CSCE 689: Special Topics in Trustworthy NLP

Lecture 17: Model Explainability and Interpretability (1)

Kuan-Hao Huang
khhuang@tamu.edu

(Some slides adapted from NAACL-24 Tutorial: Explanations in the Era of Large Language Models)

Course Project – Computations

- HPRC (https://hprc.tamu.edu/resources/)
  - FASTER: A100 GPUs, A10 GPUs, A30 GPUs, A40 GPUs and T4 GPUs
  - GRACE: A100 GPUs, RTX 6000 GPUs, T4 GPUs, and A40 GPUs

Model Explainability and Interpretability

Hello! Could you help me reserve a table at the *"The Best"* restaurant for tomorrow at 12pm?

Of course! I've reserved a table at the *"The Best"* restaurant for tomorrow at 12pm.

I generate this response is because I saw you mention reserve, one restaurant name, and one specific time. Therefore…

Hello! Could you help me reserve a table at the *"The Best"* restaurant for tomorrow at 12pm?

Of course! I've reserved a table at the *"The Best"* restaurant for tomorrow at 12pm.

I generate this response is because I saw you mention tomorrow. It is usually strongly related to restaurant reservation.

Provide additional information to decide if we should trust the answers

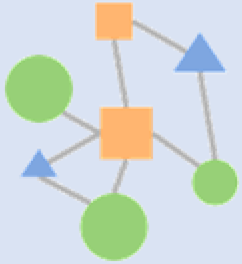
Model Explainability and Interpretability

Hello! Could you help me reserve a table at the *"The Best"* restaurant for tomorrow at 12pm?

Of course! I've reserved a table at the *"The Best"* restaurant for tomorrow at 12pm.

Hello! Could you help me reserve a table at the *"The Best"* restaurant for tomorrow at 12pm?

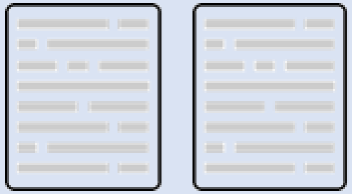
Of course! I've reserved a table at the *"The Best"* restaurant for tomorrow at 12pm.



Reasoning graph

Hello! Could you help me reserve a table at the *"The Best"* restaurant for tomorrow at 12pm?

Of course! I've reserved a table at the *"The Best"* restaurant for tomorrow at 12pm.



Supporting documents

What Are Good Explanations?

- Faithfulness
- Plausibility
- Informativeness
- …

Good Explanations Should Be Faithful

- A faithful interpretation is one that accurately represents the reasoning process behind the model's prediction

Good Explanations Should Be Plausible

- An explanation is considered plausible if it is coherent with human reasoning and understanding
- Plausibility is also referred to as persuasiveness or understandability
- An explanation might be plausible but not faithful. Currently, many explanations are more plausible than faithful
- Example of faithful, but not plausible explanation: a copy of model weights

Good Explanations Should Be Informative

Hi prof, I have just finished this paper. Which venue do you think would best suit it?

NAACL, because its deadline is just 3 days away, and it will be in Mexico, not far from here.

NAACL, because it is a top NLP conference.

Which explanation is more informative?

Good Explanations Should Be…

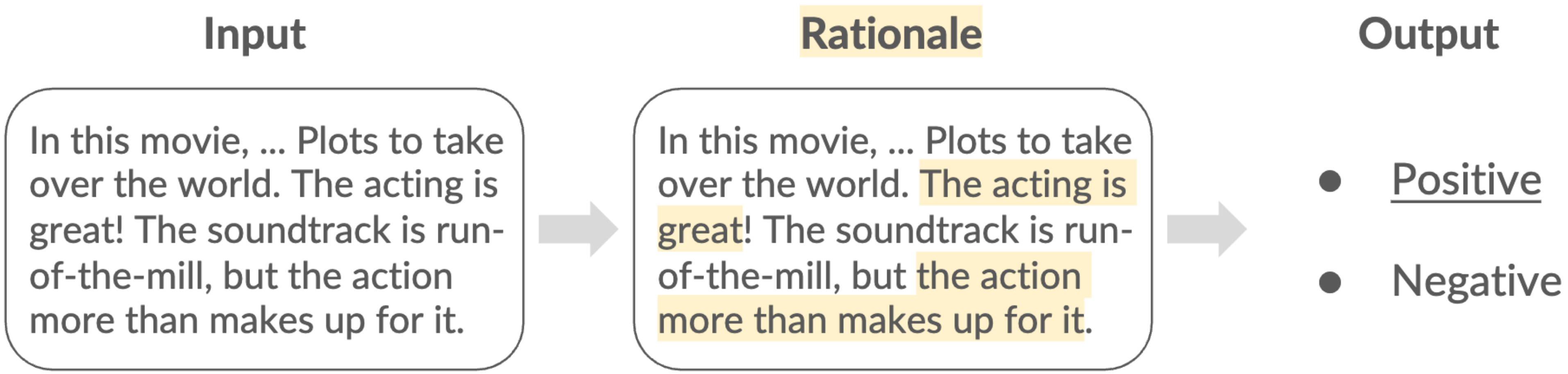
- Useful
- Simple
- Complete
- Stable
- …

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

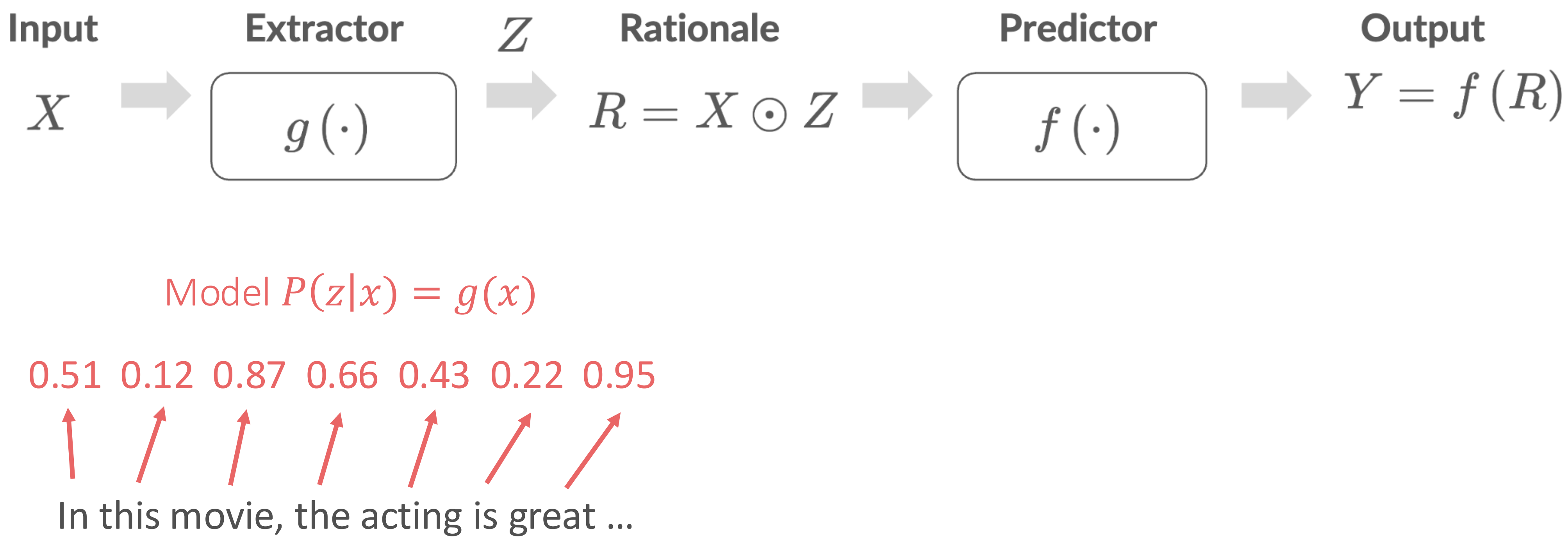
Extractive Rationales

- Rationales: short snippets in inputs that support outputs



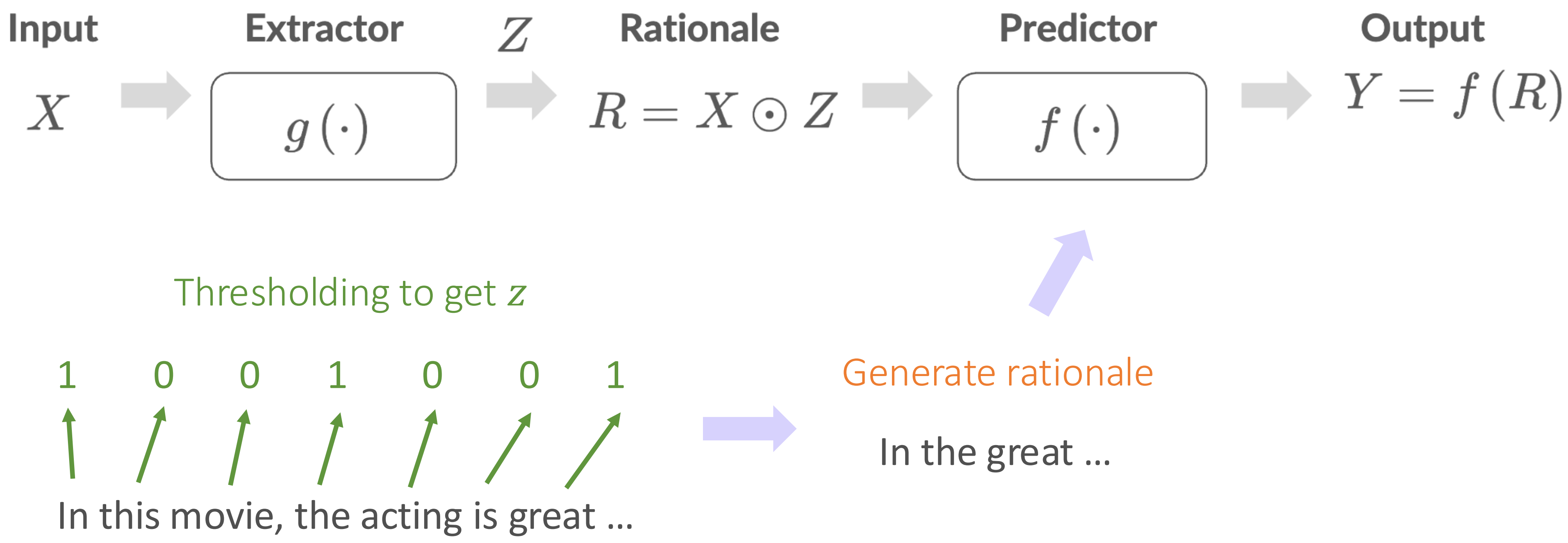
Extractive Rationales

- Pipeline model



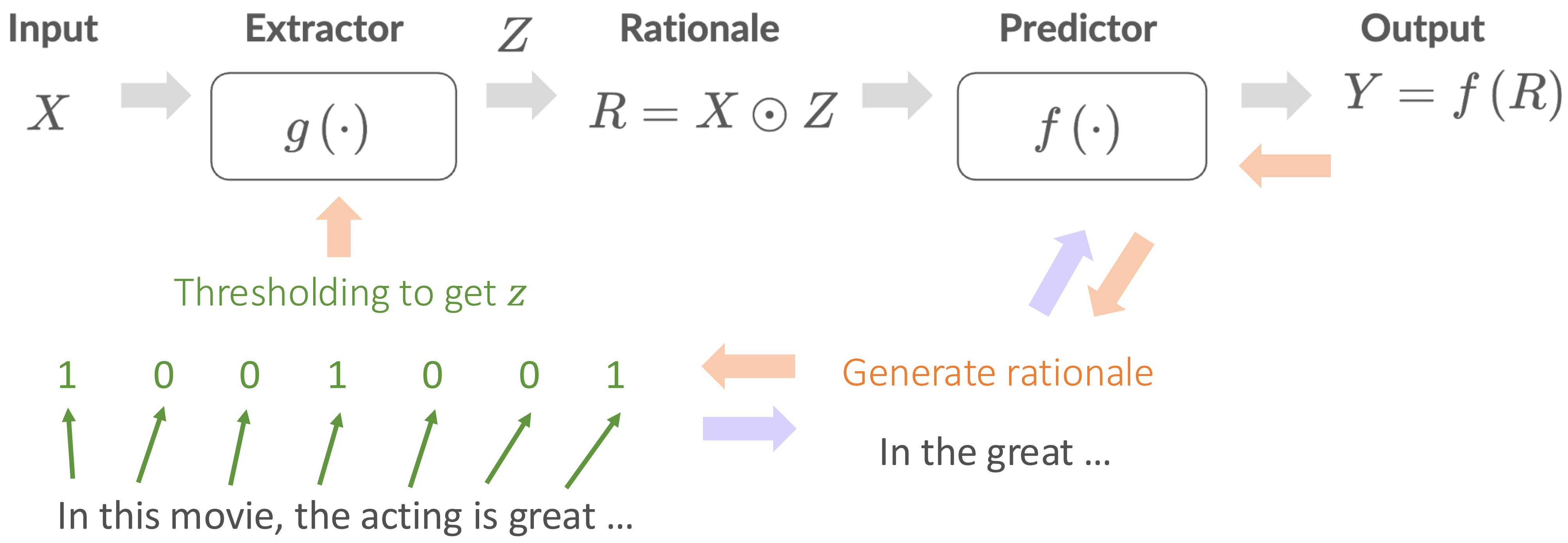
Extractive Rationales

- Pipeline model



Extractive Rationales

- Pipeline model



Results

Method	Appearance		Smell		Palate	
	% precision	% selected	% precision	% selected	% precision	% selected
SVM	38.3	13	21.6	7	24.9	7
Attention model	80.6	13	88.4	7	65.3	7
Generator (independent)	94.8	13	93.8	7	79.3	7
Generator (recurrent)	96.3	14	95.1	7	80.2	7

Examples

a beer that is not sold in my neck of the woods , but managed to get while on a roadtrip . poured into an imperial pint glass with a generous head that sustained life throughout . nothing out of the ordinary here , but a good brew still . body was kind of heavy , but not thick . the hop smell was excellent and enticing . very drinkable

very dark beer . pours a nice finger and a half of creamy foam and stays throughout the beer . smells of coffee and roasted malt . has a major coffee-like taste with hints of chocolate . if you like black coffee , you will love this porter . creamy smooth mouthfeel and definitely gets smoother on the palate once it warms . it 's an ok porter but i feel there are much better one 's out there .

i really did not like this . it just seemed extremely watery . i dont ' think this had any carbonation whatsoever . maybe it was flat , who knows ? but even if i got a bad brew i do n't see how this would possibly be something i 'd get time and time again . i could taste the hops towards the middle , but the beer got pretty nasty towards the bottom . i would never drink this again , unless it was free . i 'm kind of upset i bought this .

a : poured a nice dark brown with a tan colored head about half an inch thick , nice red/garnet accents when held to the light . little clumps of lacing all around the glass , not too shabby . not terribly impressive though s : smells like a more guinness-y guinness really , there are some roasted malts there , signature guinness smells , less burnt though , a little bit of chocolate … … m : relatively thick , it is n't an export stout or imperial stout , but still is pretty hefty in the mouth , very smooth , not much carbonation . not too shabby d : not quite as drinkable as the draught , but still not too bad . i could easily see drinking a few of these .

Takeaways

- Rationales can be one kind of explanations
- Potential performance trade-off
- Cannot apply to general models

"Why Should I Trust You?"
Explaining the Predictions of Any Classifier

Marco Tulio Ribeiro
University of Washington
Seattle, WA 98105, USA
marcotcr@cs.uw.edu

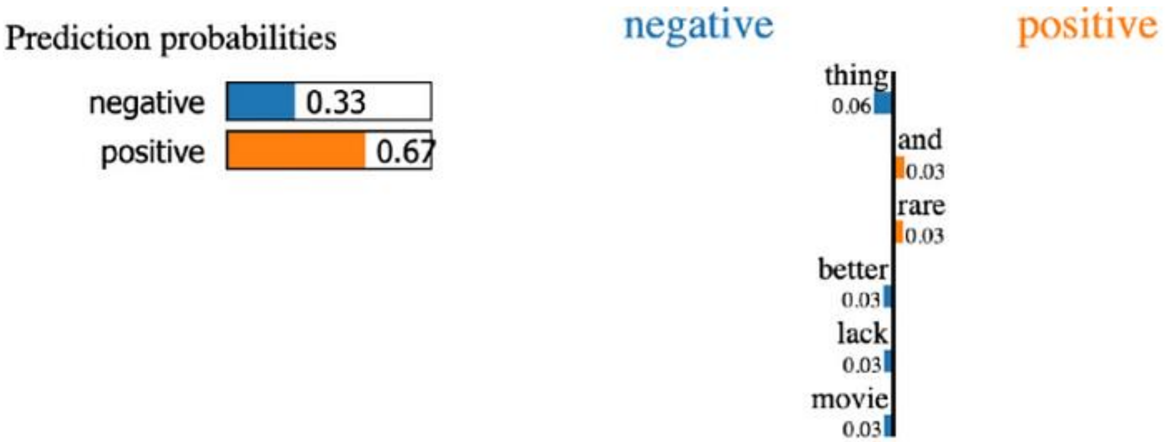
Sameer Singh
University of Washington
Seattle, WA 98105, USA
sameer@cs.uw.edu

Carlos Guestrin
University of Washington
Seattle, WA 98105, USA
guestrin@cs.uw.edu

Key Contributions

- Generate explanations for black-box models
- LIME: Local Interpretable Model-agnostic Explanations

Example



Text with highlighted words

This amazing documentary gives us a glimpse into the lives of the brave women in Cameroun's judicial system-- policewomen, lawyers and judges. Despite tremendous difficulties-- lack of means, the desperate poverty of the people, multiple languages and multiple legal precedents depending on the region of the country and the religious/ethnic background of the plaintiffs and defendants-- these brave, strong women are making a difference.lbr /Ilbr /IThis is a rare thing-- a truly inspiring movie that restores a little bit of faith in humankind. Despite the atrocities we see in the movie, justice does get served thanks to these passionate, hardworking women.lbr /Ilbr /II only hope this film gets a wide release in the United States. The more people who see this film, the better.

LIME

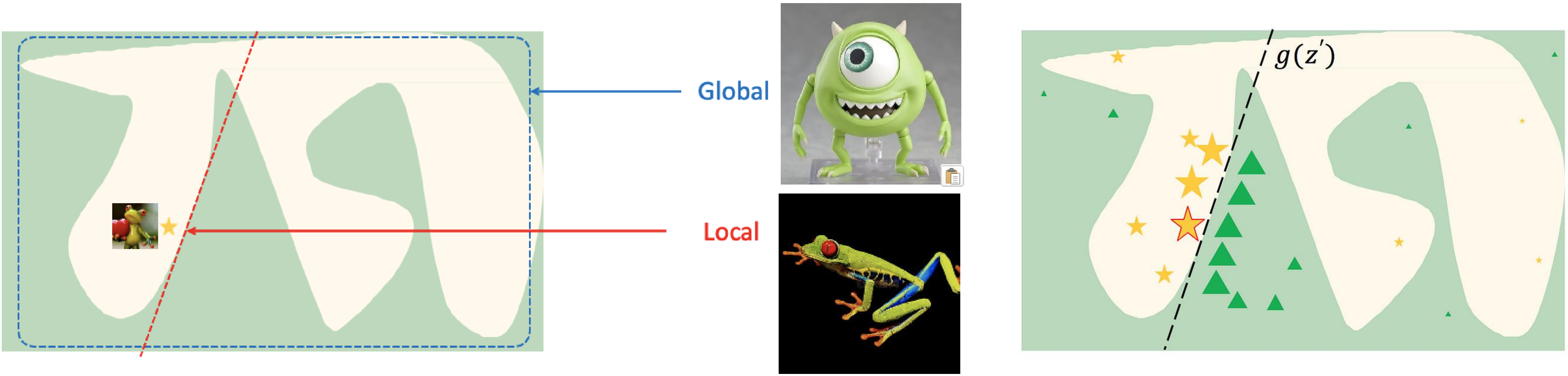
- Analysis model f
- Train a local interpretable model based on f and perturbed examples
- For one example, get prediction from f
  - "The storyline is boring, but the actors are great." → Positive (0.76)
- Perturb examples
  - "The storyline is boring, but the actors are [mask]." → Negative (0.35)
  - "The storyline is [mask], but the actors are great." → Positive (0.85)
  - "The storyline is boring, but the [mask] are great." → Positive (0.70)
  - "The [mask] is boring, but the actors are great." → Negative (0.48)

LIME

- New training examples for local interpretable model
    - “The storyline is boring, but the actors are great. → Positive (0.76)
    - “The storyline is boring, but the actors are [mask]. → Negative (0.35)
    - “The storyline is [mask], but the actors are great. → Positive (0.85)
    - “The storyline is boring, but the [mask] are great. → Positive (0.70)
    - “The [mask] is boring, but the actors are great. → Negative (0.48)
- Train a linear model to approximate the decision boundary
    - Text feature: bag-of-word, TF-IDF, n-gram, …
- The linear weights can be explanations
    - great (+2.7), boring (-3.6), but (+0.6), …

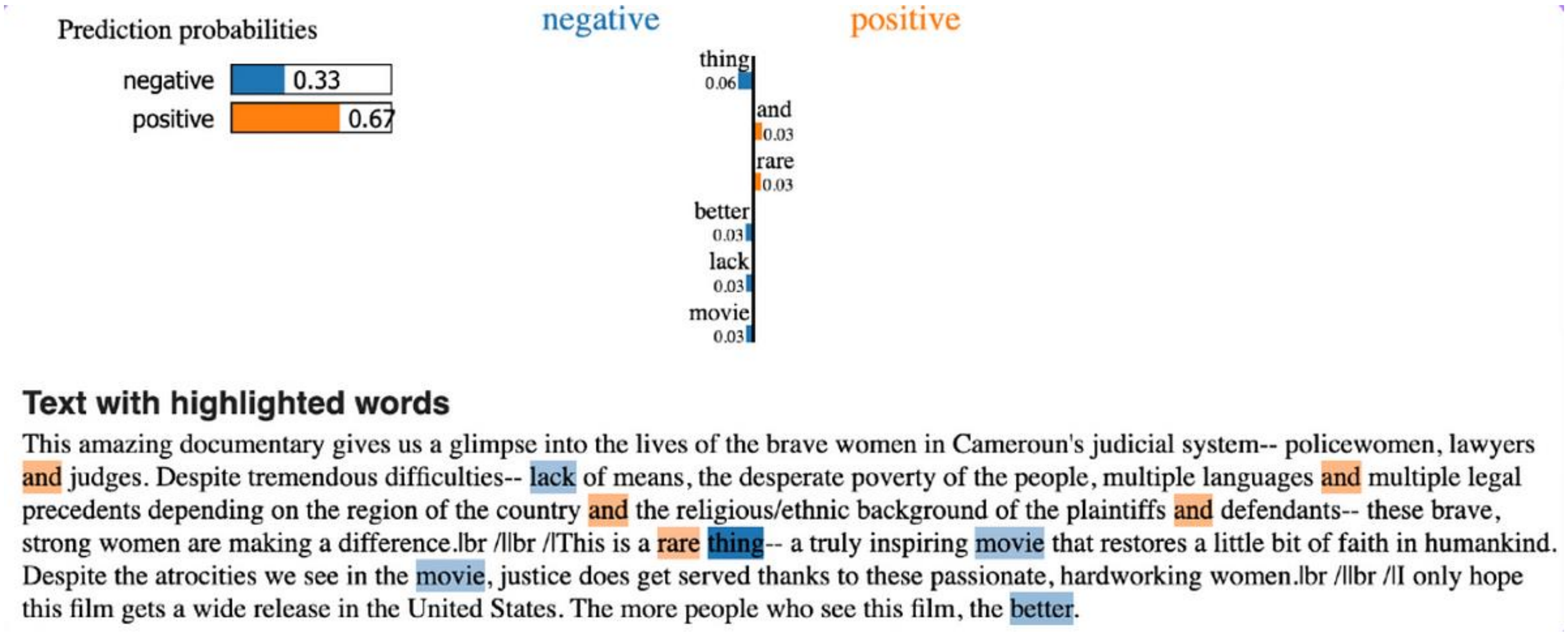
Local Faithfulness

- Train a surrogate model (interpretable model) to locally approximate the boundary



https://medium.com/sherry-ai/23898753bea5

Example


Prediction probabilities
negative 0.33
positive 0.67
negative
positive
thing 0.06
and 0.03
rare 0.03
better 0.03
lack 0.03
movie 0.03
Text with highlighted words
This amazing documentary gives us a glimpse into the lives of the brave women in Cameroun's judicial system-- policewomen, lawyers and judges. Despite tremendous difficulties-- lack of means, the desperate poverty of the people, multiple languages and multiple legal precedents depending on the region of the country and the religious/ethnic background of the plaintiffs and defendants-- these brave, strong women are making a difference.Ibr /IIbr /IThis is a rare thing-- a truly inspiring movie that restores a little bit of faith in humankind. Despite the atrocities we see in the movie, justice does get served thanks to these passionate, hardworking women.Ibr /IIbr /II only hope this film gets a wide release in the United States. The more people who see this film, the better.

On the Sensitivity and Stability of Model Interpretations in NLP

Fan Yin, Zhouxing Shi, Cho-Jui Hsieh, and Kai-Wei Chang
University of California, Los Angeles
{fanyin20, zshi, chohsieh, kwchang}@cs.ucla.edu;

How about White-Box Models

- LIME is for black-box models
- Can we do better for white-box models?

Gradient-Based Explanations

The storyline is boring, but the actors are great. $\mathcal{L}\big(y, f(x)\big)$

Gradient Norm (↑)

$$\left\|\frac{\partial \mathcal{L}\big(y, f(x)\big)}{\partial x_i}\right\|_2$$

Gradient Norm x Input (↑)

$$\left(\frac{\partial \mathcal{L}\big(y, f(x)\big)}{\partial x_i}\right)^{\top} x_i$$

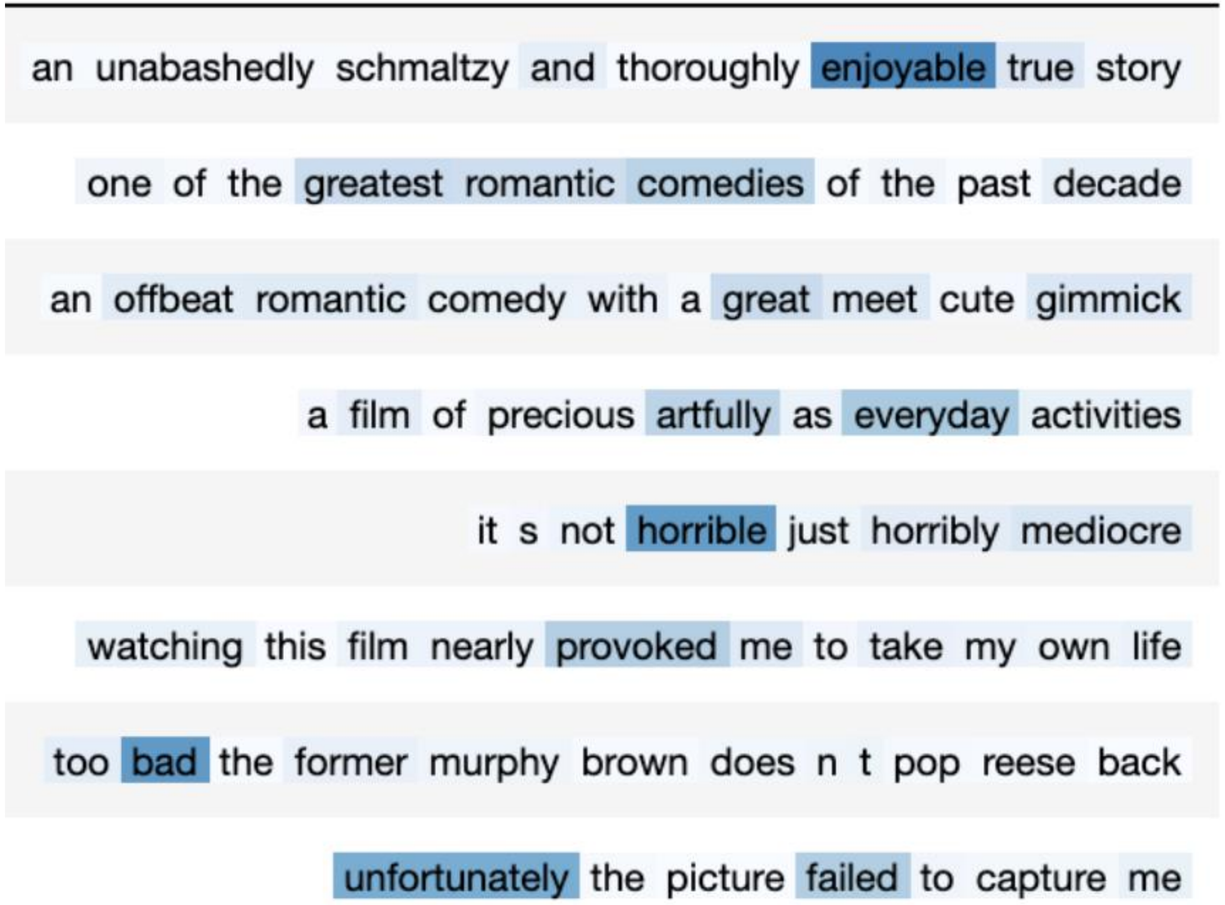
Leave-One-Out Word Importance

The storyline is boring, but the actors are great. $\mathcal{L}(y, f(x))$

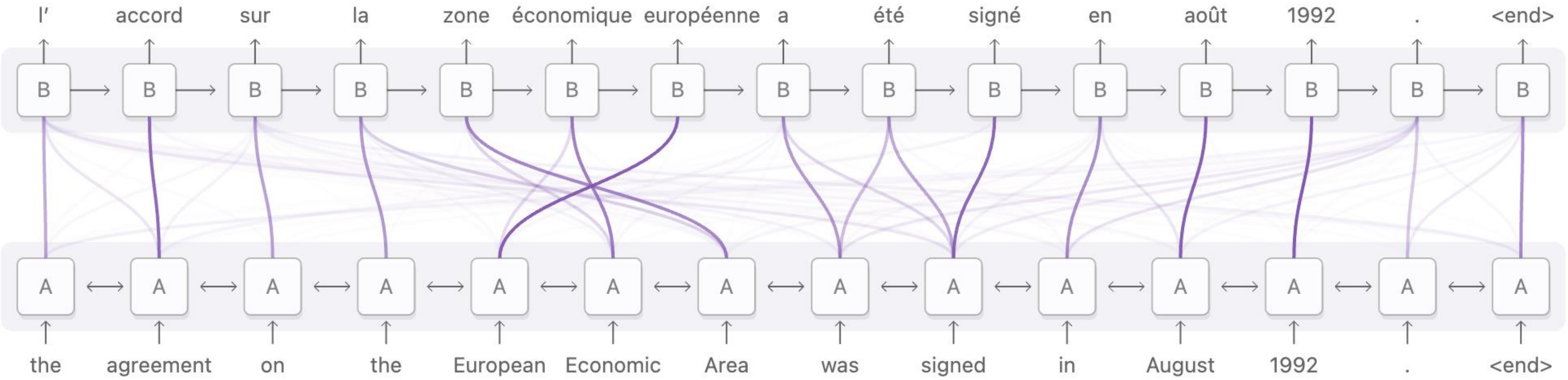
The storyline is [mask], but the actors are great. $\mathcal{L}(y, f(x'))$

$$\mathcal{L}(y, f(x')) - \mathcal{L}(y, f(x))$$

Examples


an unabashedly schmaltzy and thoroughly enjoyable true story
one of the greatest romantic comedies of the past decade
an offbeat romantic comedy with a great meet cute gimmick
a film of precious artfully as everyday activities
it s not horrible just horribly mediocre
watching this film nearly provoked me to take my own life
too bad the former murphy brown does n t pop reese back
unfortunately the picture failed to capture me

Attention?



l' accord sur la zone économique européenne a été signé en août 1992 . <end>
B B B B B B B B B B B B B B B
A A A A A A A A A A A A A A
the agreement on the European Economic Area was signed in August 1992 . <end>

Attention is not Explanation

Sarthak Jain
Northeastern University
jain.sar@husky.neu.edu

Byron C. Wallace
Northeastern University
b.wallace@northeastern.edu

Attention is not not Explanation

Sarah Wiegreffe*
School of Interactive Computing
Georgia Institute of Technology
saw@gatech.edu

Yuval Pinter*
School of Interactive Computing
Georgia Institute of Technology
uvp@gatech.edu

Experiments

- Correlation between attention-based and gradient-based/leave-one-out

		Gradient (BiLSTM) τ_g		Gradient (Average) τ_g		Leave-One-Out (BiLSTM) τ_{loo}	
Dataset	Class	Mean $\pm$ Std.	Sig. Frac.	Mean $\pm$ Std.	Sig. Frac.	Mean $\pm$ Std.	Sig. Frac.
SST	0	0.34 ± 0.21	0.48	0.61 ± 0.20	0.87	0.27 ± 0.19	0.33
	1	0.36 ± 0.21	0.49	0.60 ± 0.21	0.83	0.32 ± 0.19	0.40
IMDB	0	0.44 ± 0.06	1.00	0.67 ± 0.05	1.00	0.34 ± 0.07	1.00
	1	0.43 ± 0.06	1.00	0.68 ± 0.05	1.00	0.34 ± 0.07	0.99
ADR Tweets	0	0.47 ± 0.18	0.76	0.73 ± 0.13	0.96	0.29 ± 0.20	0.44
	1	0.49 ± 0.15	0.85	0.72 ± 0.12	0.97	0.44 ± 0.16	0.74
20News	0	0.07 ± 0.17	0.37	0.79 ± 0.07	1.00	0.06 ± 0.15	0.29
	1	0.21 ± 0.22	0.61	0.75 ± 0.08	1.00	0.20 ± 0.20	0.62
AG News	0	0.36 ± 0.13	0.82	0.78 ± 0.07	1.00	0.30 ± 0.13	0.69
	1	0.42 ± 0.13	0.90	0.76 ± 0.07	1.00	0.43 ± 0.14	0.91
Diabetes	0	0.42 ± 0.05	1.00	0.75 ± 0.02	1.00	0.41 ± 0.05	1.00
	1	0.40 ± 0.05	1.00	0.75 ± 0.02	1.00	0.45 ± 0.05	1.00
Anemia	0	0.47 ± 0.05	1.00	0.77 ± 0.02	1.00	0.46 ± 0.05	1.00
	1	0.46 ± 0.06	1.00	0.77 ± 0.03	1.00	0.47 ± 0.06	1.00
CNN	Overall	0.24 ± 0.07	0.99	0.50 ± 0.10	1.00	0.20 ± 0.07	0.98
bAbI 1	Overall	0.25 ± 0.16	0.55	0.72 ± 0.12	0.99	0.16 ± 0.14	0.28
bAbI 2	Overall	-0.02 ± 0.14	0.27	0.68 ± 0.06	1.00	-0.01 ± 0.13	0.27
bAbI 3	Overall	0.24 ± 0.11	0.87	0.61 ± 0.13	1.00	0.26 ± 0.10	0.89
SNLI	0	0.31 ± 0.23	0.36	0.59 ± 0.18	0.80	0.16 ± 0.26	0.20
	1	0.33 ± 0.21	0.38	0.58 ± 0.19	0.80	0.36 ± 0.19	0.44
	2	0.31 ± 0.21	0.36	0.57 ± 0.19	0.80	0.34 ± 0.20	0.40

Experiments

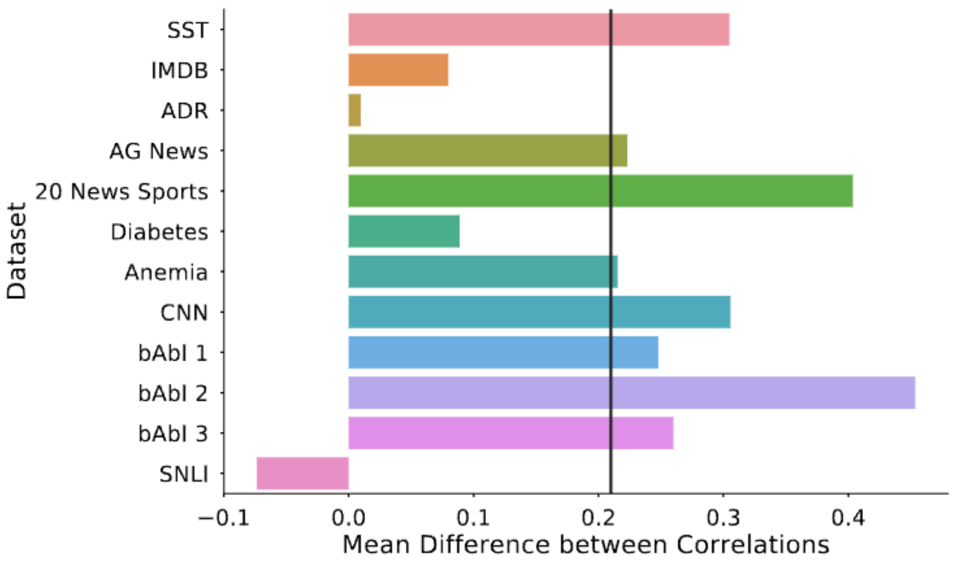


Figure 6: Mean difference in correlation of (i) LOO vs. Gradients and (ii) Attention vs. LOO scores using BiLSTM Encoder + Tanh Attention. On average the former is more correlated than the latter by >0.2 τ_{loo}.

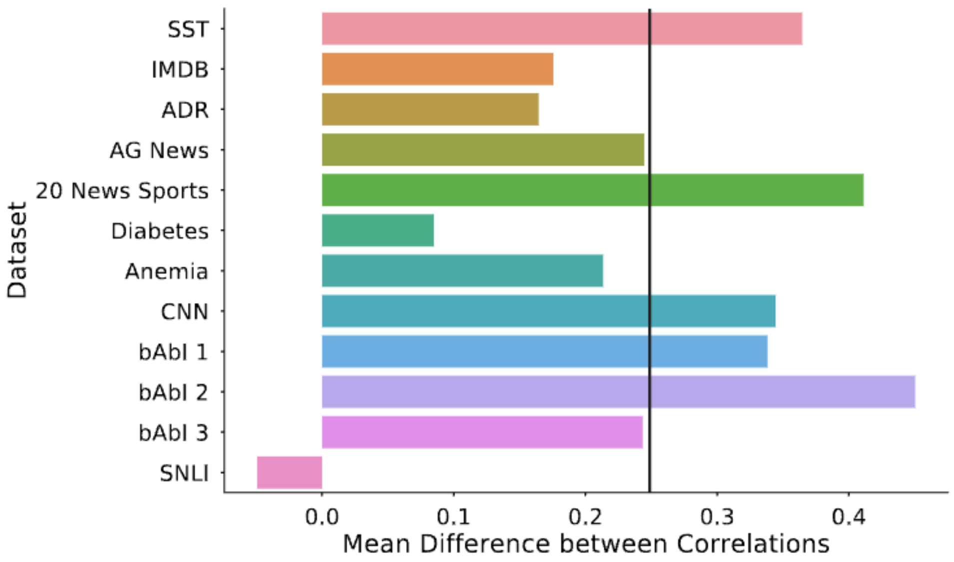
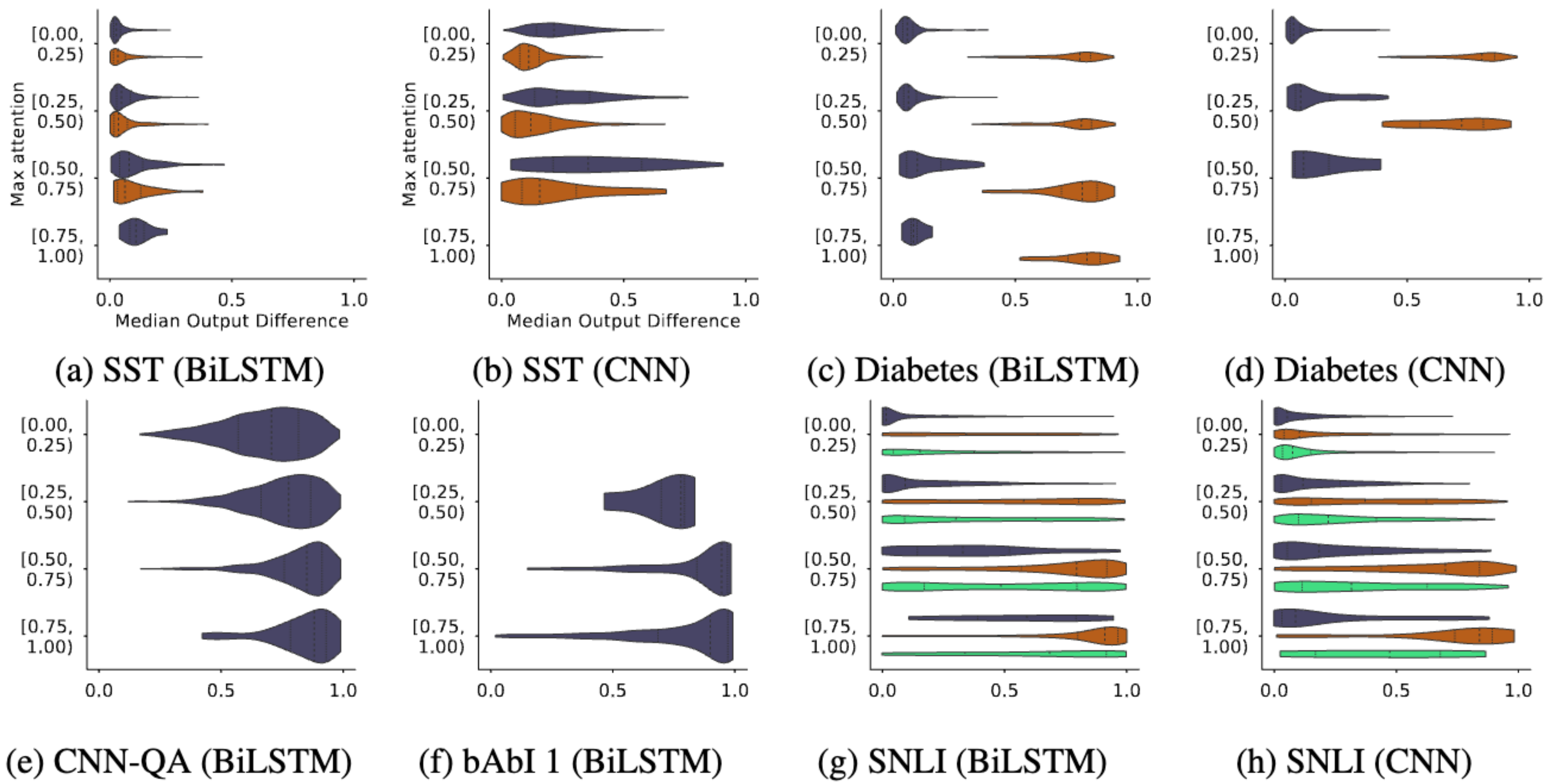


Figure 7: Mean difference in correlation of (i) LOO vs. Gradients and (ii) Attention vs. Gradients using BiLSTM Encoder + Tanh Attention. On average the former is more correlated than the latter by ∼0.25 τ_g.

Permutate Attention Weights



Adversarial Attention Weights

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 years old kid anymore

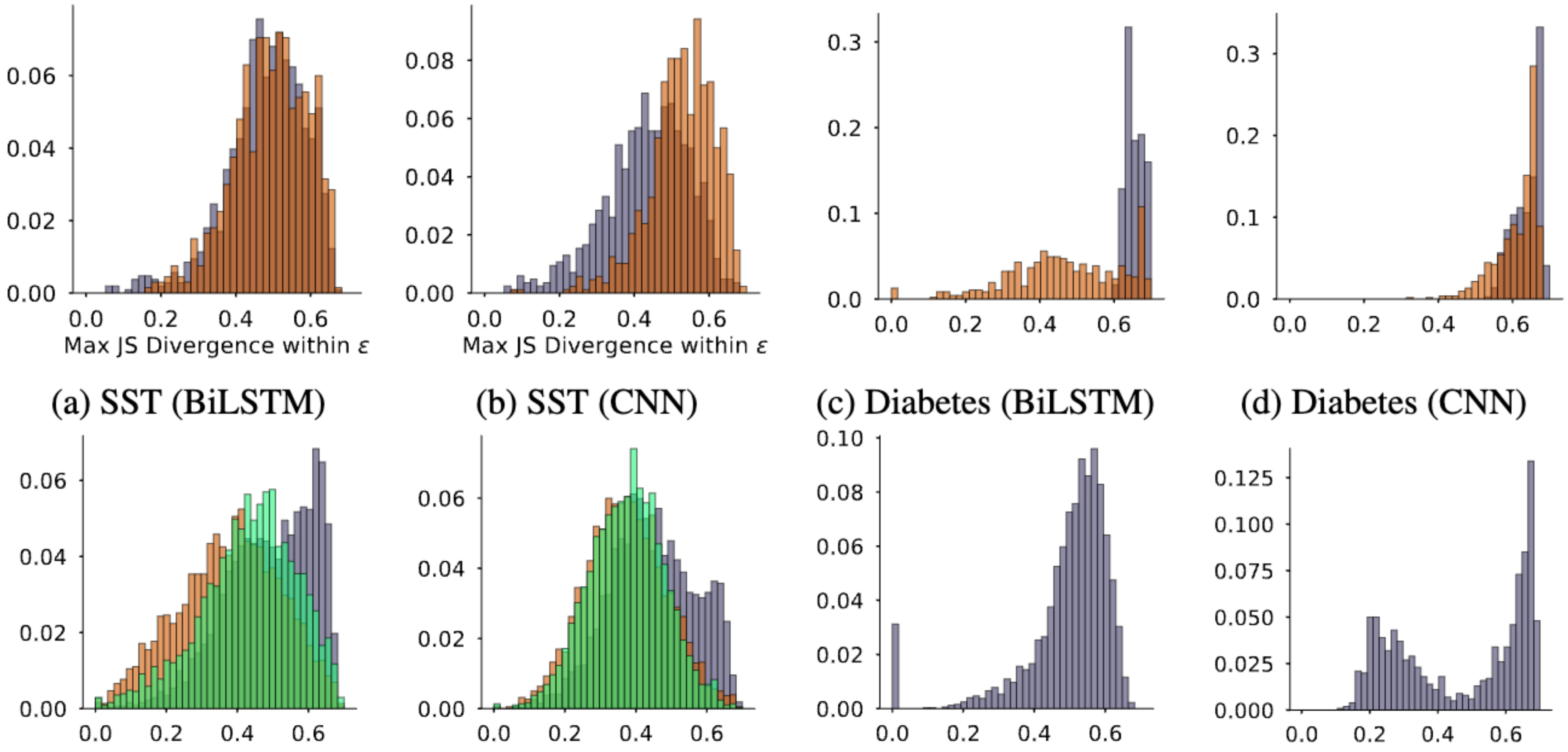
original α

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

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 years old kid anymore

adversarial $\tilde{\alpha}$

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



(a) SST (BiLSTM) (b) SST (CNN) (c) Diabetes (BiLSTM) (d) Diabetes (CNN)

(e) SNLI (BiLSTM) (f) SNLI (CNN) (g) CNN-QA (BiLSTM) (h) BAbI 1 (BiLSTM)

Takeaways

- Attention weight is not stable enough to be explanations

Attention is not Explanation

Sarthak Jain
Northeastern University
jain.sar@husky.neu.edu

Byron C. Wallace
Northeastern University
b.wallace@northeastern.edu

Attention is not not Explanation

Sarah Wiegreffe*
School of Interactive Computing
Georgia Institute of Technology
saw@gatech.edu

Yuval Pinter*
School of Interactive Computing
Georgia Institute of Technology
uvp@gatech.edu

Uniform Attentions

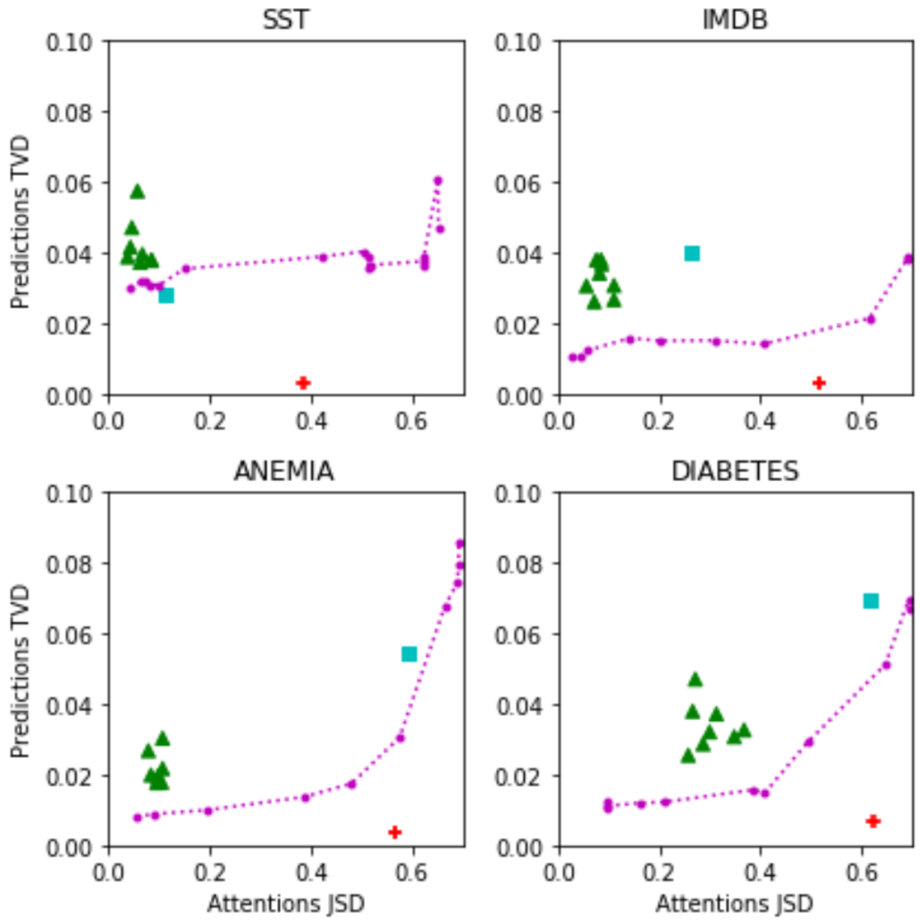
- If attention models are not useful compared to very simple baselines, there is no point in using their outcomes for any type of explanations

Dataset	Attention (Base)		Uniform
	Reported	Reproduced	
Diabetes	0.79	0.775	0.706
Anemia	0.92	0.938	0.899
IMDb	0.88	0.902	0.879
SST	0.81	0.831	0.822
AgNews	0.96	0.964	0.960
20News	0.94	0.942	0.934

Training an Adversary

- Attention distribution is not a primitive
  - We need to re-train for adversarial attention weights

$$\mathcal{L}(\mathcal{M}_a, \mathcal{M}_b)^{(i)} = \text{TVD}(\hat{y}_a^{(i)}, \hat{y}_b^{(i)}) - \lambda\ \text{KL}(\boldsymbol{\alpha}_a^{(\mathbf{i})} \parallel \boldsymbol{\alpha}_b^{(\mathbf{i})})$$



Takeaways

- Is attention good explanations?

Personal Thoughts