



# **Rationalizing Neural Predictions**

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#### Motivation

- Complex (neural) models come at the cost of interpretability
- Applications often need interpretable justifications rationales.

this beer **pours ridiculously clear with tons of carbonation** that forms a rather impressive rocky head that settles slowly into a fairly dense layer of foam. **this is a real good lookin' beer**, unfortunately it gets worse from here ... first, **the aroma is kind of bubblegum-like and grainy.** next, the taste is sweet and grainy with an unpleasant bitterness in the finish. ... ... overall, the fat weasel is good for a fairly cheap buzz, but only if you like your beer grainy and bitter .



review with rationales

#### Motivation

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There is no evidence of extranodal extension. BREAST (RIGHT), EXCISIONAL BIOPSY: INVASIVE DUCTAL CARCINOMA (SEE TABLE #1). DUCTAL CARCINOMA IN-SITU, GRADE 1. ATYPICAL DUCTAL HYPERPLASIA. LOBULAR NEOPLASIA (ATYPICAL LOBULAR HYPERPLASIA). TABLE OF PATHOLOGICAL FINDINGS #1 INVASIVE CARCINOMA

... ...



prediction: high risk of recurring cancer

Doctors won't trust machines, unless evidence is provided

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- Applications often need interpretable justifications rationales.

# Our goal: make powerful models more interpretable by learning rationales behind the prediction

### **Problem Setup**

Interpretability via providing concise evidence from input

Rationales (evidence) should be:

- short and coherent pieces
- sufficient for correct prediction

#### Rationales are not provided during training

in contrast to (Zaidan et al., 2007; Marshall et al., 2015; Zhang et al., 2016)

#### Use powerful neural nets to avoid accuracy loss

in contrast to (Thrun, 1995; Craven and Shavlik, 1996; Ribeiro et al., 2016)

Generator gen(x)

Encoder *enc(z)* 

two modular components gen() and enc()





#### generator specifies the distribution of rationales

input x



prediction y

encoder makes prediction given rationale

input x



prediction y

two components optimized jointly

#### Generator Implementations



independent selection, feedforward net

#### Generator Implementations



independent selection, bi-directional RNNs

### **Generator Implementations**



#### dependent selection, bi-directional RNNs

choose networks based on the data/application

# Training Objective



Minimizing expected cost:

$$\min_{\theta} \sum_{(\mathbf{x},\mathbf{y})\in D} \mathbb{E}_{\mathbf{z}\sim gen(\mathbf{x})} \left[ cost(\mathbf{z},\mathbf{y}) \right]$$

intractable because summation over z is exponential

### Learning Method

• Possible to sample the gradient, e.g.:

$$\mathbb{E}_{\mathbf{z} \sim \text{gen}(\mathbf{x})} \left[ \text{cost}(\mathbf{z}, \mathbf{y}) \ \frac{\partial \log P(\mathbf{z} | \mathbf{x})}{\partial \theta_g} \right]$$
$$\approx \ \frac{1}{N} \sum_{i=1}^{N} \text{cost}(\mathbf{z}_i, \mathbf{y}_i) \frac{\partial \log P(\mathbf{z}_i | \mathbf{x}_i)}{\partial \theta_g}$$

where *zi* are sampled rationales

• Stochastic gradient decent on sampled gradients

# Learning as Policy Gradient Method



#### Experiments

Three real-world datasets and applications for evaluation:

Predicting sentiment for product reviews

Parsing medical pathology reports

Finding similar posts on QA forum

# **Evaluation: Product Review**

Dataset: multi-aspect beer reviews from *BeerAdvocate* (McAuley et al, 2012) 1.5m in total 1,000 reviews annotated at sentence level with aspect label (used only for evaluation)

#### Task: predict ratings and rationales for each aspect

this beer **pours ridiculously clear with tons of carbonation** that forms a rather impressive rocky head that settles slowly into a fairly dense layer of foam. **this is a real good lookin' beer**, unfortunately it gets worse from here ... first, **the aroma is kind of bubblegum-like and grainy.** next, the taste is sweet and grainy with an unpleasant bitterness in the finish. ... ... overall, the fat weasel is good for a fairly cheap buzz, but only if you like your beer grainy and bitter .

Ratings
Look: 5 stars
Aroma: 2 stars

# Evaluation: Product Review

Set-up: ratings are fractional; treat the task as regression following (McAuley et al, 2012) use recurrent networks for *gen()* and *enc()* 

Metrics: precision: percentage of selected words in correct sentences

mean squared error on sentiment prediction

**Baselines:** SVM classifier attention-based RNN

#### **Sentiment Prediction**



#### Sentiment Prediction



rationales getting close performance to full text

#### **Sentiment Prediction**



advantage of neural models over linear classifiers still clear

#### Precision of Rationales

#### Examples and precisions of rationales

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

poured into a snifter . **produces a small coffee head that reduces quickly . black as night** . pretty typical imp . **roasted malts** hit on the nose . **a little sweet chocolate follows** . big toasty character on the taste . in between i 'm getting plenty of dark chocolate and some bitter espresso . it finishes with hop bitterness . **nice smooth mouthfeel with perfect carbonation for the** style . overall a nice stout i would love to have again , maybe with some age on it .



#### more examples available at

https://github.com/taolei87/rcnn/tree/master/code/rationale

#### Precision of Rationales



proper modeling leads to better rationale

#### Learning Curves

Learning curves of cost(z) on dev and precision on test



find good rationales after epochs of exploration

# Evaluation: Parsing Pathology Report

- **Dataset:** patients' pathology reports from hospitals such as MGH
- Task:check if a disease/symptom is positive in textbinary classification for each category

- Statistics: several thousand report for each category pathology report is long (>1000 words) but structured
- Model: use CNNs fro gen() and enc()

# **Evaluation: Parsing Pathology Report**

Category:

IDC

LCIS

Accession Number <unk> Report Status Final Type Surgical Pathology ... Pathology Report: LEFT BREAST ULTRASOUND GUIDED CORE NEEDLE BIOPSIES ... INVASIVE DUCTAL CARCINOMA poorly differentiated modified Bloom Richardson grade III III measuring at least 0 7cm in this limited specimen Central hyalinization is present within the tumor mass but no necrosis is noted No lymphovascular invasion is identified No in situ carcinoma is present Special studies were performed at an outside institution with the following results not reviewed ESTROGEN RECEPTOR NEGATIVE PROGESTERONE RECEPTOR NEGATIVE ...

... **Extensive** LCIS DCIS **Invasive** carcinoma of left breast FINAL DIAGNOSIS BREAST **LEFT LOBULAR CARCINOMA IN SITU PRESENT** ADJACENT TO PREVIOUS BIOPSY SITE SEE NOTE CHRONIC INFLAMMATION ORGANIZING HEMORRHAGE AND FAT NECROSIS BIOPSY SITE NOTE There is a second area of focal lobular carcinoma in situ noted with pagetoid spread into ducts No vascular invasion is seen The margins are free of tumor No tumor seen in 14 lymph nodes examined BREAST left breast is a <unk> gram 25 x 28 x 6cm left ...

97%

F-score:

98%

LVI

FINAL DIAGNOSIS BREAST RIGHT EXCISIONAL BIOPSY INVASIVE DUCTAL CARCINOMA DUCTAL CARCINOMA IN SITU SEE TABLE 1 MULTIPLE LEVELS EXAMINED TABLE OF PATHOLOGICAL FINDINGS 1 INVASIVE CARCINOMA Tumor size <unk> X <unk> X 1 3cm Grade 2 Lymphatic vessel invasion Present Blood vessel invasion Not identified Margin of invasive carcinoma Invasive carcinoma extends to less than 0 2cm from the inferior margin of the specimen in one focus Location of ductal carcinoma in situ ...

84%

# **Evaluation:** Question Retrieval

Dataset:question posts from AskUbuntu forum<br/>(dos Santos et al., 2015; Lei et al., 2016)<br/>question pairs annotated as similar by users

Task:optimize neural representations such thatdistance between similar questions is small

#### **Rationales:**

underlined texts are question titles what is the easiest way to **install all the media codec available** for ubuntu ? i am having issues with multiple applications prompting me to install codecs before they can play my files . <u>how do i install media codecs</u> ?

please any one give the solution for this whenever i try to **convert the rpm file to deb** file i always get this problem error : <unk> : not an **rpm package** ( or package **manifest** ) error executing `` lang=c rpm -qp -- queryformat % { name } <unk> ' '' : at <unk> line 489 thanks . <u>converting **rpm file**</u> <u>to debian file</u>

#### Conclusion

- We present a prototype framework for rationalizing model predictions, and evaluate it quantitatively and qualitatively on various applications
- A lot of interesting future work



poured into a snifter . produces a small coffee head that reduces quickly . black as night . pretty typical imp . roasted malts hit on the nose . a little sweet chocolate follows . big toasty character on the taste . good looking
heavy palate
chocolate smell



#### *improve training (variance reduction)*

•••

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Thank you!

Code & data available at

https://github.com/taolei87/rcnn/tree/master/code/rationale

## Past Approaches

- How model interpretability is achieved ?
  - learning sparse, interpretable word vectors
     (Faruqui et al., 2015; Herbert and Vecchi, 2015)
  - learning interpretable approximations of neural networks (e.g. "if-then" rules, linear classifiers and decision trees) (*Thrun, 1995; Craven and Shavlik, 1996; Ribeiro et al., 2016*)



# Past Approaches

- How rationales (evidence) are defined / obtained ?
  - improve text classifications using rationale annotations (e.g. when training data is limited)

(Zaidan et al., 2007; Marshall et al., 2015; Zhang et al., 2016)

#### input x



#### **Rationales for Product Review**





Rationales improve user experience