	TRG	0.93%
(0.77%)	11-What is the scope of the system's capability?		•	What if / How to be	33-How should instance feature change to get different prediction?	TRG	0.93%
	12-How's the output used for other systems modules?		•	(15.54%)	34-What kind of instance gets a different prediction?	TRG/EXP	4.79%
	13-How accurate/precise/reliable are the predictions?	CFD	1.18%		35-What's the scope of change permitted to get the same prediction?	TRG	0.93%
	14-How often does the system make mistakes?		*		36-What's the highest feature can have to get the same prediction?	TRG/FAT	44.91%
Performance	15-In what situations is the system to be incorrect?	CFD/EXP/TRG			37-What is necessary feature present to guarantee this prediction?	TRG/FAT	44.91%
(2.03%)	16-What are the limitations of the system?		•		38-What kind of instance gets this prediction?	EXP	3.86%
	17-What kind of mistake is the system likely to make?	EXP	5.05%		39-How/what/why will the system change/improve/drift over time?		•
	18-Is the system's performance good enough for?		•		40-How to improve the system?		•
	, , ,			Others (11.49%)	41-Why using or not using this feature/rule/data?	FAT/RUL/EXP	57.46%
	19-How does the system make predictions?	TUP/RUL/EXP		(11.45/0)	42-What does [ML terminology] mean?		*
How (Global)	20-What features does the system consider?	FAT	43.99%		43-What are the results of other people using the system?	,	•
(30.31%)	21-What is the system's overall logic?	RUL/FAT	53.60%		To think are the results of other people using the system:		_
	22-What kind of algorithm is used?		*				

0.0%

Findings

	4 Miles to blood of data days the secretary larger frame	EXP	3.86%		23-Why/how is this instance given this prediction?	JL/TUP/FAT/FRT/EXP	74.70%
	1-What kind of data does the system learn from?				, , ,		
	2-What is the source of the data?		*	Why /	24-What instance feature leads to the system's prediction?	FAT	43.99%
I	3-How were the labels/ground-truth produced?		★ V		25-Why are [instance A and B] given the same prediction?	JL/TUP/FAT/FRT/EXP	74.70%
Input/Data (0.55%)	4-What is the sample size?		*	(45.14%)	26-Why/how is this instance NOT predicted?	TRG	0.93%
(515570)	5-What data is the system NOT using?		•		27-Why is the instance predicted P instead of Q?	TRG	0.93%
	6-What are the limitations/biases of the data?		•		28-Why are [instance A and B] given different predictions? TRG/	RUL/TUP/FAT/FRT/EXP	75.62%
	7-How much data [like this] is the system trained on?		*		29-What would the system predict if this instance changes to	.? CFD/EXP/TRG	5.97%
	8-What kind of output does the system give?	EXP	3.86%		30-What would system predict if this instance feature changes to?	CFD/FAT/TRG	46.10%
	9-What does the system output mean?		*		31-What would the system predict for [a different instance	e]? CFD/TRG	2.11%
Output (0.77%)	10-How can I best utilize the output of the system?		•		32-How should this instance change to get a different prediction?	TRG	0.93%
(0.7778)	11-What is the scope of the system's capability?		•	What if / How to be	33-How should instance feature change to get different prediction?	TRG	0.93%
	12-How's the output used for other systems modules?		•	(15.54%)	34-What kind of instance gets a different prediction?	TRG/EXP	4.79%
	13-How accurate/precise/reliable are the predictions?	CFD	1.18%		35-What's the scope of change permitted to get the same prediction?	? TRG	0.93%
	14-How often does the system make mistakes?		*		36-What's the highest feature can have to get the same prediction?	TRG/FAT	44.91%
Performance	15-In what situations is the system to be incorrect?	CFD/EXP/TRG	5.97%		37-What is necessary feature present to guarantee this prediction?	TRG/FAT	44.91%
(2.03%)	16-What are the limitations of the system?		•		38-What kind of instance gets this prediction?	EXP	3.86%
	17-What kind of mistake is the system likely to make?	EXP	5.05%		39-How/what/why will the system change/improve/drift over time?		•
	18-Is the system's performance good enough for?				40-How to improve the system?		•
				Others (11.49%)	41-Why using or not using this feature/rule/data?	FAT/RUL/EXP	57.46%
How	19-How does the system make predictions?	TUP/RUL/EXP		(11.40 /0)	42-What does [ML terminology] mean?		*
(Global)	20-What features does the system consider?	FAT	43.99%		43-What are the results of other people using the system?	?	•
(30.31%)	21-What is the system's overall logic?	RUL/FAT	53.60%				
	22-What kind of algorithm is used?		*	0.0%		100	0.0%

9 out of 43 questions: how AI systems CAN provide specific predictions

Findings

	1-What kind of data does the system learn from?	EXP	3.86%		23-Why/how is this instance given this prediction? RUL/TUP/FAT/FRT/EXP	74.70%
	2-What is the source of the data?		*		24-What instance feature leads to the system's prediction?	43.99%
	3-How were the labels/ground-truth produced?		*	Why /	25-Why are [instance A and B] given the same prediction? RUL/TUP/FAT/FRT/EXP	74.70%
Input/Data	4-What is the sample size?		*	Why not (45.14%)	26-Why/how is this instance NOT predicted? TRG	0.93%
(0.55%)	5-What data is the system NOT using?		•	1	27-Why is the instance predicted P instead of Q? TRG	0.93%
	6-What are the limitations/biases of the data?		•		28-Why are [instance A and B] given different predictions? TRG/RUL/TUP/FAT/FRT/EX	75.62%
	7-How much data [like this] is the system trained on?		*		29-What would the system predict if this instance changes to? CFD/EXP/TR	G 5.97%
	8-What kind of output does the system give?	EXP	3.86%		30-What would system predict if this instance feature changes to? CFD/FAT/TR	G 46.10%
	9-What does the system output mean?		*		31-What would the system predict for [a different instance]? CFD/TRG	2.11%
Output	10-How can I best utilize the output of the system?		•		32-How should this instance change to get a different prediction?	0.93%
(0.77%)	11-What is the scope of the system's capability?		•	What if /	33-How should instance feature change to get different prediction?	0.93%
	12-How's the output used for other systems modules?		•	How to be (15.54%)	34-What kind of instance gets a different prediction? TRG/EXP	4.79%
	13-How accurate/precise/reliable are the predictions?	CFD	1.18%		35-What's the scope of change permitted to get the same prediction?	0.93%
	14-How often does the system make mistakes?	5. 5	*		36-What's the highest feature can have to get the same prediction? TRG/FAT	44.91%
Performance	15-In what situations is the system to be incorrect?	CFD/EXP/TRG		1	37-What is necessary feature present to guarantee this prediction? TRG/FAT	44.91%
(2.03%)	16-What are the limitations of the system?		•		38-What kind of instance gets this prediction?	3.86%
	17-What kind of mistake is the system likely to make?	EXP	5.05%	,	39-How/what/why will the system change/improve/drift over time?	•
	18-Is the system's performance good enough for?				40-How to improve the system?	•
	19-How does the system make predictions?	TUP/RUL/EXP	22 620/	Others (11.49%)	41-Why using or not using this feature/rule/data? FAT/RUL/EX	57.46%
How	20-What features does the system consider?	FAT	43.99%		42-wnat does [will terminology] mean?	*
(Global)	21-What is the system's overall logic?		53.60%		43-What are the results of other people using the system?	•
(30.31%)	22-What kind of algorithm is used?	KOLTAI	33.60 /6	0.0%		00.0%
	22-Wilat Killy Of algorithm IS USEQ?		_	0.0%		JU.U%

16 out of **43** questions: what AI systems CANNOT achieve

Explaining the Road Not Taken

Users are interested in explanations for the road not taken -- namely, why AI chose current prediction instead of a legitimate counterpart

Website: https://human-centered-exnlp.github.io/

Open 200+ NLP Explanation Form Annotations

ID	Title	Year	Venue (Abbreviation List)	Feature Attribution (FAT)	Probing (PRB)	Tuple/Graph (TUP)	Projection Space (PSP)	Rule/Grammar (RUL)	Free Text (FRT)	Concept/Sense (CPT)	Example (EXP)	Trigger (TRG)	Word Cloud (WCL)	Images (IMG)	Confidence Score (CFD)
1	* Why should I trust you?* Explaining the predictions of any classifier	2016	KDD	Quote			ā	5					â		
2	A causal framework for explaining the predictions of black-box sequence-to-sequence models	2017	EMNLP	Quote	-	Quote		-							
3	A Diagnostic Study of Explainability Techniques for Text Classification	2020	EMNLP	Quote	*	*		*				*	*		
4	A Meaning-based English Math Word Problem Solver with Understanding, Reasoning and Explanation	2016	COLING	-	-		2	Quote	Quote	i i					
5	A primer in bertology: What we know about how bert works	2020	TACL	Quote		Quote	8	+							
6	A Shared Attention Mechanism for Interpretation of Neural Automatic Post-Editing Systems	2018	ACL	Quote		5.	7.				-		-		
7	A structural probe for finding syntax in word representations	2019	NAACL			Quote		*			-	e e			
8	A Survey of the State of Explainable Al for Natural Language Processing	2020	AACL-IJCNLP	Quote		*		Quote	Quote		-				-
9	Aliennip interpret: A framework for explaining predictions of nlp models	2019	EMNLP	Quote	140			Quote					-		-
10	An Information Bottleneck Approach for Controlling Conciseness in Rationale Extraction	2020	EMNLP	Quote		-	ž.	2			2	ū.	2	12	

Thank you!



Hua Shen



Ting-Hao (Kenneth) Huang



huashen218@psu.edu



@SarahHShen1



