

# MOVING BEYOND SUPERVISED REALM

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# NLP@ICLR

DEEP BIAFFINE ATTENTION FOR NEURAL  
DEPENDENCY PARSING

REASONET: LEARNING TO STOP READING IN MA-  
CHINE COMPREHENSION

VOCABULARY SELECTION STRATEGIES  
FOR NEURAL MACHINE TRANSLATION

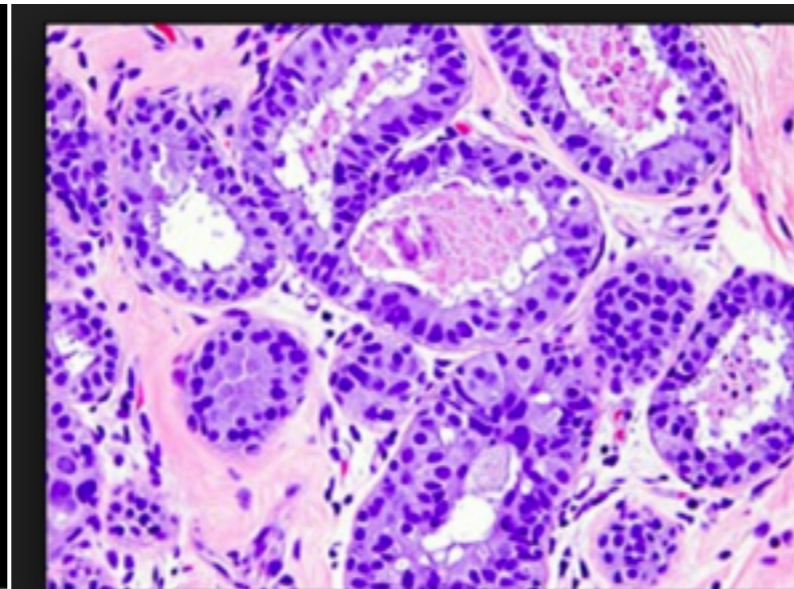
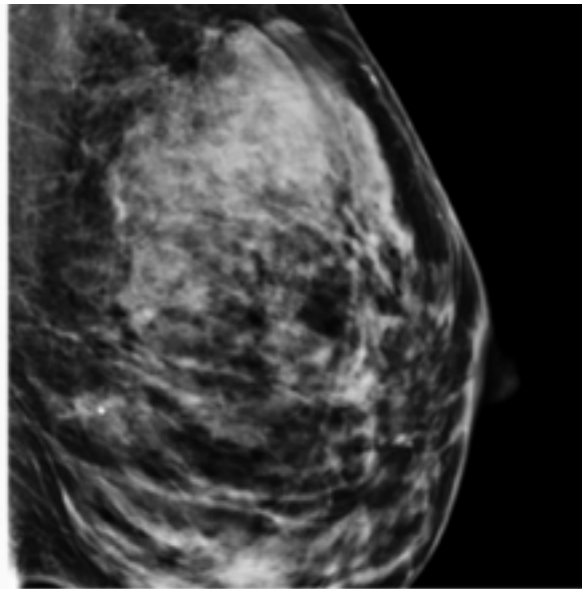
DEEP CHARACTER-LEVEL NEURAL MACHINE  
TRANSLATION BY LEARNING MORPHOLOGY

ITERATIVE REFINEMENT  
FOR MACHINE TRANSLATION

A CONVOLUTIONAL ENCODER MODEL FOR NEURAL  
MACHINE TRANSLATION

REFERENCE-AWARE LANGUAGE MODELS

# Modeling Disease Progression



AST	8~ 40 U/L
ALT	5~ 40 U/L
LDH	50~400 U/L
ALP	80~280 U/L
γ-GTP	0~ 50 U/L
ZTT	4~ 12 KU
TTT	0~ 5 KU
Total bilirubin	0.4~0.9 mg/dℓ
Direct bilirubin	0~0.4 mg/dℓ
Indirect bilirubin	0.4~0.5 mg/dℓ
Total protein	6.0~9.0 g/dℓ



Clinical Prediction

**Predict Recurrences, Sensitivity to Treatment,  
Population at Risk**

# Game of 20 Questions

***What are the chances of recurrence?***

***Treatment A vs Treatment B?***

***Drug A vs Drug B?***

	No. Patients		HR (95% CI)	HR (95% CI)	No. Events		5-yr DFS %		P
	Tamoxifen+OFS	Tamoxifen			T+OFS	Tamoxifen	T+OFS	Tamoxifen	
All Patients	1015	1018		0.83 (0.66-1.04)	139	160	86.6	84.7	.10
Age at Randomization									.76
< 35	121	112		0.68 (0.41-1.10)	29	35	77.2	67.1	
35-39	184	203		0.78 (0.49-1.24)	33	41	81.7	80.1	
40-44	311	307		0.92 (0.59-1.43)	38	41	87.3	86.2	
45-49	301	305		1.01 (0.60-1.72)	28	27	92.1	92.4	
≥ 50	98	91		0.64 (0.30-1.39)	11	16	88.3	85.2	
Lymph Node Status									.33
pN0	662	662		0.69 (0.48-0.97)	54	76	92.5	89.8	
pN+ 1-3	257	258		1.03 (0.69-1.56)	47	45	80.7	80.8	
pN+ 4+	96	98		0.81 (0.52-1.26)	38	39	62.5	58.7	
Tumor Size									.12
< 1 cm	160	167		0.45 (0.22-0.92)	11	24	92.7	85.7	
1-2 cm	496	509		0.76 (0.52-1.12)	45	59	92.0	89.8	
> 2-5 cm	293	280		0.87 (0.60-1.26)	56	59	80.4	78.1	
> 5 cm	41	35		1.60 (0.74-3.43)	19	10	55.2	68.9	
Unknown	25	27			8	8			

**Answers:**

- Check this clinical study, but it is [old, inconclusive,...]
- Your decision at the end

Today, almost all of our cancer treatment insights come from a tiny subset of clinical trial patients. In the United States, 1.7 million people are diagnosed each year with cancer, but only 3% enroll in clinical trials. To improve care for every patient, we need insights from the other 97% of people receiving cancer care.



# Data Science Perspective on Clinical Research

- Abstract clinical records into a database



ID	AGE	RACE	STUDY	PROC	BIRTHS	MA_AGE	ASSESS	DENSITY	FINDING	FINDING T
9527	78	2	6/12/06	BIDXU-L	0		P	3	CALCS	N
32875	56	1	7/11/06	BIDX-B	0		N	3		
2247	72	1	4/12/06	BIDXU-R	0		N	3		
45521	61	1	3/30/06	BIDX-B	0		B	3	CALCS	S
48987	41	1	4/5/06	BIDX-B	0		P	3	CALCS	N
4179	67	1	5/12/06	BIDX-B	0		P	2	CALCS	N
26300	59	1	3/31/06	BIDXU-L	0		N	3		
67960	64	1	4/7/06	BIDXU-R	0		P	3	MASS	O
43283	61 W		7/21/06	BIDX-B	0		B	3		
43319	51	1	4/7/06	BIDX-B	0		N	3		

- Run multivariate analysis to identify the correlation between features and outcomes

Standard data analysis methodology in modeling disease progression, treatment efficacy, and diagnosis

# Manually Constructed Databases Rule!

- Seriously labour intensive
- Fraught with unknown values (see # of births) and errors

ID	AGE	RACE	STUDY	PROC	BIRTHS	MA_AGE	ASSESS	DENSITY	FINDING	FINDING T
9527	78		2 6/12/06	BIDXU-L	0		P	3	CALCS	N
32875	56		1 7/11/06	BIDXB-B	0		N	3		
2247	72		1 4/12/06	BIDXU-R	0		N	3		
45521	61		1 3/30/06	BIDXB-B	0		B	3	CALCS	S
48987	41		1 4/5/06	BIDXB-B	0		P	3	CALCS	N
4179	67		1 5/12/06	BIDXB-B	0		P	2	CALCS	N
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67960	64		1 4/7/06	BIDXU-R	0		P	3	MASS	O
43283	61	W	7/21/06	BIDXB-B	0		B	3		
43319	51		1 4/7/06	BIDXB-B	0		N	3		

Can we automate database construction from raw text?

# Looking for Ways to Contribute





# Predicting Progression of Atypical Lesions

Clinical goal: use chemo prevention to modify the risk of atypical breast lesions

Method: observe lesion progression over time

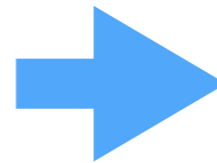
- some lesion types are rare
- analysis requires large corpus of pathology reports



**Kevin S. Hughes, M.D., FACS**  
**Surgical Director, Breast Screening**  
**Co-Director, Avon Comprehensive Breast Evaluation Center**  
**Massachusetts General Hospital**

# Parsing Pathology Reports into Database

Pathology Report: REMOVED\_ACCESSION\_ID  
 ACCESSIONED ON: REMOVED\_DATE  
 CLINICAL DATA: Carcinoma **right breast**.  
 \*\*\* FINAL DIAGNOSIS \*\*\*  
 LYMPH NODE (SENTINEL), EXCISION  
 ( REMOVED\_CASE\_ID ): METASTATIC  
 CARCINOMA IN 1 OF 1 LYMPH NODE.  
 NOTE: The metastatic deposit spans 0.19cm and  
 is identified on H&E and cytokeratin immunostains.  
 A second cytokeratin-positive but cauterized focus  
 likely also represents metastatic tumor (<0.1cm ).  
 There is **no evidence of extranodal extension**.  
 BREAST (RIGHT), EXCISIONAL BIOPSY  
 ( REMOVED\_ACCESSION\_ID :  
 REMOVED\_CASE\_ID -B): **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



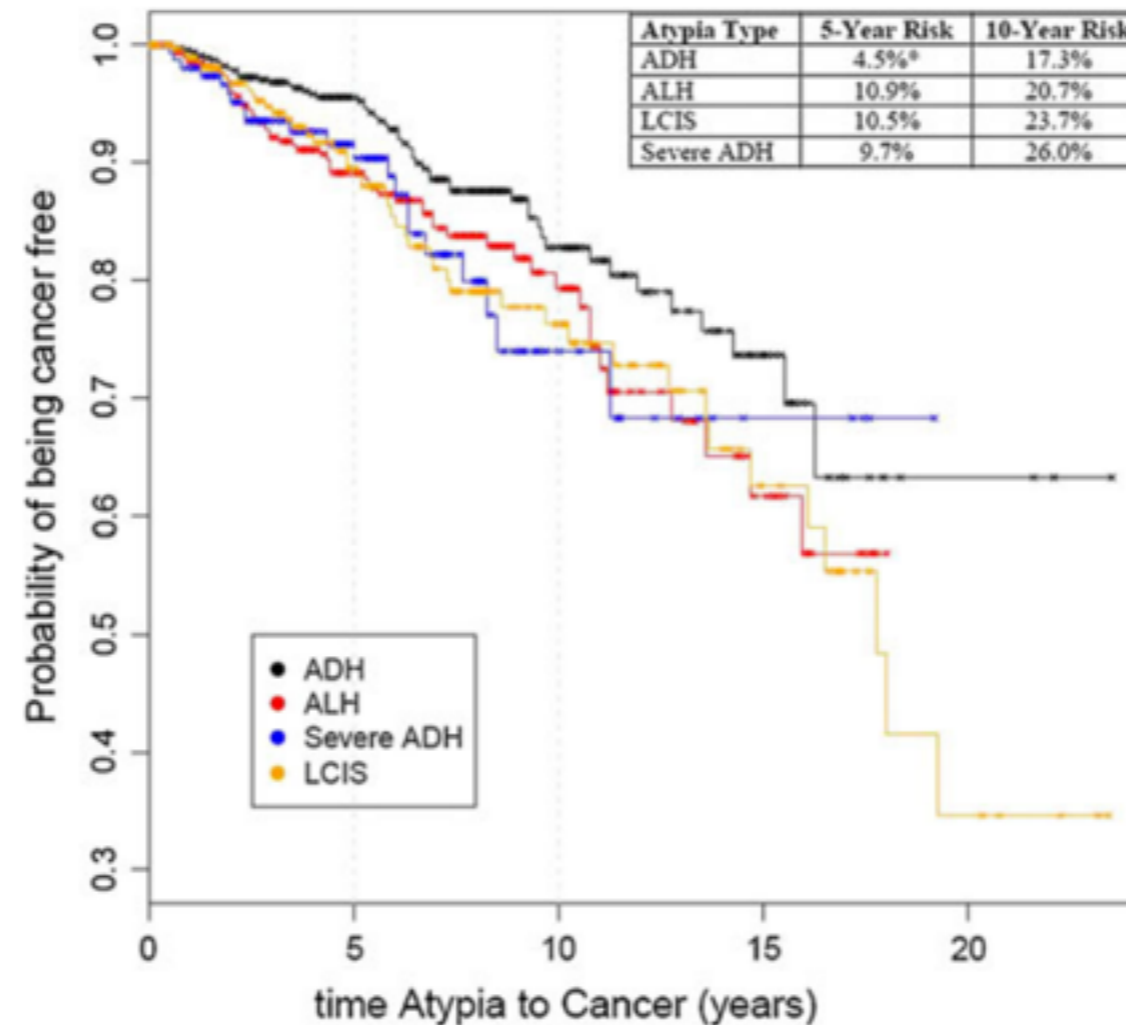
Name	Extraction
Breast Side	Right
Ductal Carcinoma in Situ	Present
Invasive Lobular Carcinoma	Absent
Invasive Ductal Carcinoma	Present
Cancer	Present
Lobular Carcinoma in Situ	Absent
Atypical Ductal Hyperplasia	Present
Atypical Lobular Hyperplasia	Present
Lobular Neoplasia	Present
Flat Epithelial Atypia	Absent
Blunt Adenosis	Absent
Atypia	Present
Positive Lymph Nodes	Present
Extracapsular Axillary Nodal Extension	Absent
Isolated Cancer Cells in Lymph Nodes	Absent
Lymphovascular Invasion	Absent
Blood Vessel Invasion	Absent
Estrogen Receptor Status	Positive
Progesterone Receptor Status	Positive
HER 2 (FISH) Status	Unknown

# Categorization of Reports

## 22 ways to say LCIS

Lobular Carcinoma In-Situ	In Situ Carcinoma Is Interpreted As Lobular
Lobular Carcinoma In Situ	In Situ Carcinoma With Ductal And Lobular
Lobular Carcinoma-In-Situ	In Situ Carcinoma May Be Ductal Or Lobular
Lobular Carcinoma In -Situ	In Situ Carcinoma With Features Of Both Lobular
Lobular Cardinoma In-Situ	In-Situ Carcinoma Has Some Features Of Lobular
In-Situ Carcinoma Is Of Lobular	In-Situ Carcinoma With Both Ductal And Lobular
In-Situ Carcinoma To Be Lobular	In-Situ Carcinoma With Features Of Both Lobular
In-Situ Carcinoma With Lobular	In-Situ Carcinoma With Mixed Ductal And Lobular
	In-Situ Carcinoma Displays Both Ductal And Lobular
In-Situ Carcinoma With Both Lobular	In-Situ Carcinoma Showing Both Ductal And Lobular
In Situ Carcinoma And Atypical Lobular	In-Situ Carcinoma Are Small And Distinction Of Lobular
In Situ Carcinoma Has Ductal And Lobular	In-Situ Carcinoma With Features Of Ductal And Lobular
In-Situ Carcinoma With Ductal And Lobular	In Situ Carcinoma Demonstrates Both Ductal And Lobular

# NLP Leads to Important Clinical Finding!



**Fig. 1** Estimated 5- and 10-year breast cancer risks based on atypia type for the no chemoprevention group. \*Significantly fewer predicted breast cancers at 5 years with ADH ( $p = 0.036$ )

**The role of chemoprevention in modifying the risk of breast cancer in women with atypical breast lesions**

# NLP can Help ... But ...

## CONCLUSION

Go to:

We have created a large database of valuable clinical information from over 76, 000 breast pathology reports. While we have demonstrated the utility of NLP, we have also been struck by the inherent complexity of using NLP in medical care. The time and effort required to use NLP for a single, well-defined problem should give pause to the idea that having data in any electronic format, even free text, will help us improve medical care. The design of Electronic Medical Records that use structured data and depend less and less on free text is critical.

# NOW NORMAL WAY

- Method: train per category classifier based on ngram features
- Training size: 6,000 reports
- Predicts 20 categories, ranging from atypias to tumor markers
- Accuracy: 98.6% (evaluated by two MDs on 500 reports)
- Size: 92K reports, 50K patients, over 30 years
- Development Time: two weeks



Adam Yala, MIT

# Rule-Based IE?!!

- Common in Medical and Bio Informatics

**Using Natural Language Processing to Improve Efficiency of Manual Chart Abstraction in Research: The Case of Breast Cancer Recurrence**

[David S. Carrell](#), [Scott Halgrim](#), [Diem-Thy Tran](#), [Diana S. M. Buist](#), [Jessica Chubak](#), [Wendy W. Chapman](#), and

[Marco Antonio Valenzuela-Escarcega](#), [Gustave Hahn-Powell](#), [Mihai Surdeanu](#), [Thomas Hicks](#):  
**A Domain-independent Rule-based Framework for Event Extraction.** ACL (System Demonstrations) 2015: 127-132

- And Beyond ...

**Rule-Based Information Extraction is Dead! Long Live Rule-Based Information Extraction Systems!**

[Laura Chiticariu](#), [Yunyao Li](#), [Frederick Reiss](#)

*EMNLP*, pp. 827-832, 2013

# Aspect Transfer

## Pathology report:

FINAL DIAGNOSIS: BREAST (LEFT) ... [INVASIVE CARCINOMA](#)  
[Tumor size: num x num x num cm](#) [Grade: 3](#). [Lymphatic vessel invasion: Not identified](#). Blood vessel invasion: Suspicious.  
Margin of invasive carcinoma ...

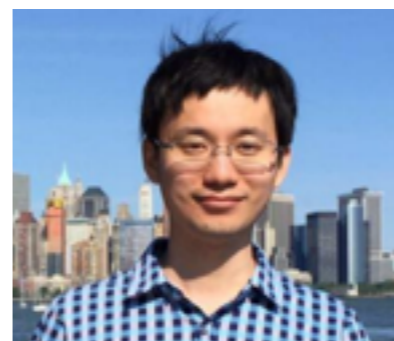
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## Diagnosis results:

IDC: Positive

LVI: Negative

*Transfer:* Source: IDC → Target: LVI



Yuan Zhang



Tommi Jaakkola



# Multi-Aspect Transfer

*Same report; Different key sentences*

Source Aspect: IDC

Target Aspect: LVI

FINAL DIAGNOSIS: BREAST (LEFT) ... INVASIVE CARCINOMA  
Tumor size: num x num x num cm Grade: 3. Lymphatic vessel  
invasion: Not identified. Blood vessel invasion: Suspicious.  
Margin of invasive carcinoma ...

# What to Transfer?

FINAL DIAGNOSIS: BREAST (LEFT) ... INVASIVE CARCINOMA  
Tumor size: num x num x num cm Grade: 3. Lymphatic vessel invasion: Not identified. Blood vessel invasion: Suspicious.  
Margin of invasive carcinoma ...

---

FINAL DIAGNOSIS: BREAST (RIGHT) The specimen examined  
by X. DCIS: Not Identified. ....

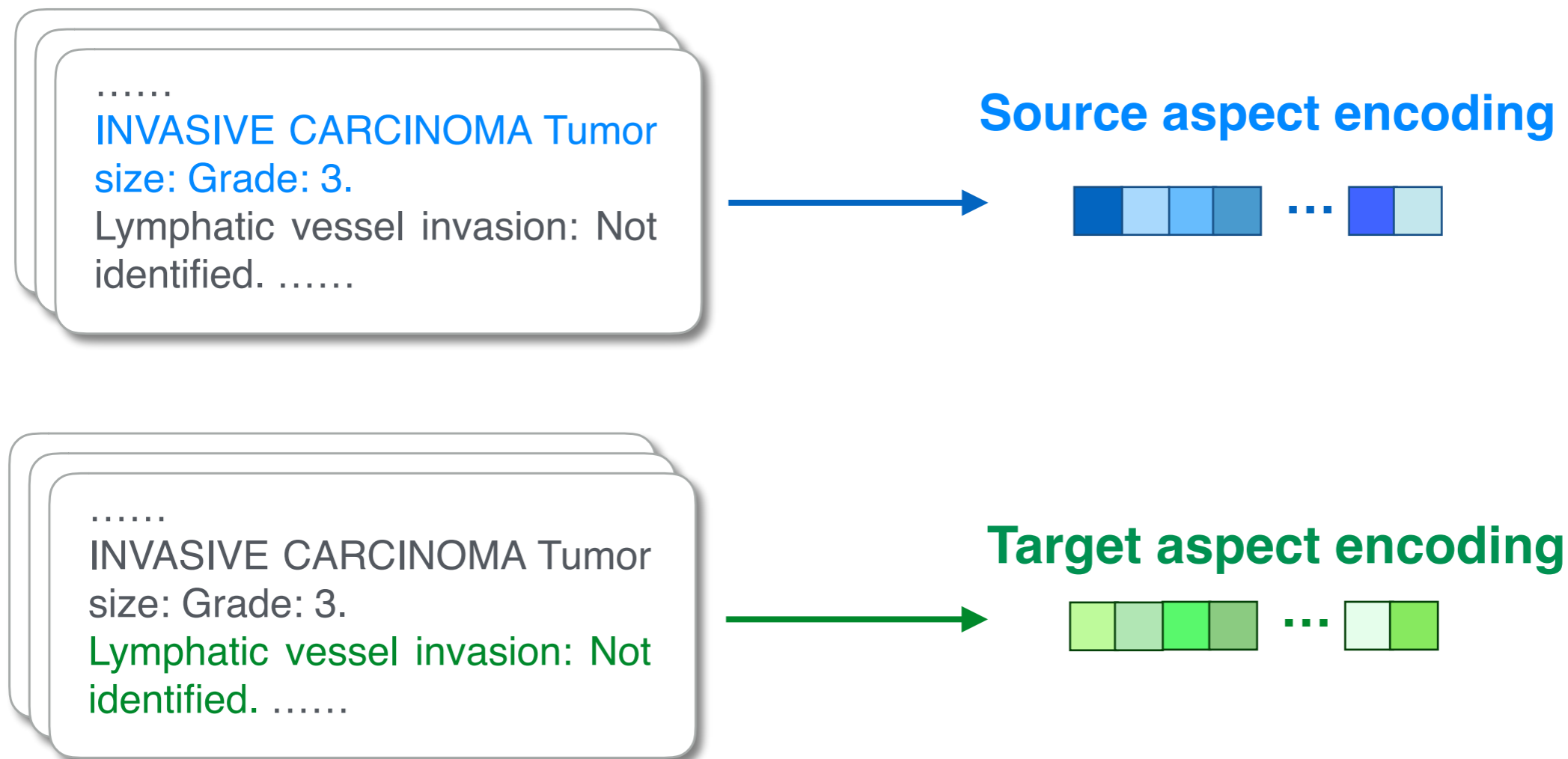
# Available Supervision

	Source	Target
Labeled Data	✓	✗
Unlabeled Data	✓	✓
Relevance Rules	✓	✓

- Relevance rules: common names of aspects
  - ALH: Atypical Lobular Hyperplasia, ALH
  - IDC: Invasive Ductal Carcinoma, IDC

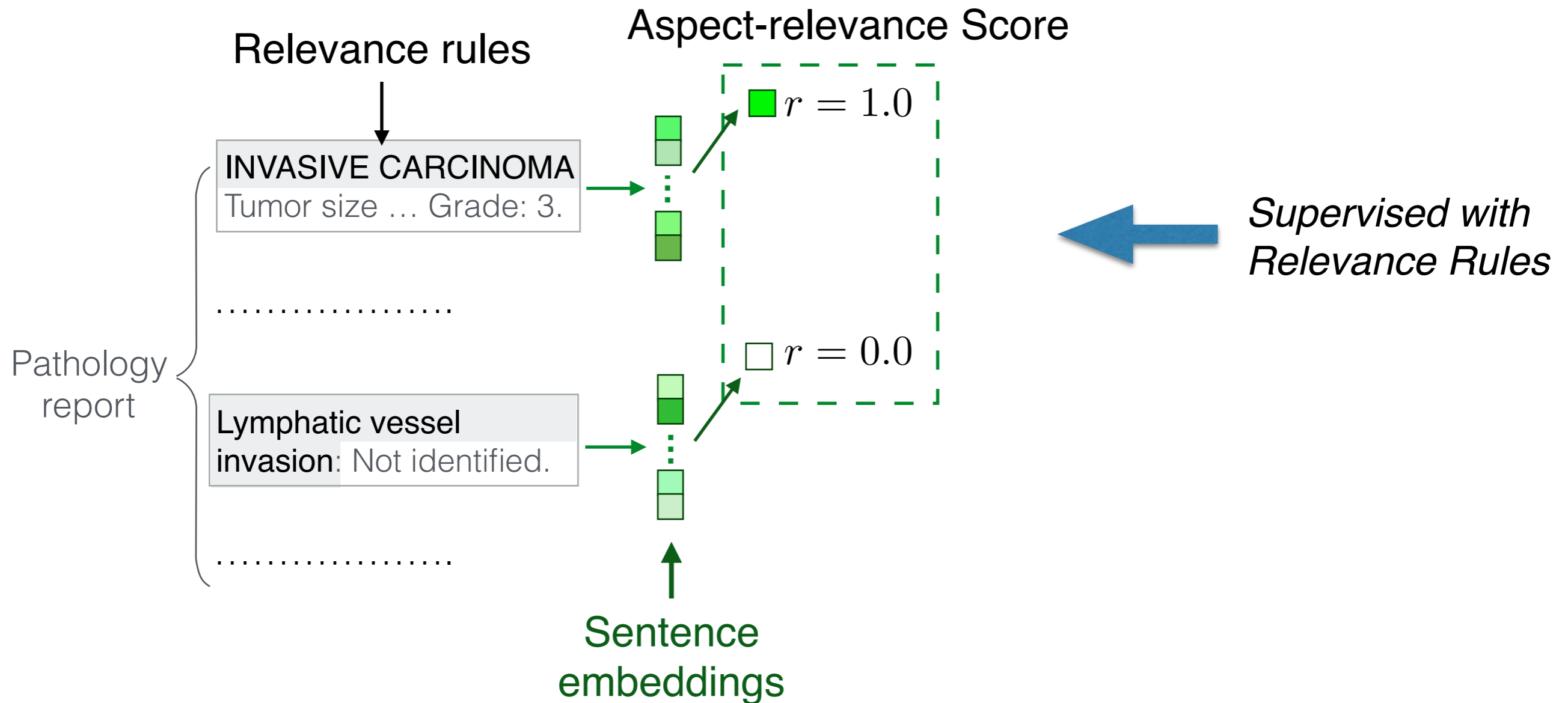
# Key Idea: Aspect-driven Encoding

- Learn differential representations for different tasks from the same input
- Leverage relevance information to learn to identify key fragments



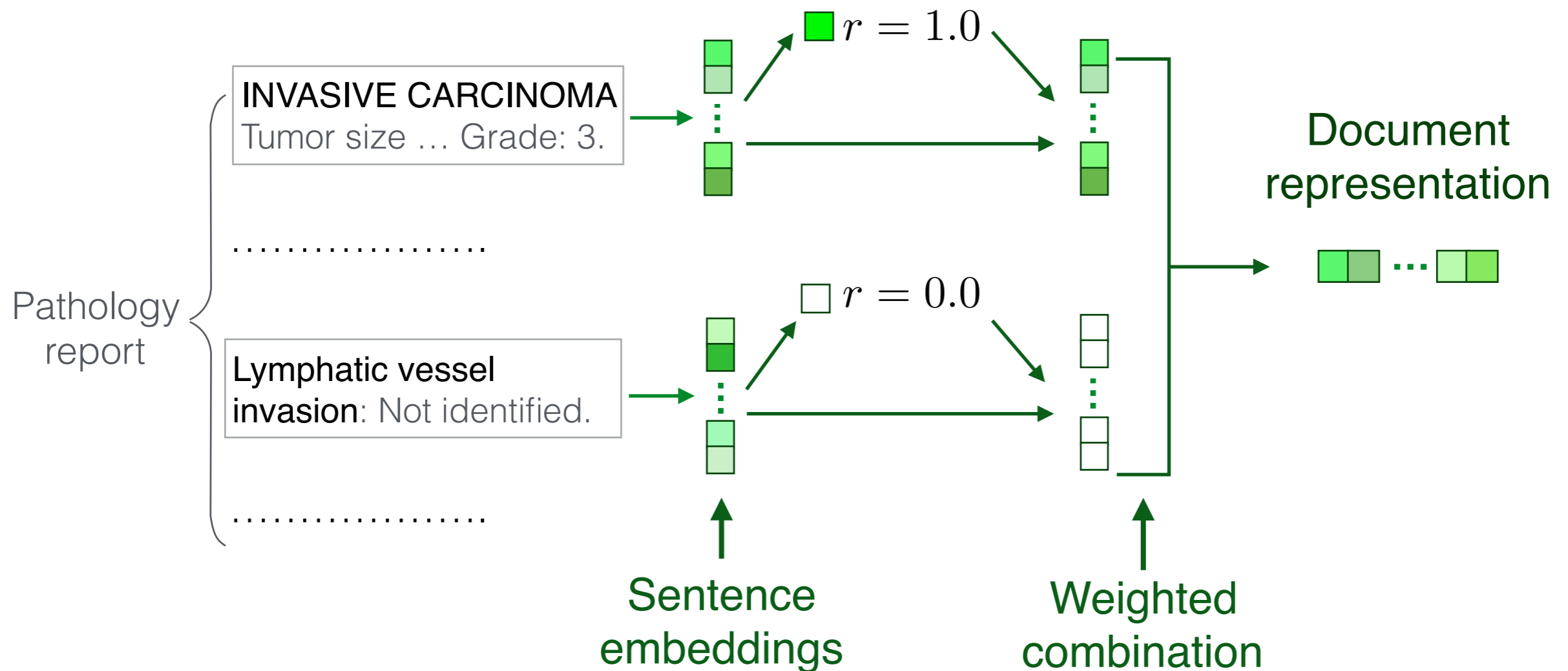
# Aspect-relevance Prediction

- Make prediction based on sentence embeddings
- Train on relevance rules (e.g., names of IDC, LVI)



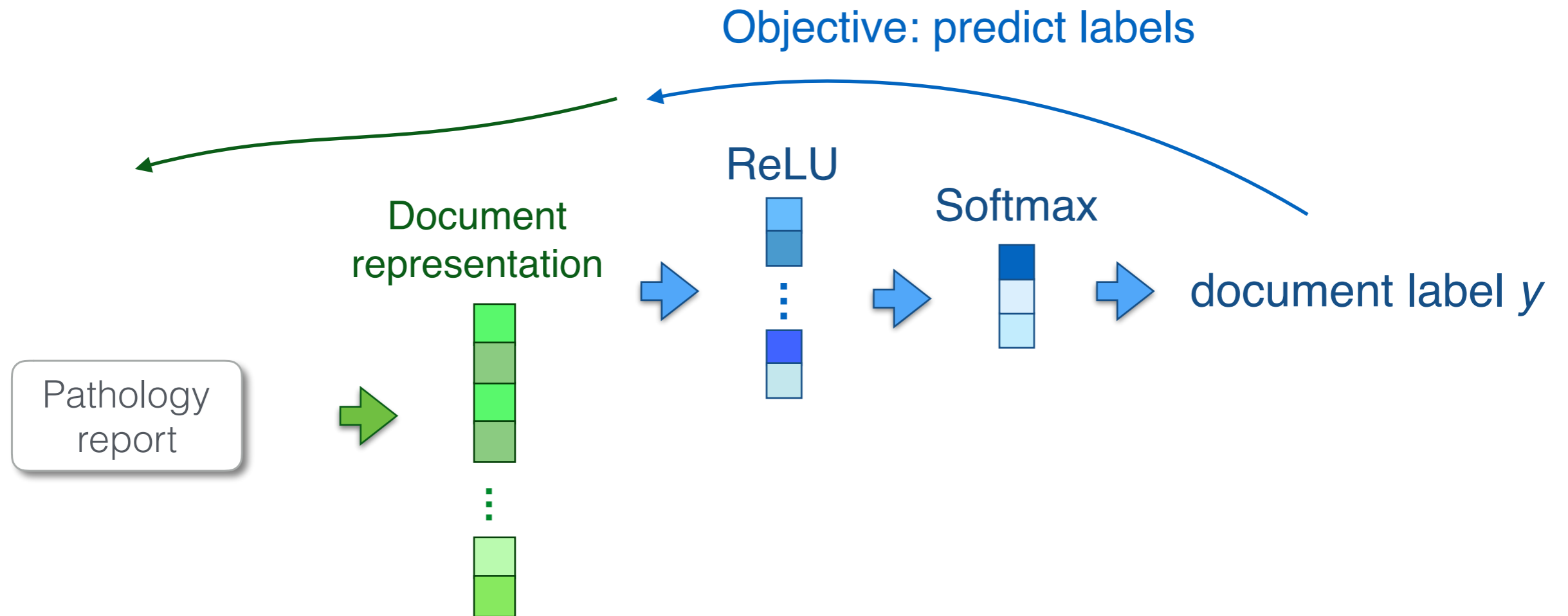
# Document Encoding

- Combine sentence vectors based on relevance weights



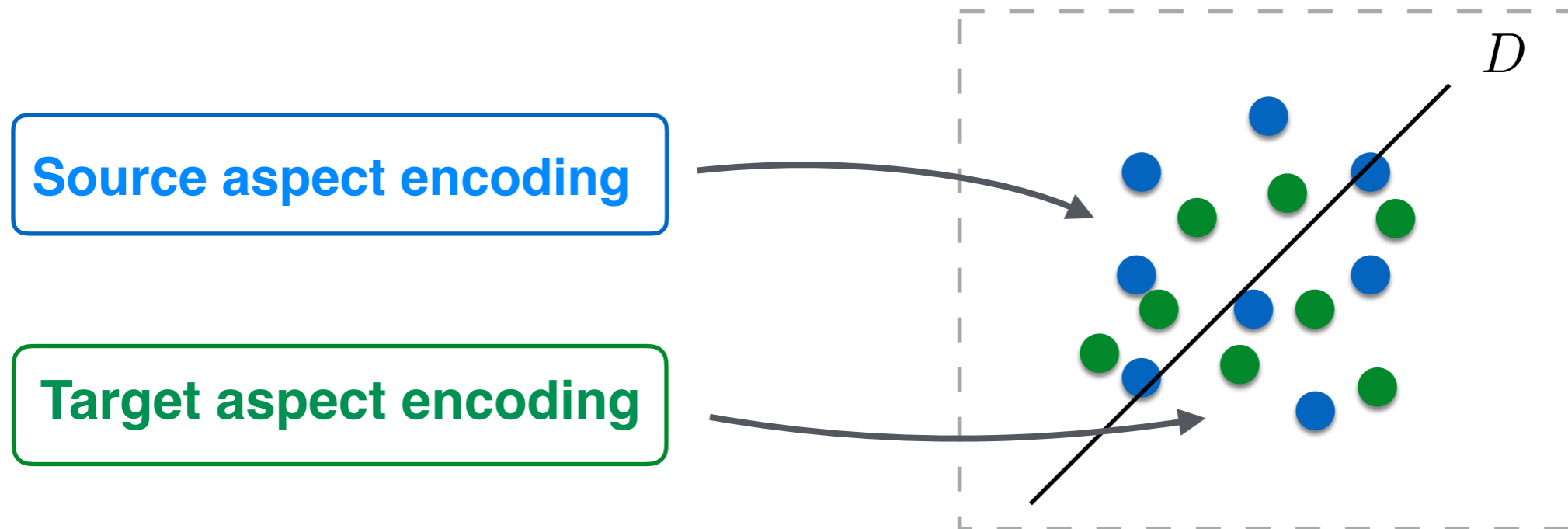
# Primary Label Predictor

- Shared for both source and target aspects
- Train on labeled data in the source aspect



# Key Idea: Domain-Adversarial Training

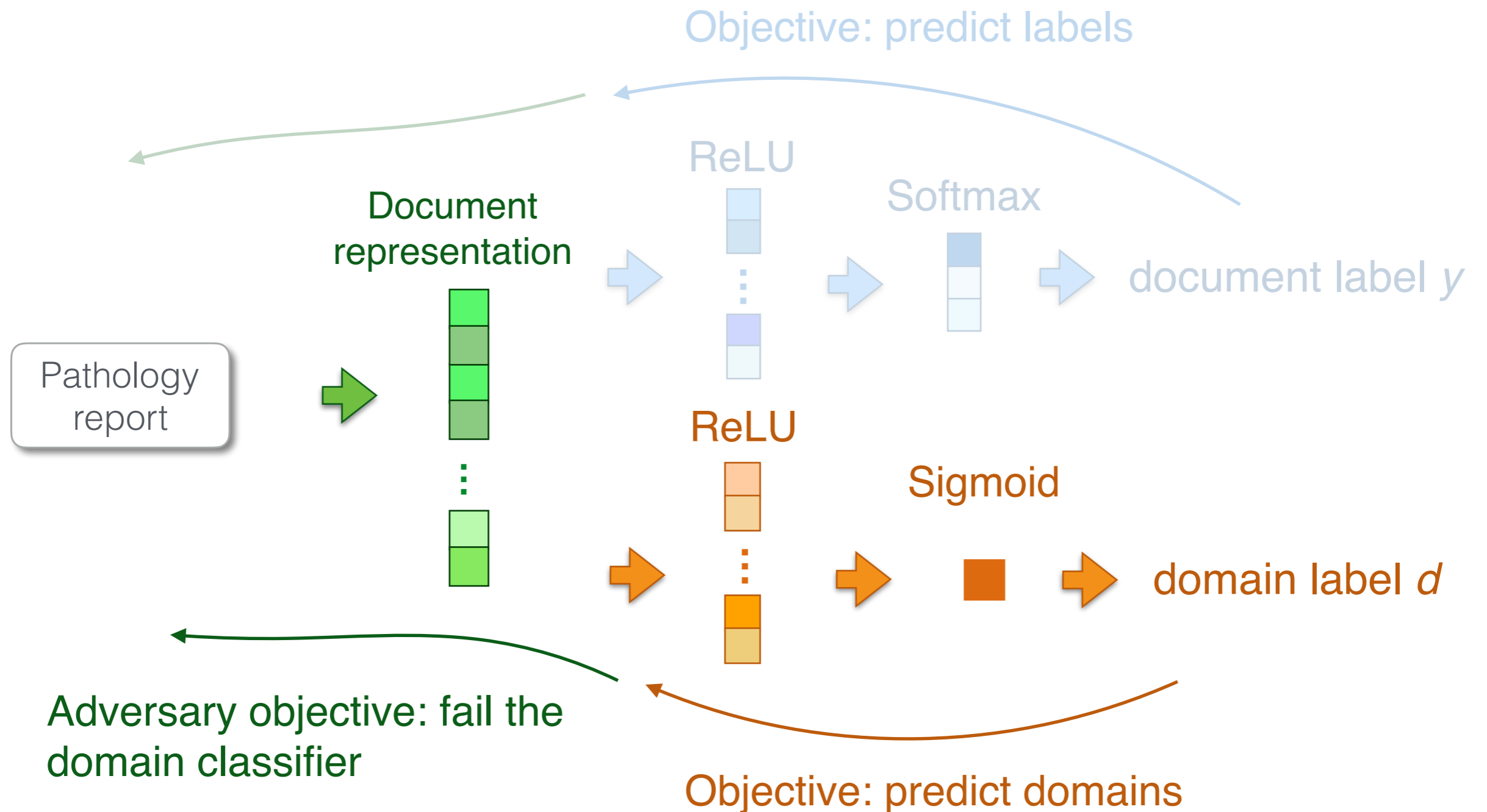
- Use domain-adversarial for learning invariant representations
  - Objective: **Not** separable by the domain



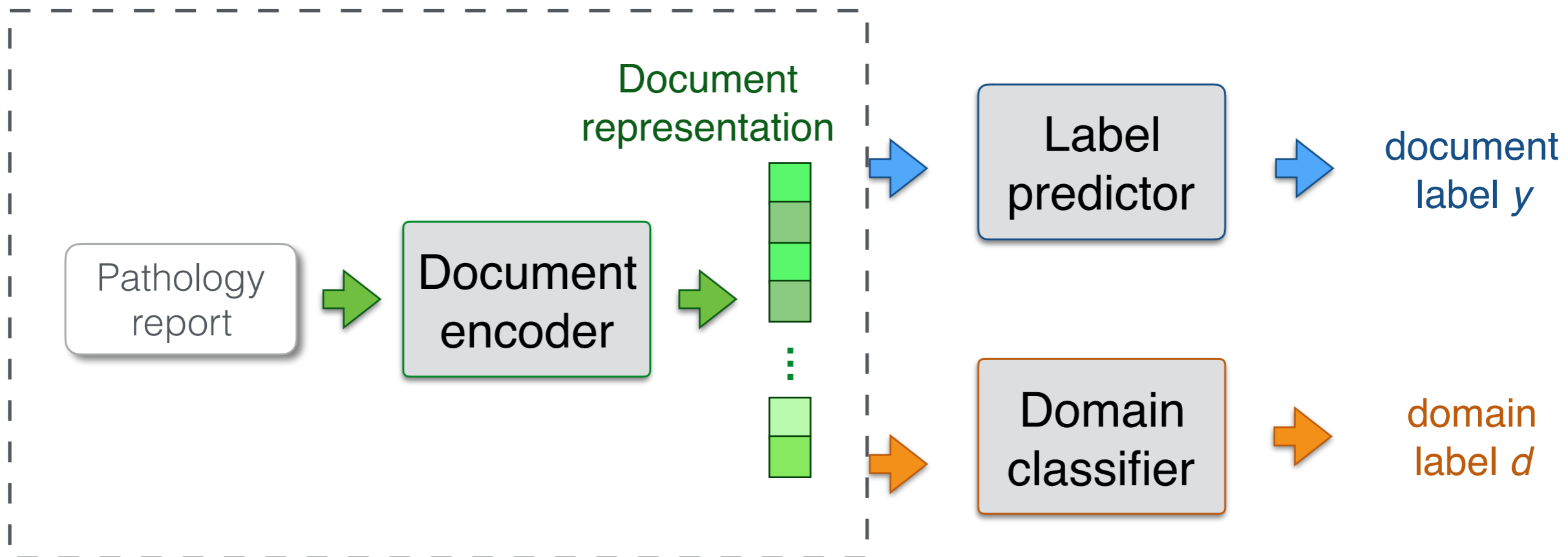


# Domain Classifier and Adversary

- Encourage learning domain-invariant features
- Train on both labeled and unlabeled data

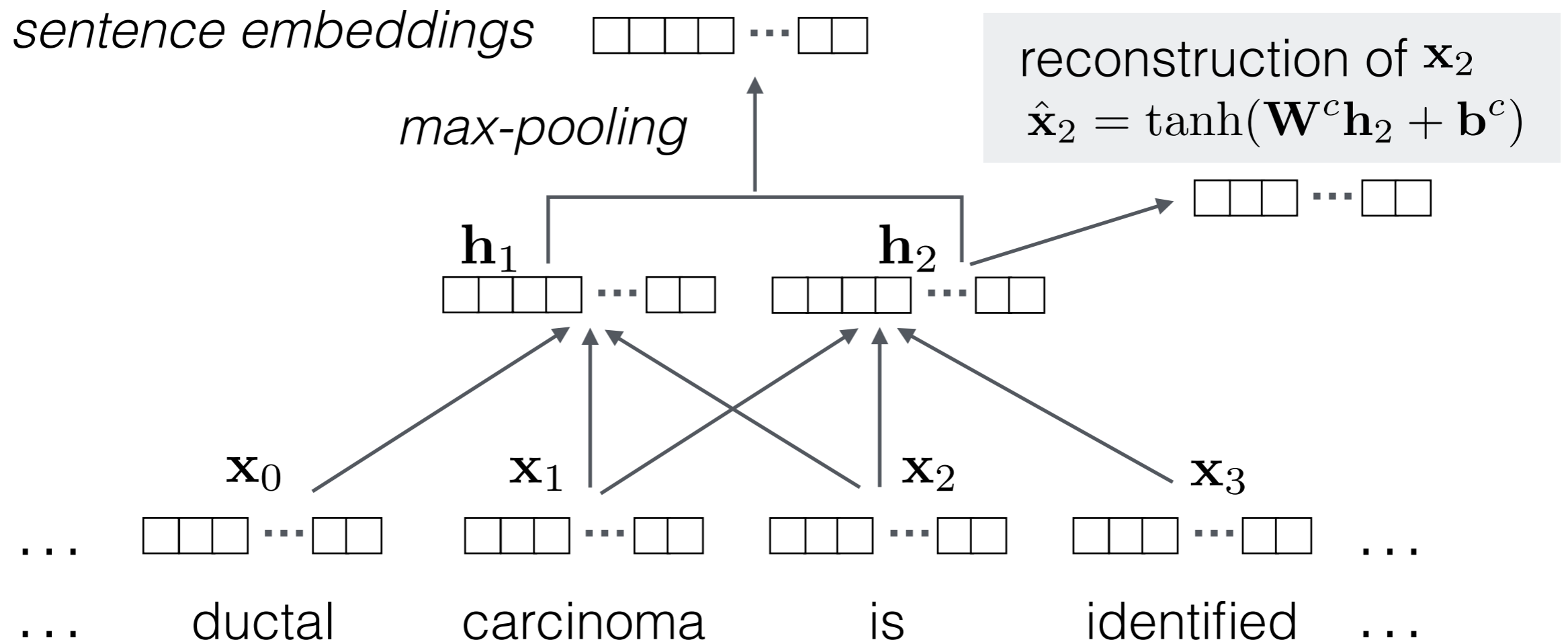


# Model Structure



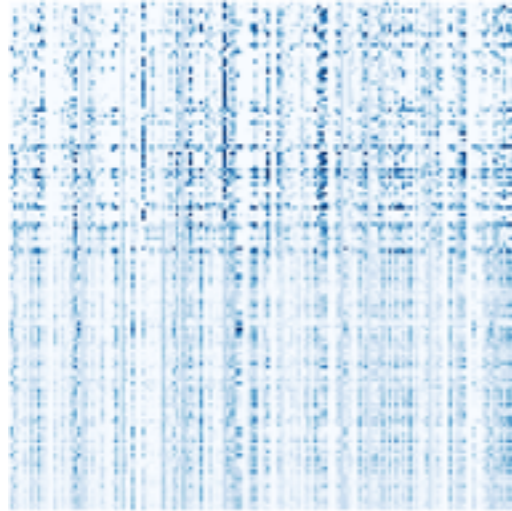
# Sentence Embedding

- Apply a CNN to each sentence
- Keep rich word-level information by **reconstruction**

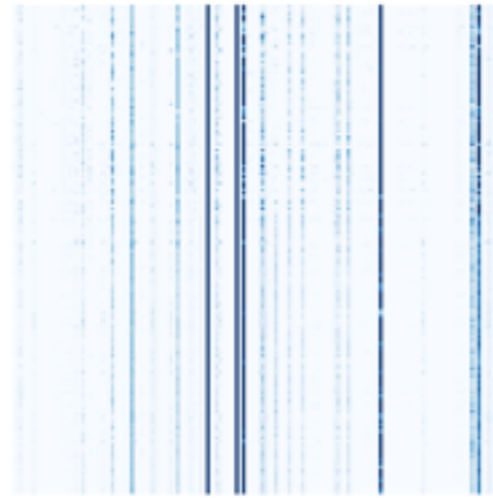


# Impact of Reconstruction

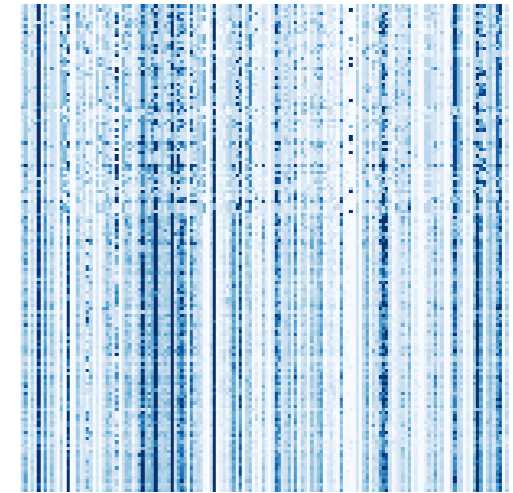
- Heat-map: each row correspond to a vector representation
  - Top: source domain; Bottom: target domain



-adversarial, -reconstruction

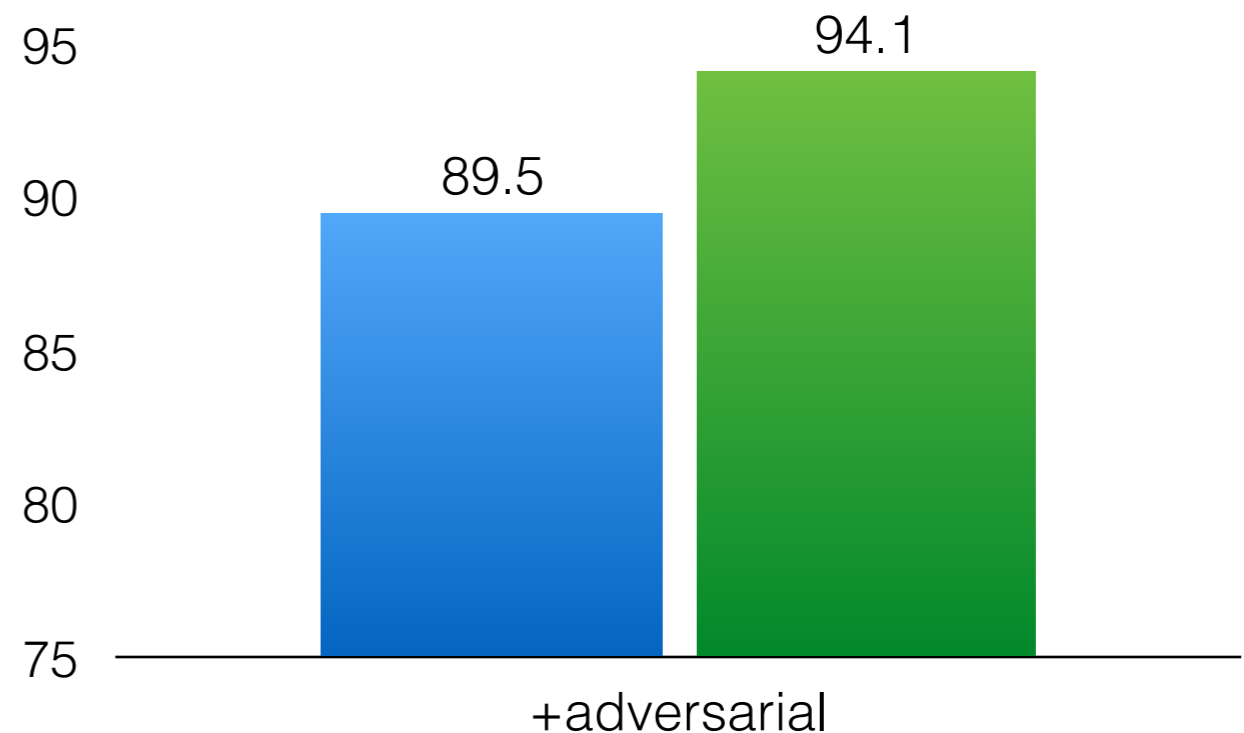


+adversarial, -reconstruction



+adversarial, +reconstruction

- Average accuracy on the pathology dataset



# Pathology Dataset

- Aspect-transfer on breast pathology reports

Source: IDC → Target: LCIS

FINAL DIAGNOSIS: BREAST (LEFT) ... INVASIVE DUCTAL CARCINOMA Grade: 3. Lobular Carcinoma In-situ: Not identified.  
Blood vessel invasion: Suspicious. ...

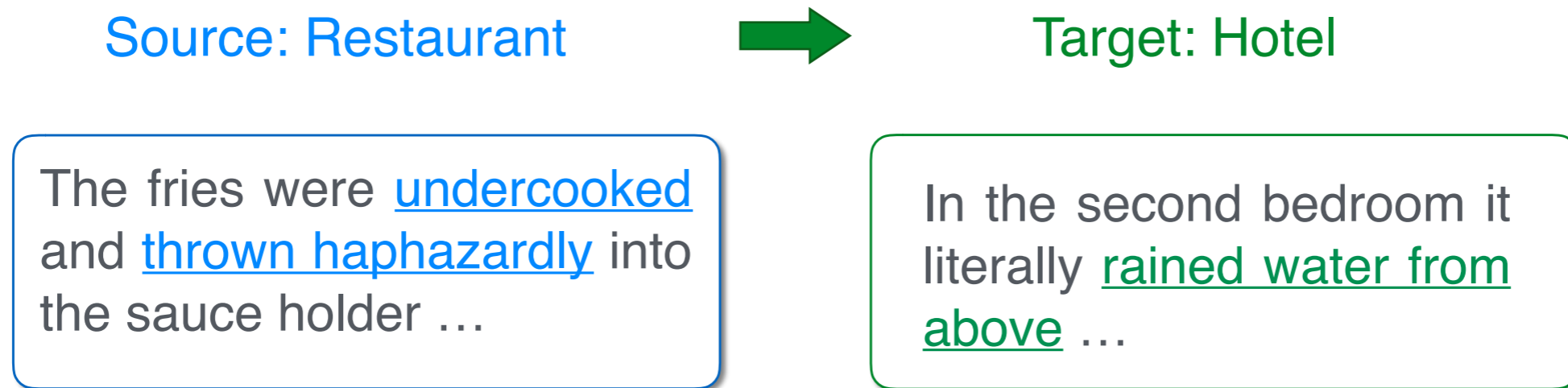
- Statistics and relevance rules:

Aspects	#Labeled	#Unlabeled	Relevance Rules
DCIS	23.8k	96.6k	DCIS, Ductal Carcinoma In-Situ
LCIS	10.7k		LCIS, Lobular Carcinoma In-Situ
IDC	22.9k		IDC, Invasive Ductal Carcinoma
ALH	9.2k		ALH, Atypical Lobular Hyperplasia

- ◆ 500 reports for testing

# Review Dataset

- Domain-transfer on reviews



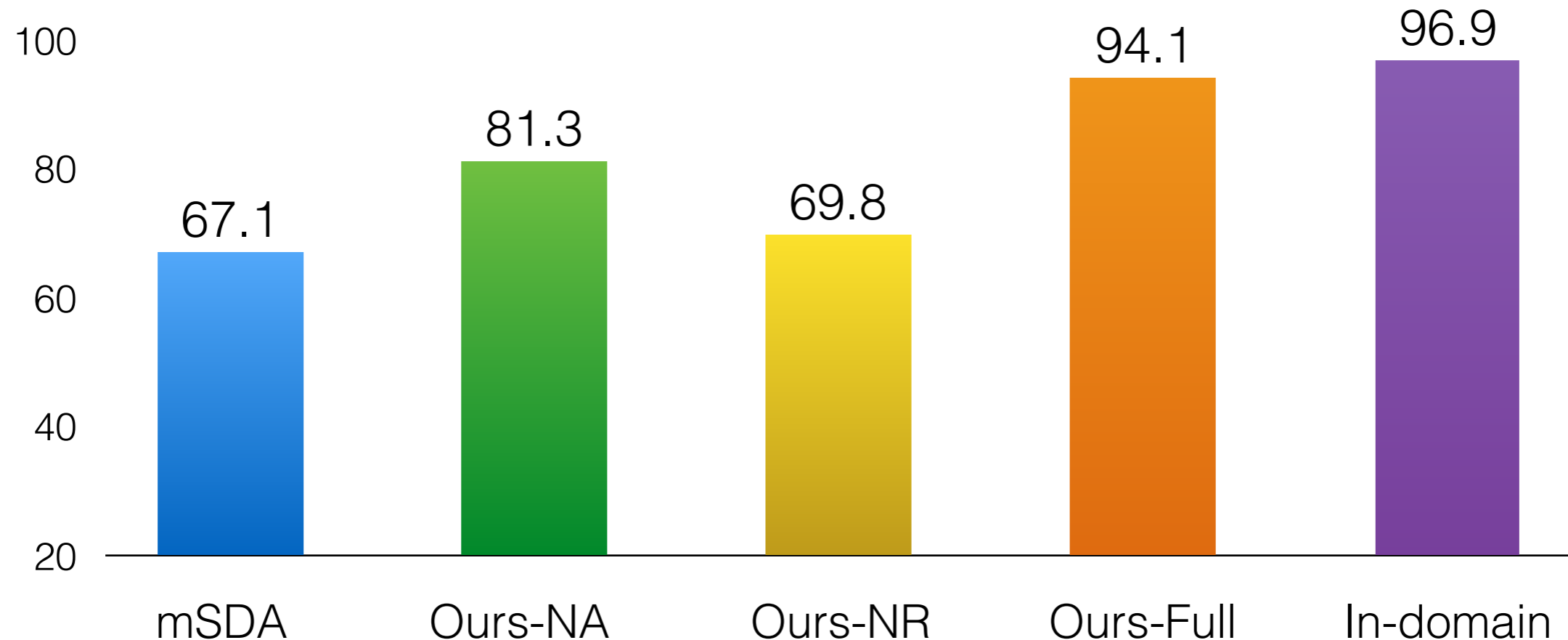
- Statistics and relevance rules:

Domains	#Labeled	#Unlabeled	Relevance Rules
Hotel	100k	100k	290 keywords from Wang et al., 2011
Restaurant	-	200k	(only one <i>overall</i> aspect)

- ◆ 2k reports for testing

# Results on Pathology Dataset

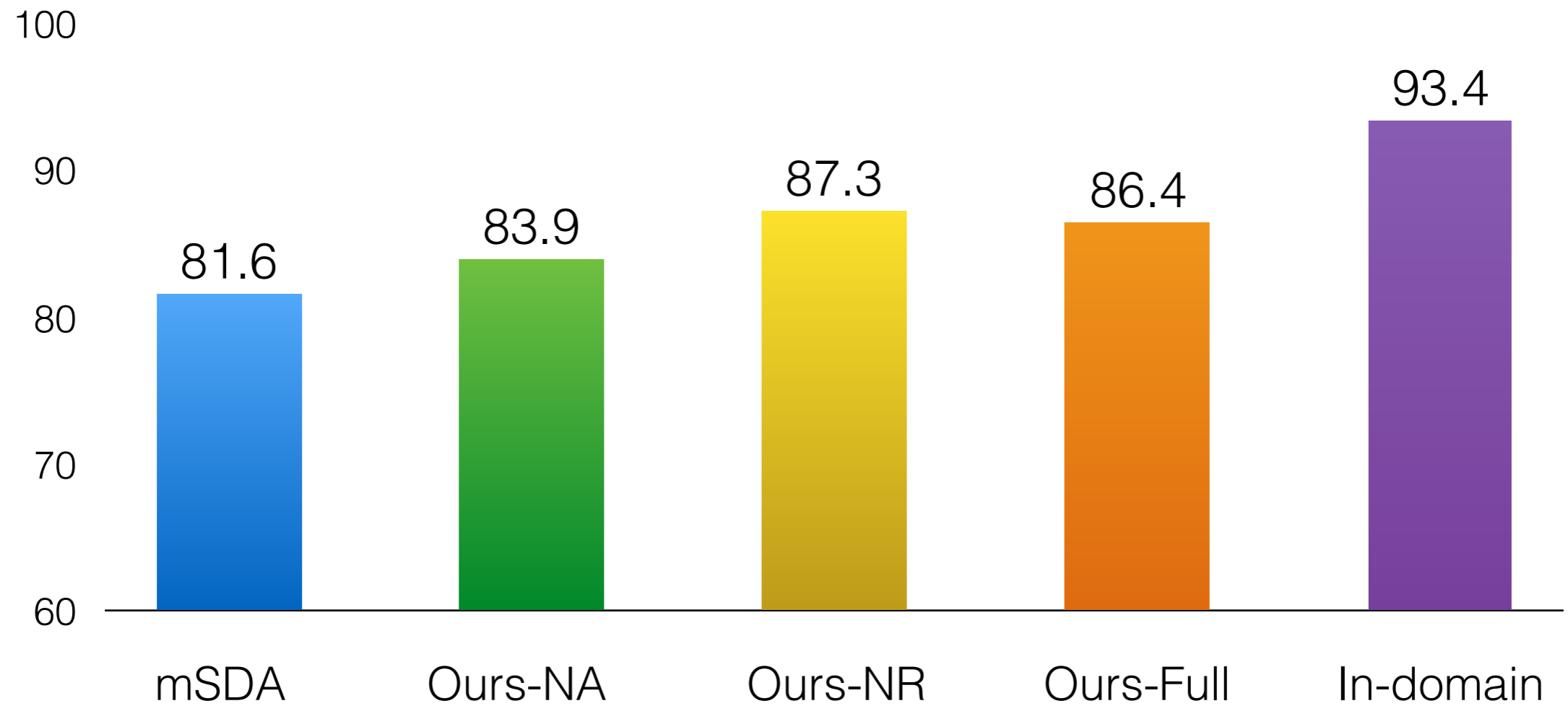
Averaged accuracy over 6 transfer scenarios



- **mSDA**: marginalized stacked denoising autoencoder (Chen et al., 2012)
- **Ours-NA**: our model without adversarial training
- **Ours-NR**: our model without aspect-relevance scoring
- **In-domain**: supervised training with in-domain annotations

# Results on Review Dataset

Averaged accuracy over 5 transfer scenarios





# Case Study of Learned Representations

## Restaurant Reviews

- the fries were **undercooked** and **thrown haphazardly** into the sauce holder . the shrimp was **over cooked** and just **deep fried** . ... even the water **tasted weird** .
- 

## Nearest Hotel Reviews by **Ours-Full: learns to map domain-specific words**

- the room was **old** . ... we did n't like the night shows at all . ...
  - however , the decor **was just fair** . ... in the second bedroom it literally **rained water from above** .
- 

## Nearest Hotel Reviews by **Ours-NA: only captures common sentiment phrases**

- rest room in this restaurant is **very dirty** . ...
- the only **problem** i had was that ... i was very ill with what was suspected to be **food poison**

- ◆ distance measured by cosine similarity between representations

# IE is hard

	Text	# Wounded
Original	<b>A 2 year old girl and four other people</b> were wounded in a shooting in West Englewood Thursday night, police said	4

# IE is hard - not always!

	Text	# Wounded
Original	<b>A 2 year old girl and four other people</b> were wounded in a shooting in West Englewood Thursday night, police said	4
Alternative	The last shooting left <b>five people</b> <b>wounded.</b>	5

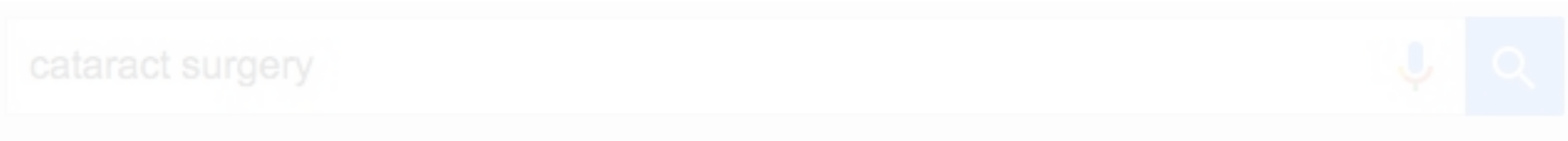
Easier to extract from alternative sources

# Test in Reading Comprehension

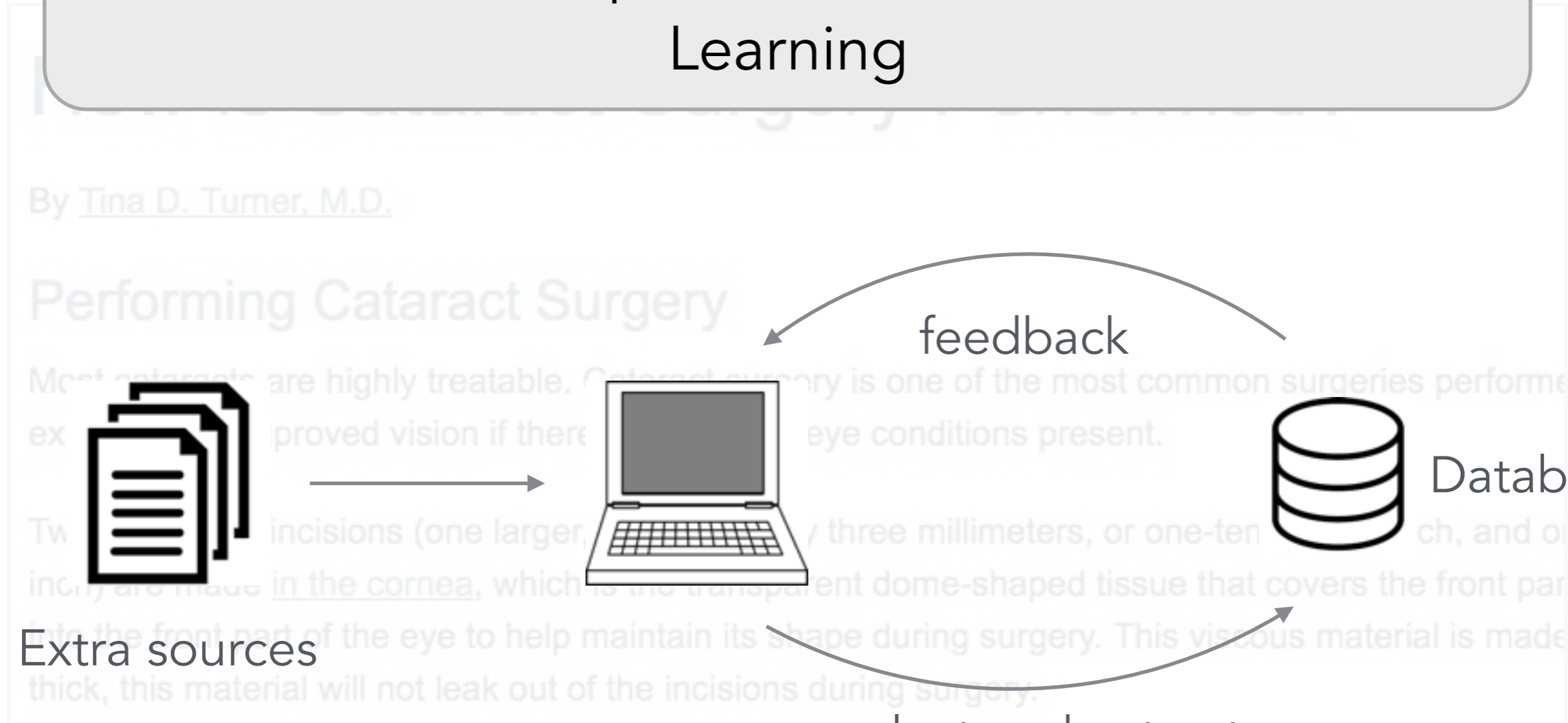
Caffeine significantly reduced ER and cyclin D1 abundance in ER(+) cells. Caffeine also reduced the pAkt levels in both ER(+) and ER(-) cells.

Your information extraction task: Identify cancerogens

# Search for Alternative Sources



Automate this process with Reinforcement Learning



# Assumptions

1. Access to a basic Information Extraction system
2. Original article to extract target entities from
3. Method to formulate different queries



The screenshot shows a news article from the Daily News. The headline reads: "S.D. dad killed wife, four kids with shotgun before setting house ablaze and killing self: authorities". The article is dated Tuesday, November 3, 2015, at 8:59 PM. The text of the article states: "PLATTE, S.D. — Financial issues appear to have contributed to an educational cooperative business manager's decision to kill his wife and four children with a shotgun before setting the family home ablaze and then shooting himself, South Dakota's attorney general said Tuesday. Attorney General Marty Jackley released the results of his office's investigation of the September deaths at a news conference in Platte, a few miles north of the burned ruins of the home where the bodies of Scott and Nicole Westerhuis and their children Kailey, Jaeci, Connor and Michael were found."

Scott and Nicole Westerhuis died along with their two sons and two daughters. (NICOLE WESTERHUIS VIA FACEBOOK)

# Acquiring External Evidence

1. Select a query to search for articles on the same event



2. Use base extractor to obtain values for entities of interest



extract

**Shooter: Scott Westerhuis**  
**NumKilled: 6**  
**Location: Platte**

3. Reconcile old and new extractions

**Shooter: Scott Westerhuis**  
**NumKilled: 4**  
**Location: S.D**

**Shooter: Scott Westerhuis**  
**NumKilled: 6**  
**Location: Platte**

# Challenges

## 1. Event Coreference

4 adults, 1 teenager shot in west Baltimore

All News Shopping Images Videos More Search tools

About 16,200,000 results (0.63 seconds)

**4 adults, 1 teenager shot in west Baltimore | Maryland News ...**  
[www.wbaltv.com/news/...shot-in-west-baltimore/32156116](http://www.wbaltv.com/news/...shot-in-west-baltimore/32156116) WBAL-TV  
Apr 3, 2015 - Five people were shot Thursday afternoon in west Baltimore.

**1 killed, 3 injured in Baltimore shooting, police say ... - WBAL**  
[www.wbaltv.com/news/...shot-in-west-baltimore.../36588266](http://www.wbaltv.com/news/...shot-in-west-baltimore.../36588266) WBAL-TV  
Nov 21, 2015 - 2 teens, 2 adults shot on Stricker Street ... man was killed and three others were injured in a shooting Saturday morning in west Baltimore, police said. ... Mom tries to buy baby for her 14-year-old daughter; WBALTV.com. Undo.

**10-year-old boy shot in West Baltimore - Baltimore Sun**  
[www.baltimoresun.com/.../baltimore.../bs-md-ci-shoot...](http://www.baltimoresun.com/.../baltimore.../bs-md-ci-shoot...) The Baltimore Sun  
Sep 3, 2015 - A 10-year-old boy was shot Thursday night, along with two adult ... Baltimore police report 6 shootings, including one of a teenage boy. ... The homicide occurred about 4:30 p.m. at Ninth and East Jeffrey streets in Brooklyn, police said. ... At 1:20 a.m., officers found a 32-year-old Baltimore man shot in the ...

Several irrelevant articles!

## 2. Reconciling Predictions

*Shooter: Scott Westerhuis*

*NumKilled: 4*

*Location: S.D*

*Shooter: Scott Westerhuis*

*NumKilled: 6*

*Location: Platte*

Varying extractions



# Learning through Reinforcement

DAILY NEWS | NEWS

Crime U.S. World Politics

## S.D. dad killed wife, four kids with shotgun before setting house ablaze and killing self: authorities

THE ASSOCIATED PRESS Tuesday, November 3, 2015, 8:59 PM

PLATTE, S.D. — Financial issues appear to have contributed to an educational cooperative business manager's decision to kill his wife and four children with a shotgun before setting the family home ablaze and then shooting himself, South Dakota's attorney general said Tuesday.

Attorney General Marty Jackley released the results of his office's investigation of the September deaths at a news conference in Platte, a few miles north of the burned ruins of the home where the bodies of Scott and Nicole Westerhuis and their children Kailey, Jaeci, Connor and Michael were found.

Scott and Nicole Westerhuis died along with their two sons and two daughters. (NICOLE WESTERHUIS VIA FACEBOOK)



extract

**Shooter: Scott Westerhuis**  
**NumKilled: 4**  
**Location: S.D**

# Learning through Reinforcement



extract

**Shooter: Scott Westerhuis**  
**NumKilled: 4**  
**Location: S.D**

search

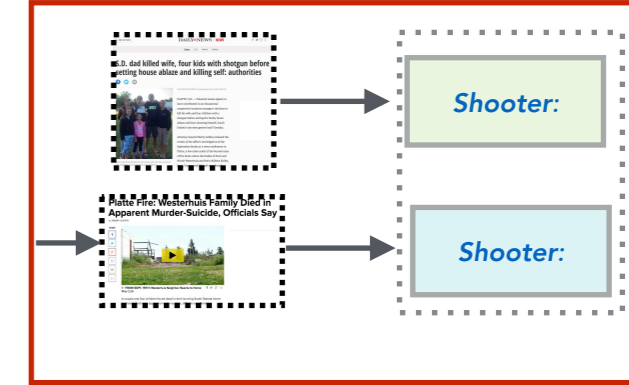


extract

**Shooter: Scott Westerhuis**  
**NumKilled: 6**  
**Location: Platte**

State

# RL: State



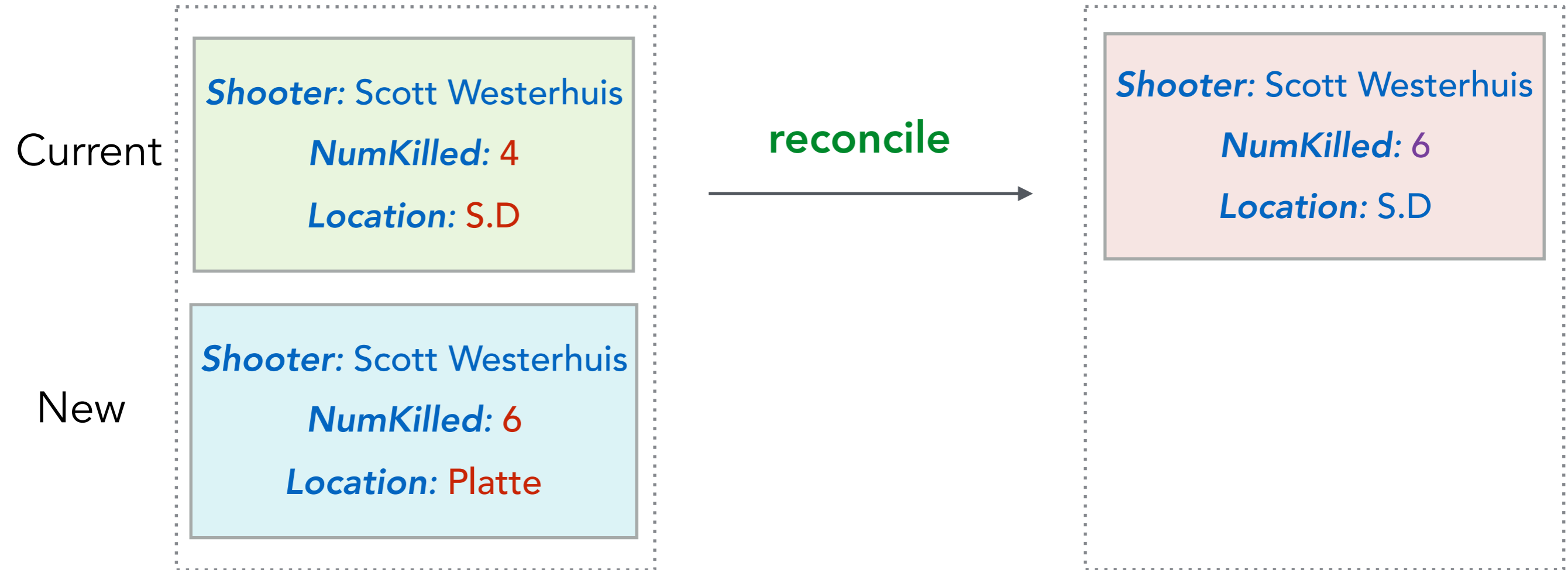
Current Values	Conf	New Values	Conf
<i>Shooter: Scott Westerhuis</i>	0.3	<i>Shooter: Scott Westerhuis</i>	0.4
<i>NumKilled: 4</i>	0.2	<i>NumKilled: 6</i>	0.6
<i>Location: S.D.</i>	0.1	<i>Location: Platte</i>	0.3



$\langle$  0.3, 0.2, 0.1, 0.4, 0.6, 0.3, 1, 0, 0, 0.65, 0, 0, 1, ..., 0, 0  $\rangle$   
 currentConf      newConf      matches      docSim      context

Real-valued vector

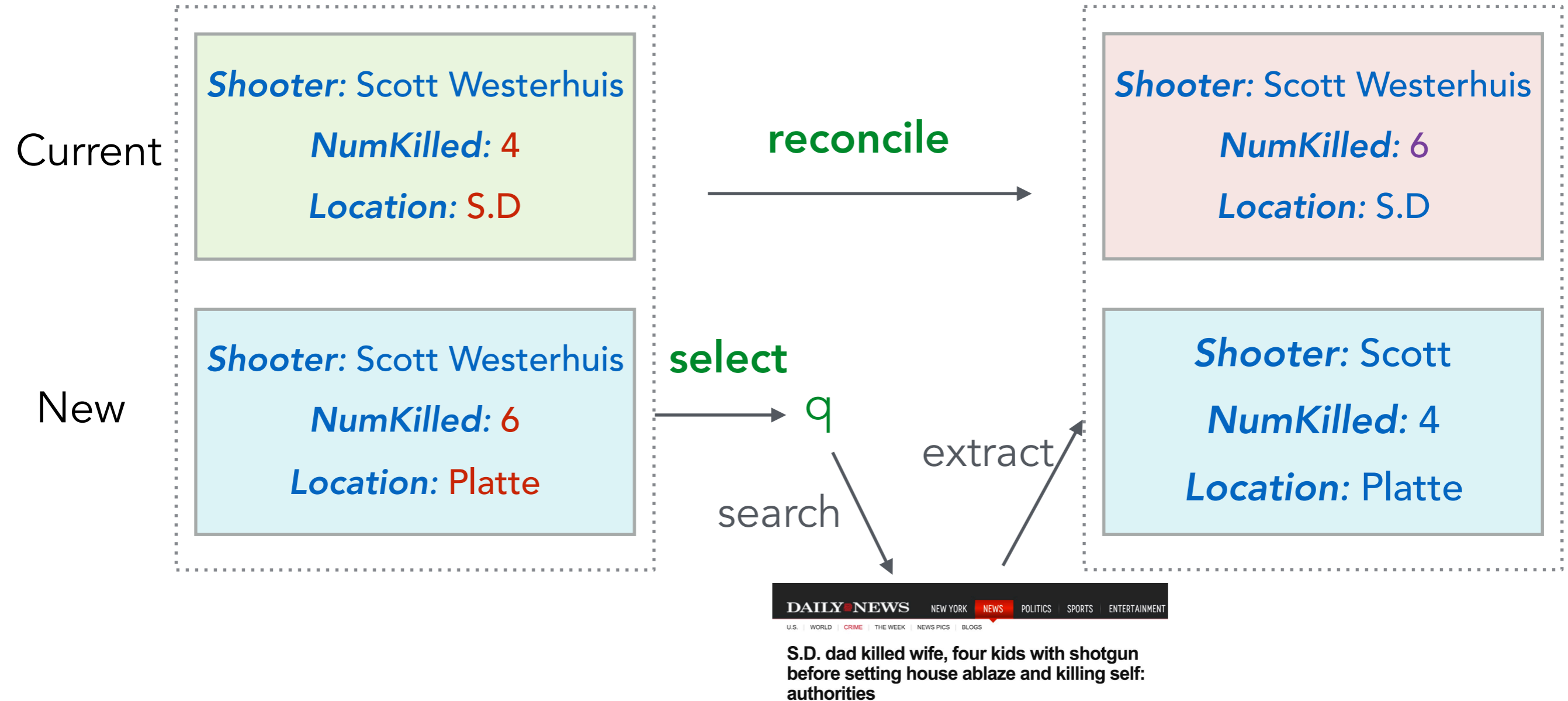
# RL: Actions



1. **Reconcile (d)** current values and new values.
  - a) Pick a single value, all values or no value from new set
  - b) Stop

$$a = (d, q)$$

# RL: Actions



2. Select next **query (q)**.

$$a = (d, q)$$

# Queries

Query templates are induced **automatically**

- Title of original article
- Content words having high mutual information with gold values

*<title>*

*<title> + ( suspect | shooter | said | men | arrested | ... )*

*<title> + ( injured | wounded | victims | shot | ... )*

# Rewards

- Change in accuracy

## Current Values

✓	<i>Shooter: Scott Westerhuis</i>
✓	<i>NumKilled: 6</i>
✓	<i>NumWounded: 0</i>
✓	<i>Location: Platte</i>

## Previous Values

✓	<i>Shooter: Scott Westerhuis</i>
✓	<i>NumKilled: 6</i>
✗	<i>NumWounded: 1</i>
✓	<i>Location: Platte</i>

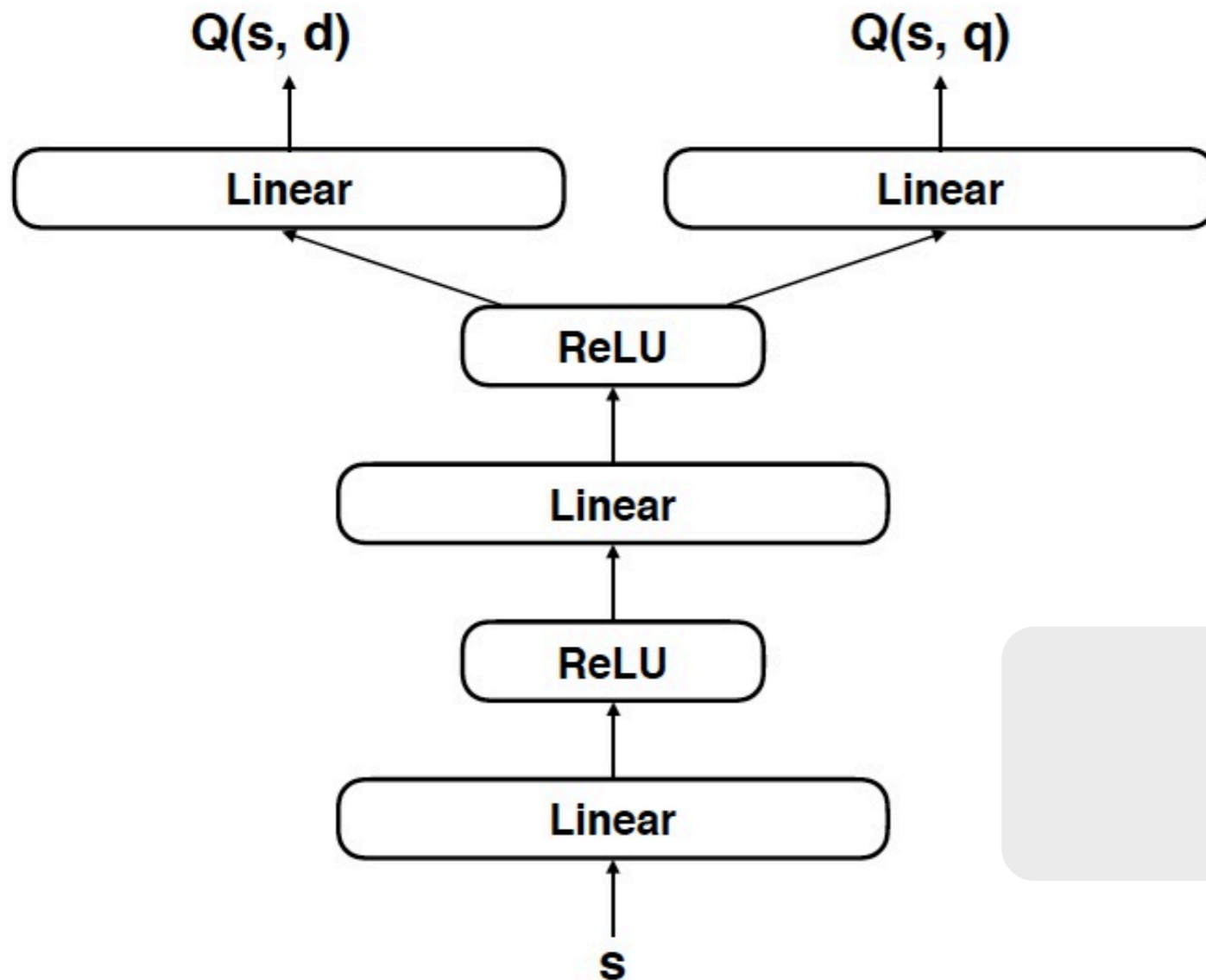
R = 1

$$R(s, a) = \sum_{\text{entity } j} \text{Acc}(e_{cur}^j) - \text{Acc}(e_{prev}^j)$$

- Small penalty for each transition

# Deep Q-Network

State space is continuous: requires function approximation



$$Q(s, a) \approx Q(s, a; \theta)$$

Trained to maximize cumulative reward



# Experiments

Two domains with multiple information sources:

1. Mass shootings in the United States
2. Adulteration events from Foodshield EMA

Number	Shootings			Adulteration		
	<b>Train</b>	<b>Test</b>	<b>Dev</b>	<b>Train</b>	<b>Test</b>	<b>Dev</b>
Source articles	306	292	66	292	148	42
Downloaded articles	8201	7904	1628	7686	5333	1537

# Base Extraction Model

# killed

# wounded

One person was killed and four other people were wounded in a shooting in Chicago's West Englewood neighborhood Monday night. The youngest victim is 13 years old.

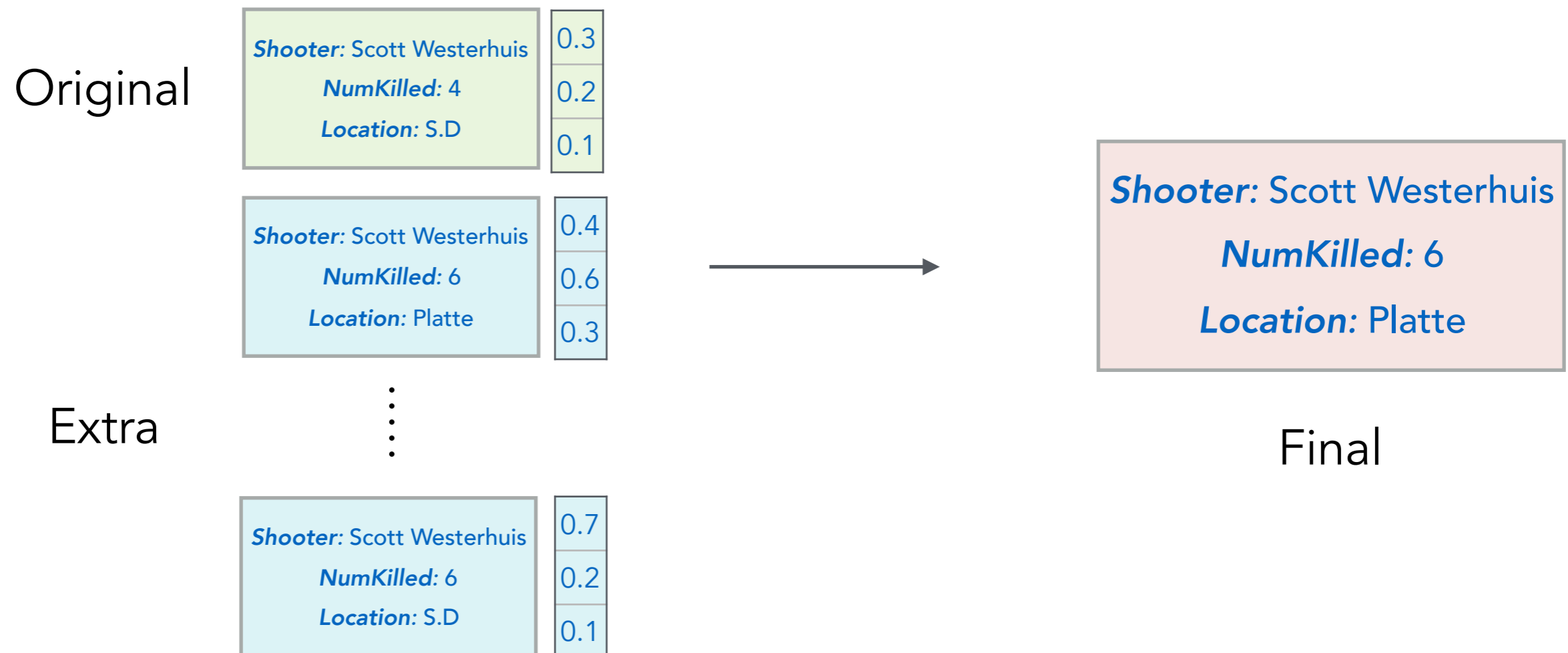
location

**Maximum Entropy classifier with contextual features to label each word**

# Baselines (1)

## Simple Reconciliation systems:

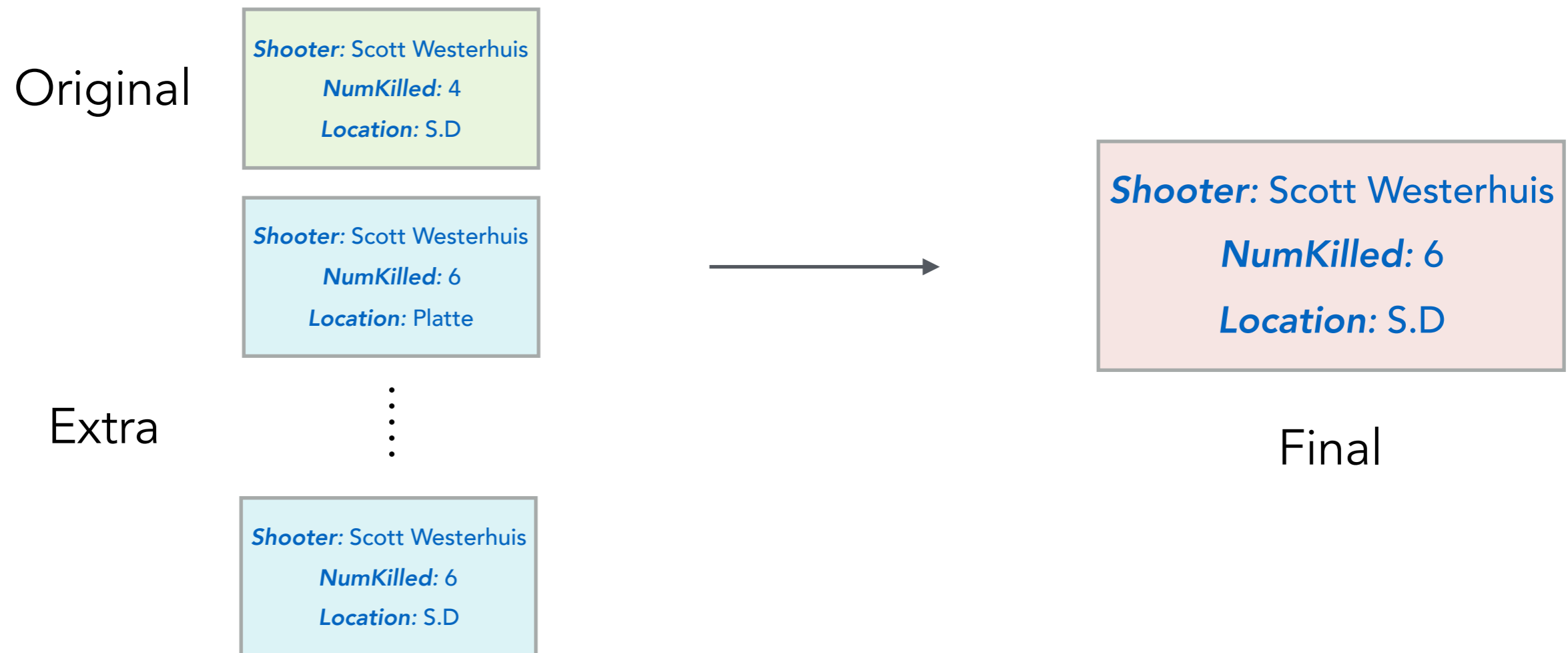
- *Confidence-based*: Choose entity value with highest confidence



# Baselines (1)

## Simple Reconciliation systems:

- *Majority-based*: Choose entity value extracted the most from all articles on the event



# Baselines (2)

## Meta-classifier for reconciliation:

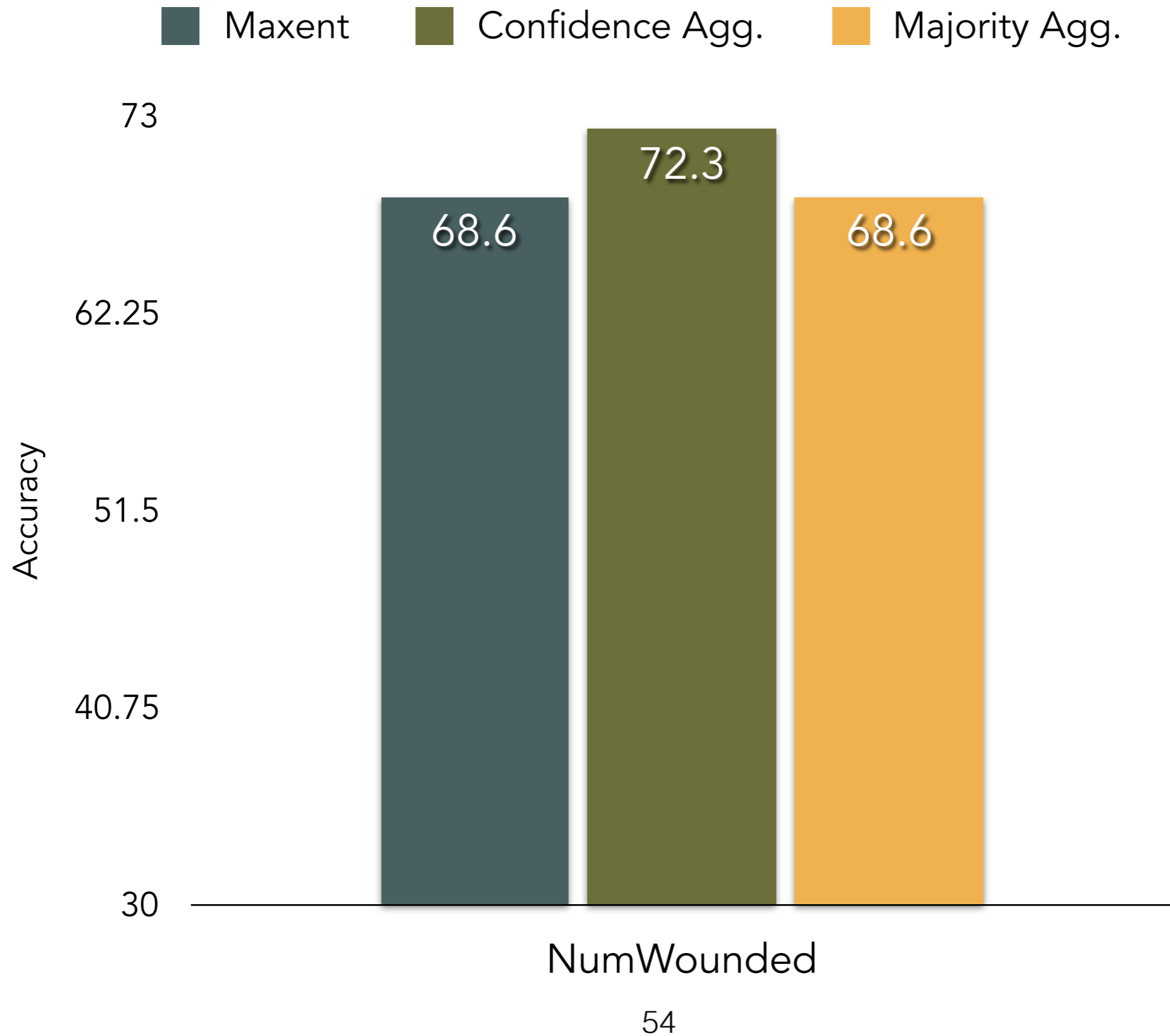
- Operates over same input space  $S$  and same set of reconciliation decisions as the RL agent.

< 0.3, 0.2, 0.1, 0.4, 0.6, 0.3, 1, 0, 0, 0.65, 0, 0, 1, ..., 0, 0 >

currentConf      newConf      matches      docSim      context

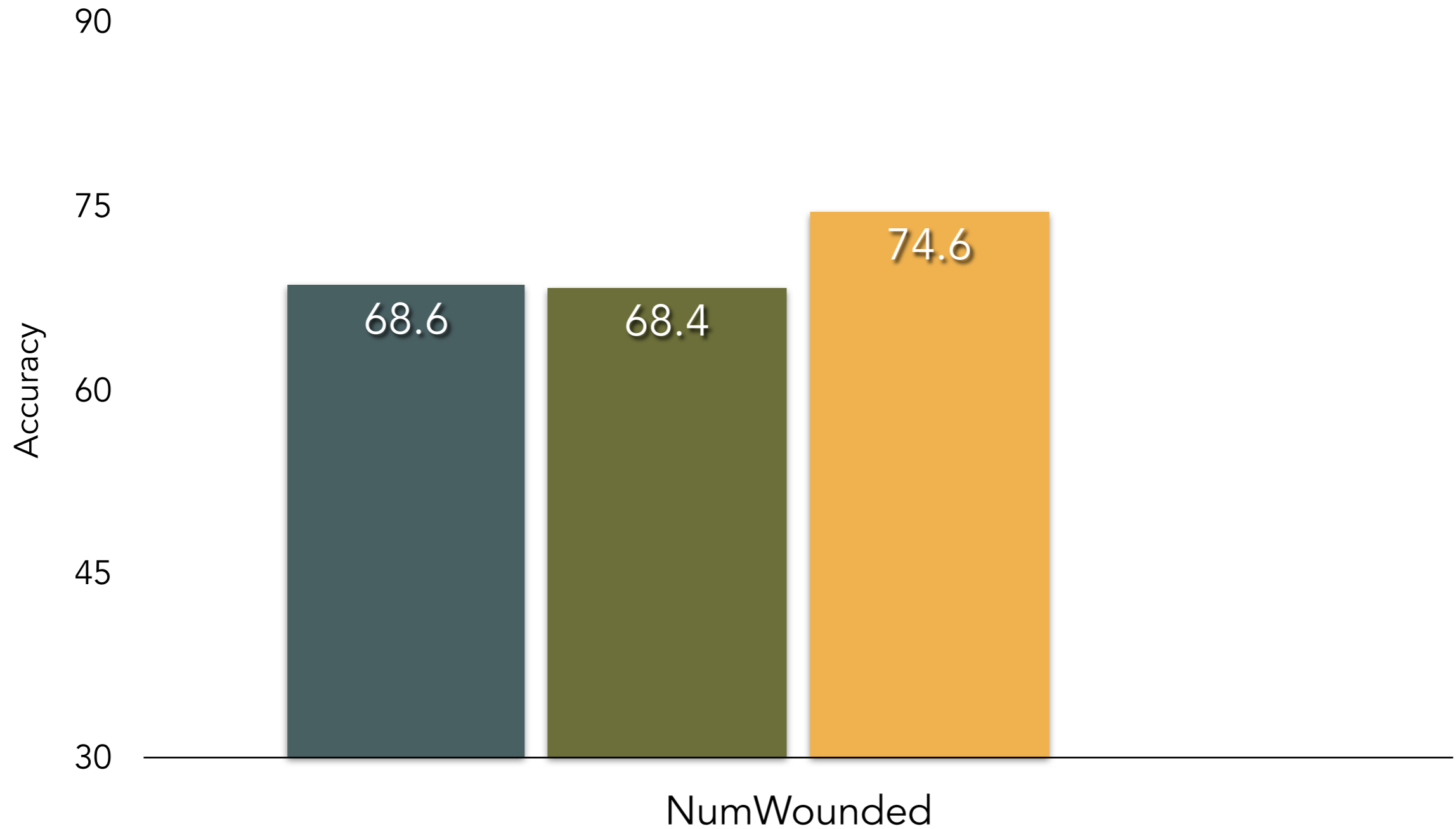
- Each state has values from original article and one extra article
- Applied to all extra articles followed by confidence-based aggregation

# Accuracy (Shootings)

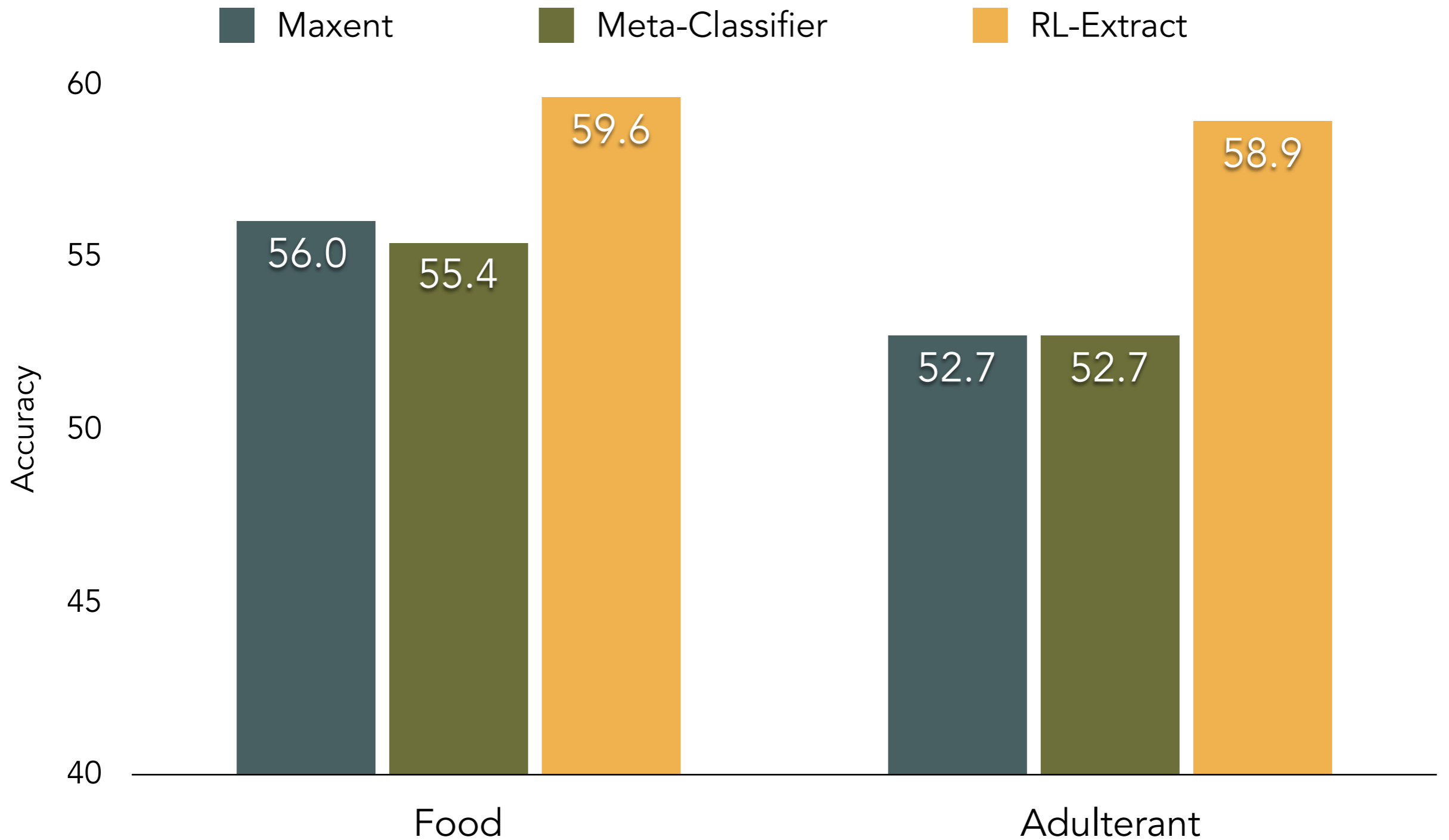


# Accuracy (Shootings)

Maxent      Meta-Classifer      RL-Extract



# Accuracy (Adulterations)





# Examples

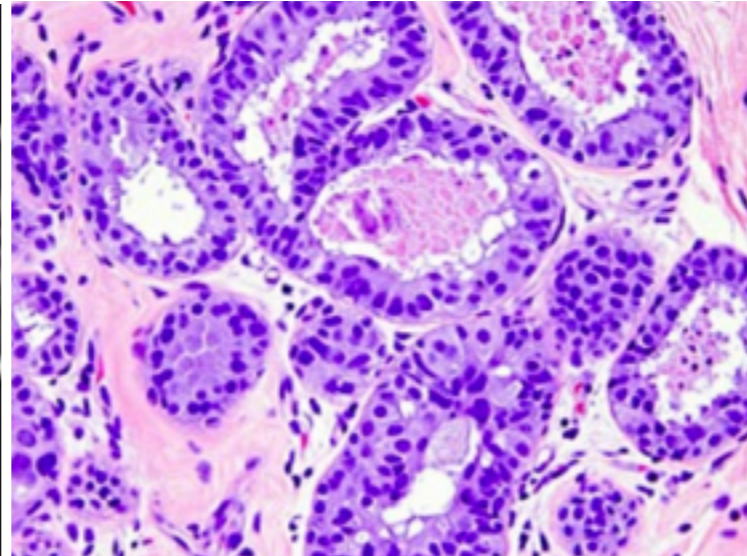
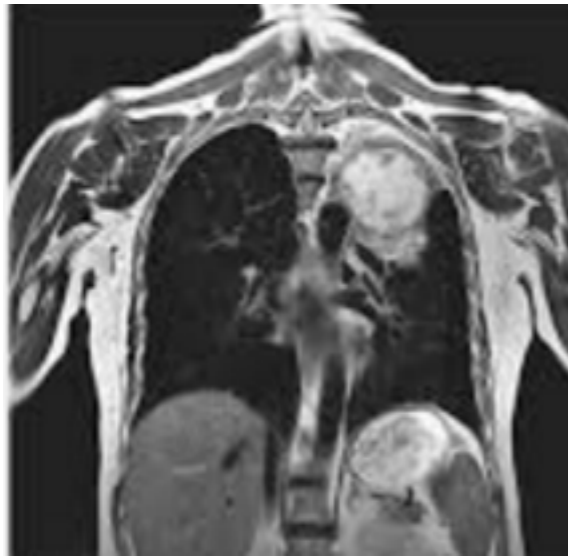
	Text	Shooter Name
Basic Extractor	A source tells Channel 2 Action News that Thomas Lee has been arrested in Mississippi ... Sgt . Stewart Smith, with the Troup County Sheriff's office, said.	Stewart
RL-Extract	Lee is accused of killing his wife, Christie; ...	Lee

# Examples

	Text	# Killed
Basic Extractor	Shooting leaves 25 year old Pittsfield man dead , 4 injured	0
RL-Extract	One man is dead after a shooting Saturday night at the intersection of Dewey Avenue and Linden Street.	1

Our system finds alternative sources of information for reliable extraction

# Predicting Clinical Outcomes from EHR



AST	8~ 40 U/L
ALT	5~ 40 U/L
LDH	50~400 U/L
ALP	80~280 U/L
γ-GTP	0~ 50 U/L
ZTT	4~ 12 KU
TTT	0~ 5 KU
Total bilirubin	0.4~0.9 mg/dl
Direct bilirubin	0~0.4 mg/dl
Indirect bilirubin	0.4~0.5 mg/dl
Total protein	6.0~9.0 g/dl



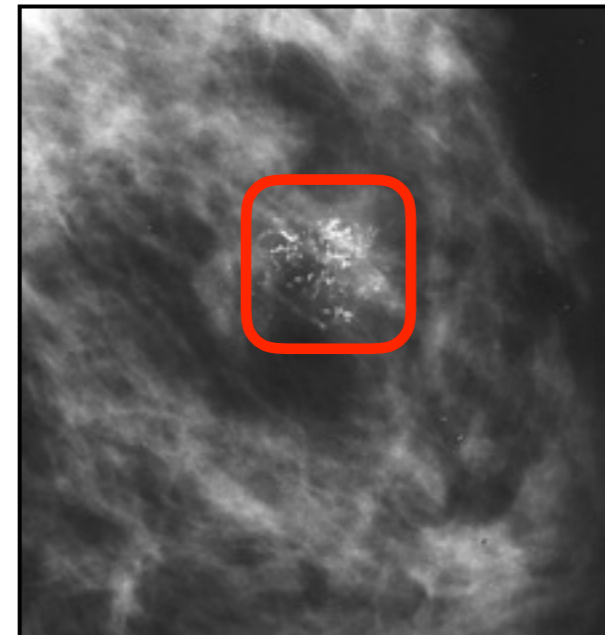
Clinical Prediction

**Doctors need to know reasons behind predictions!**

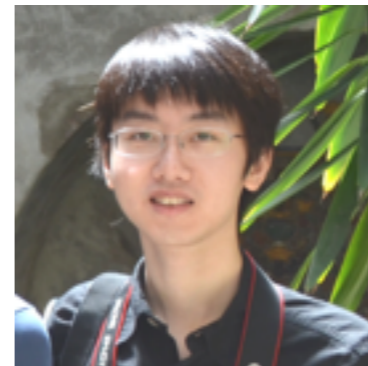
# Interpretable Neural Models

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

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



Tao Lei



Tommi Jaakkola

# 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 .

## *Ratings*

*Look:* 5 stars

*Aroma:* 2 stars

review with rationales

**Our goal:** learn to extract rationales behind predictions

# 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*)

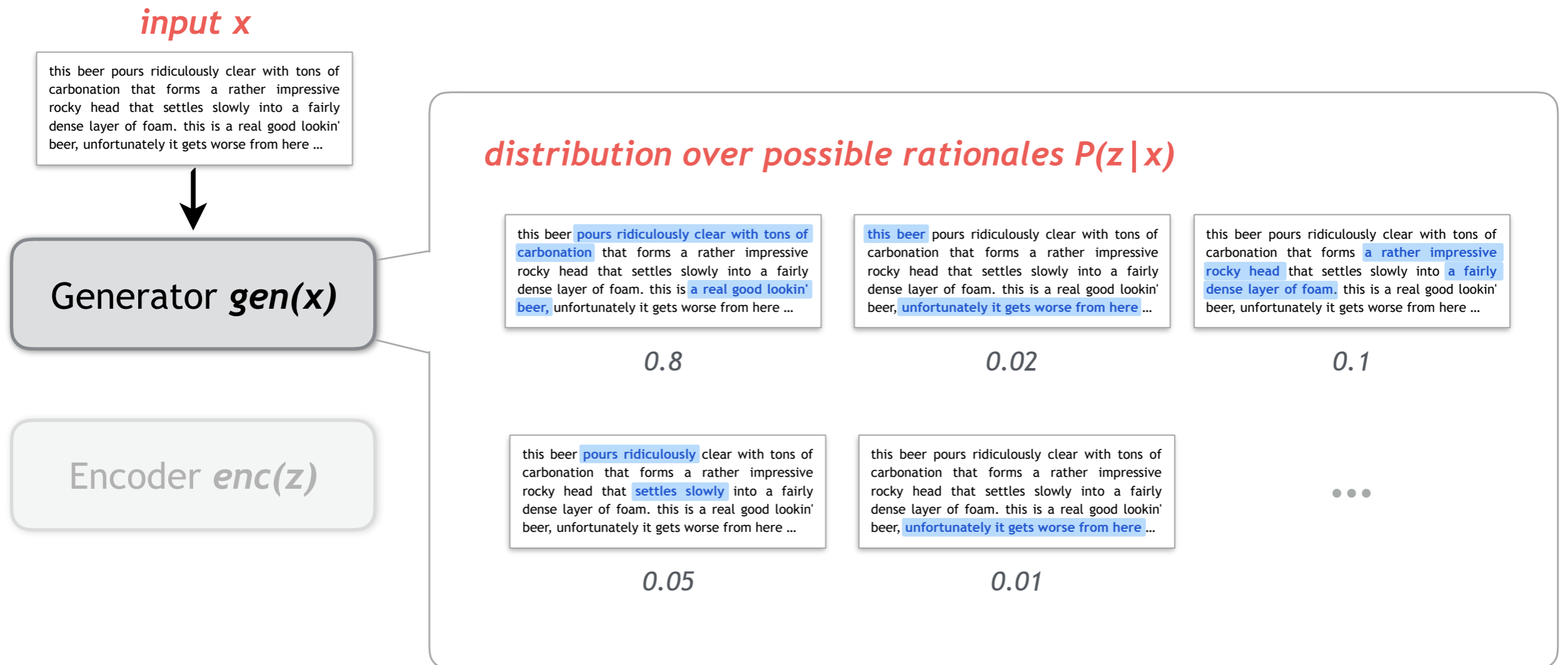
# Model Architecture

Generator *gen(x)*

Encoder *enc(z)*

two modular components *gen()* and *enc()*

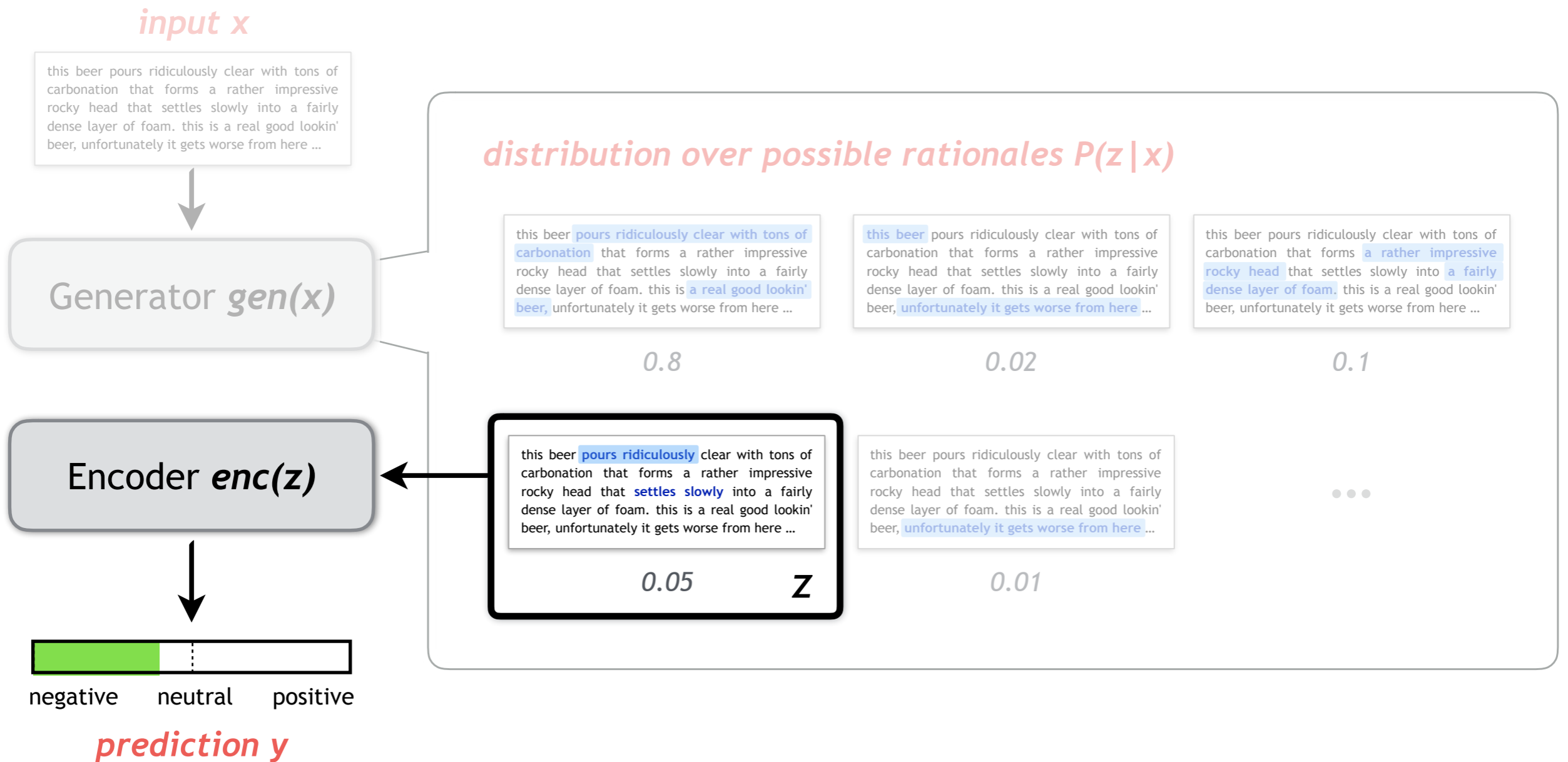
# Model Architecture



generator specifies the distribution of rationales

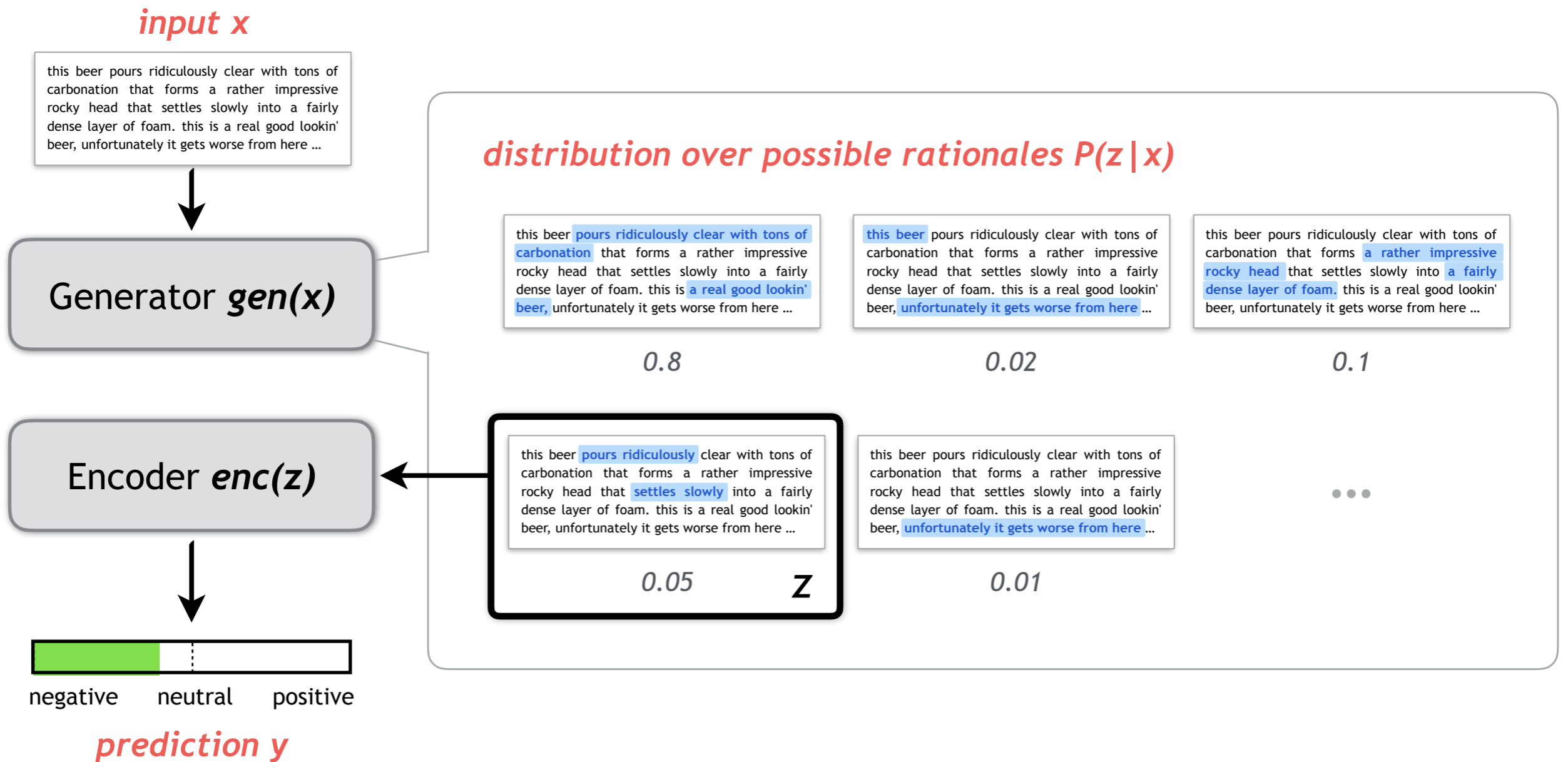


# Model Architecture



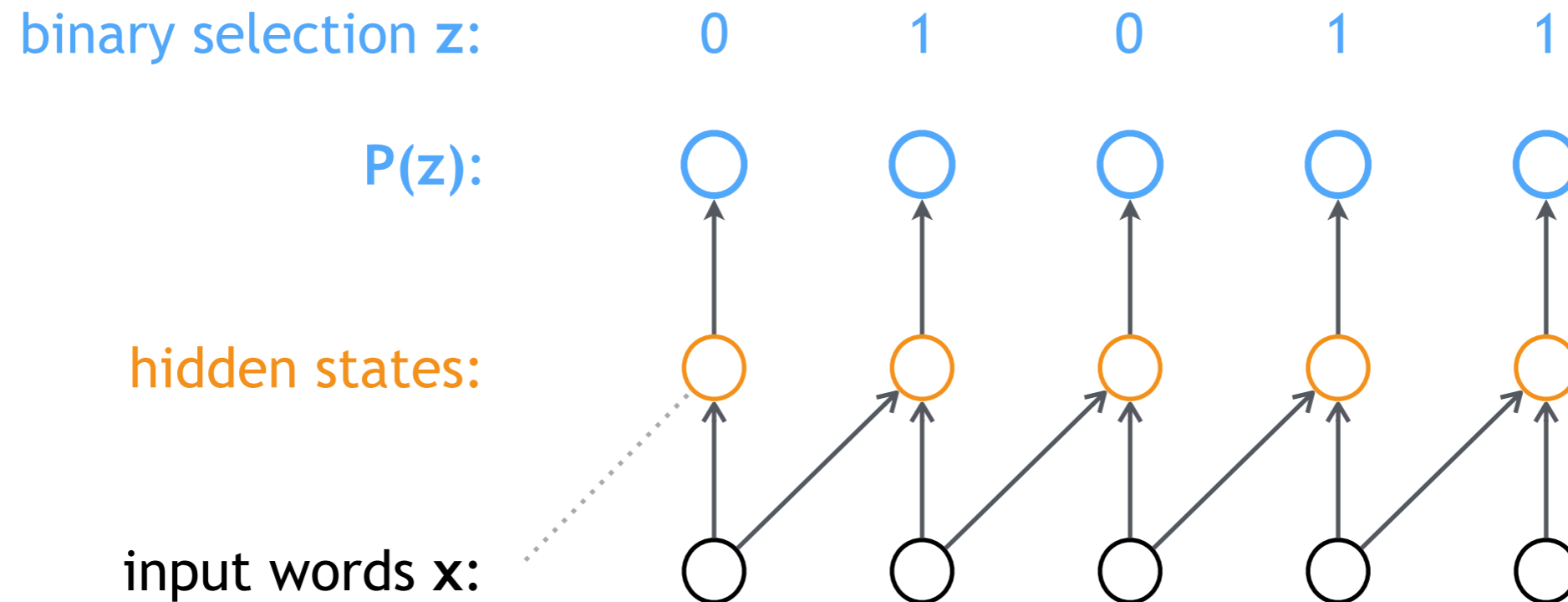
encoder makes prediction given rationale

# Model Architecture



two components optimized jointly

# Generator Implementations



independent selection, feedforward net

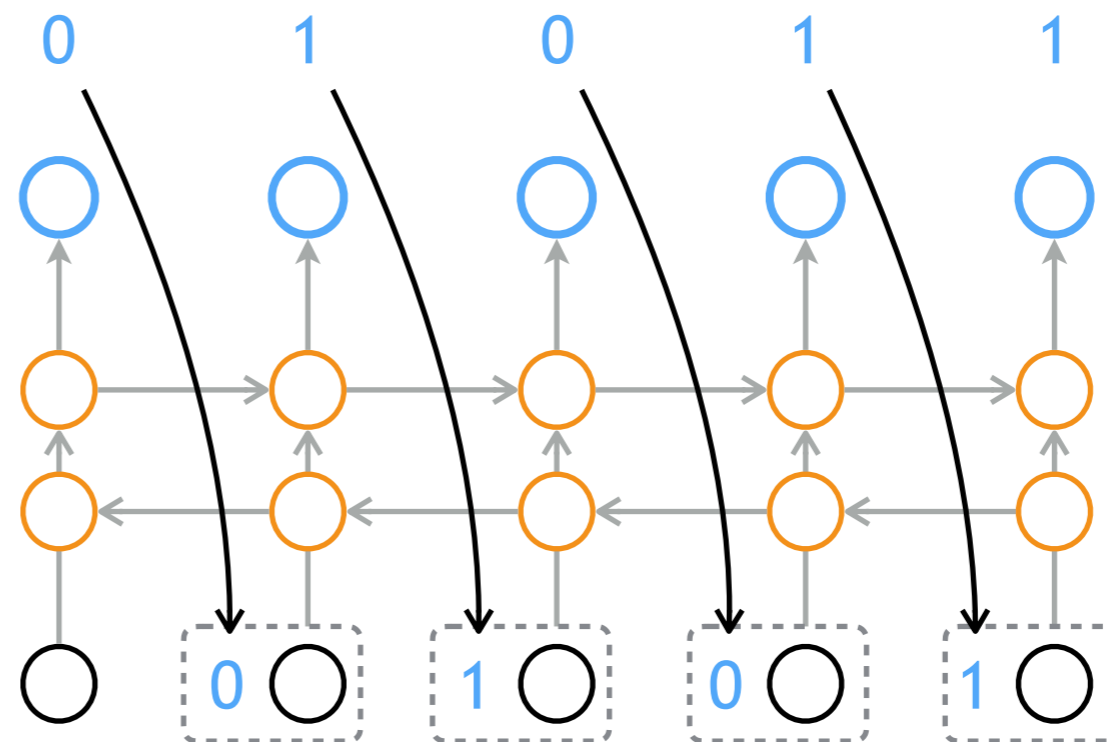
# Generator Implementations

binary selection  $z$ :

$P(z)$ :

hidden states:

input words  $x$ :



dependent selection, bi-directional RNNs

choose networks based on the data/application

# Training Objective

$$\text{cost}(\mathbf{z}, \mathbf{y}) = \underbrace{\text{loss}(\mathbf{z}, \mathbf{y})}_{\substack{\textit{sufficiency} \\ \textit{correct prediction}}} + \underbrace{\lambda_1 \|\mathbf{z}\|_1}_{\substack{\textit{sparsity} \\ \textit{rationale is short}}} + \underbrace{\lambda_2 \sum_i |\mathbf{z}_i - \mathbf{z}_{i-1}|}_{\substack{\textit{coherency} \\ \textit{continuous selection}}}$$

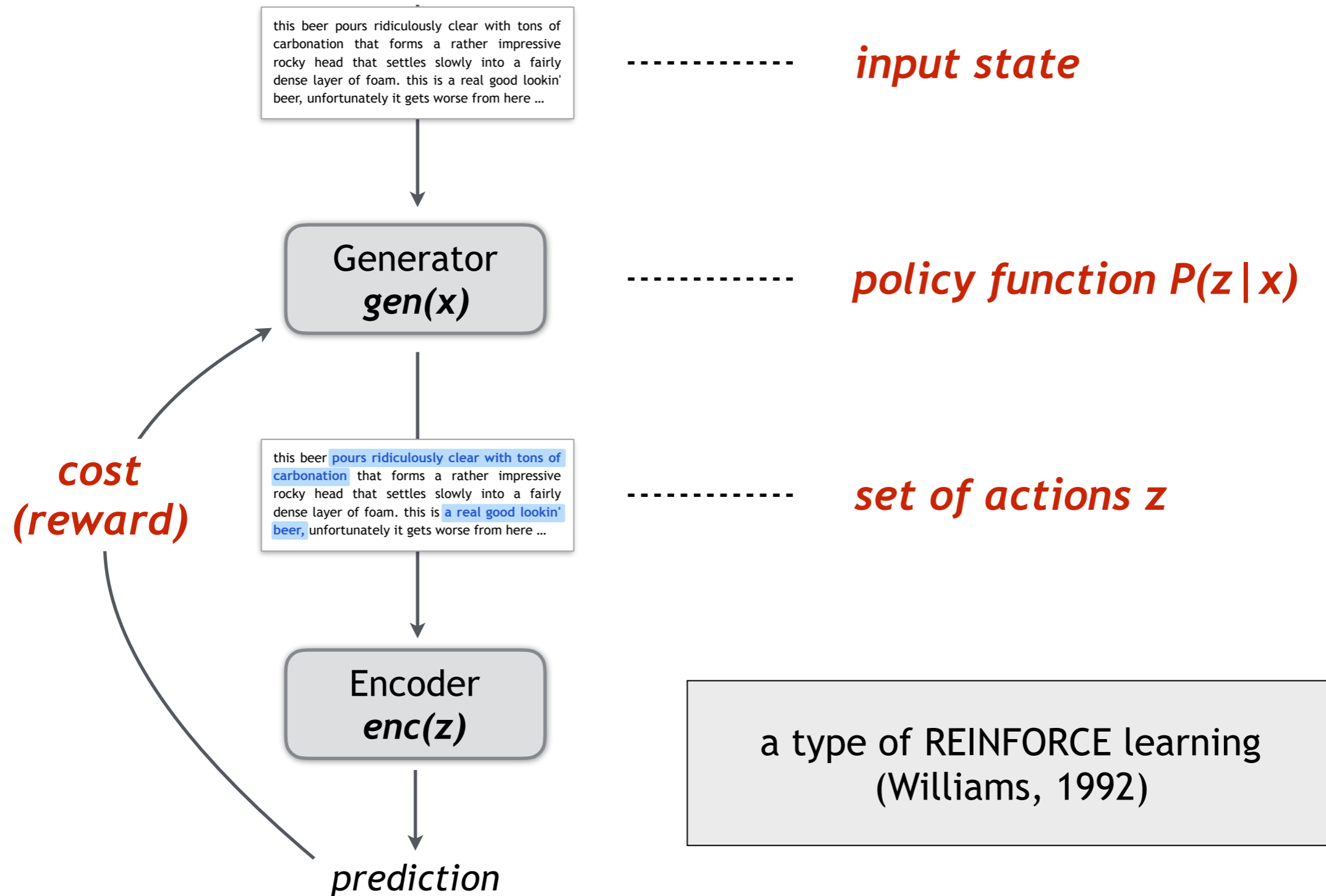
- receive this training signal after  $\mathbf{z}$  is produced

**Minimizing expected cost:**

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

- intractable because summation over  $\mathbf{z}$  is exponential

# 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

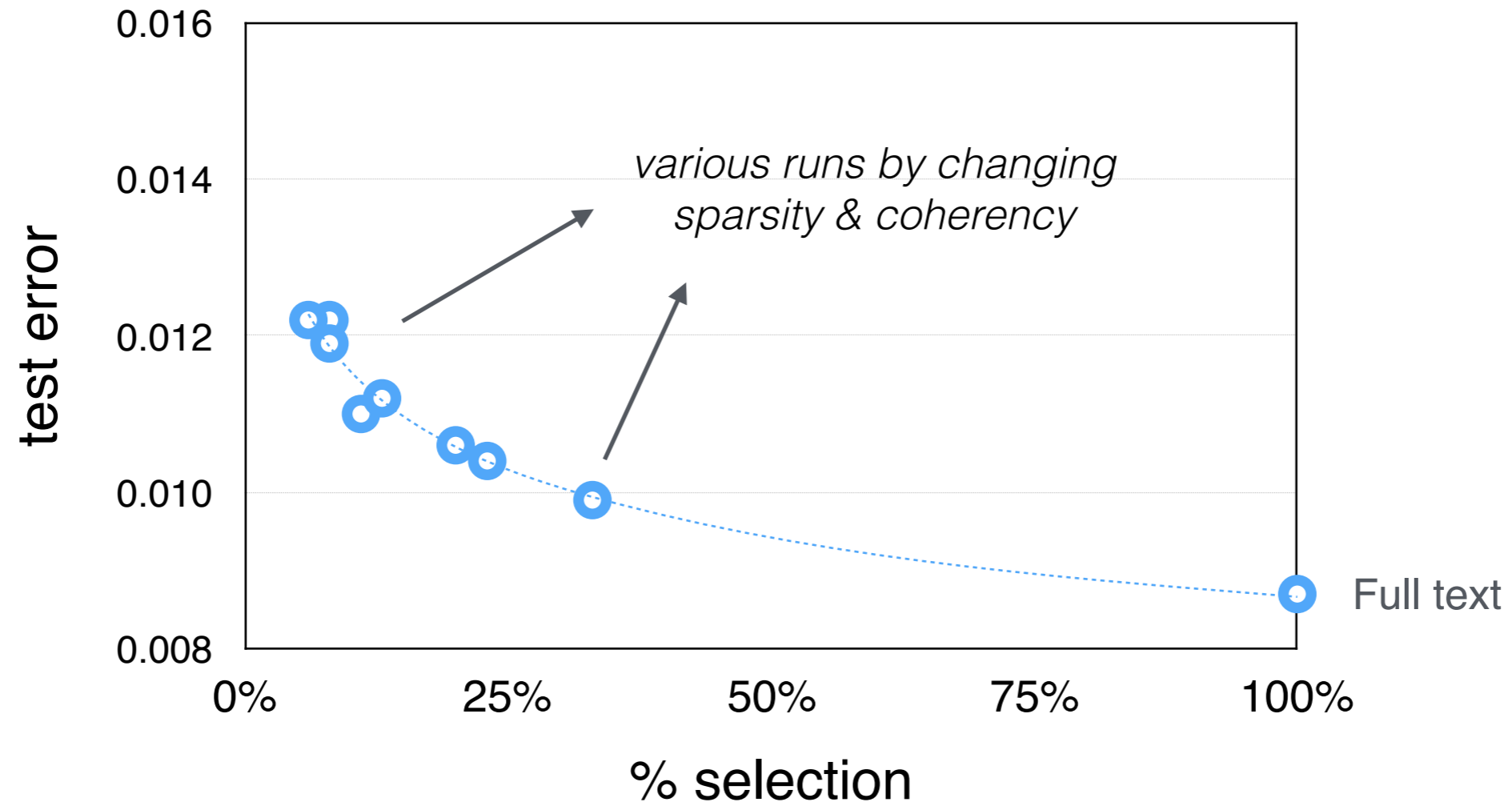
Aroma: 2 stars



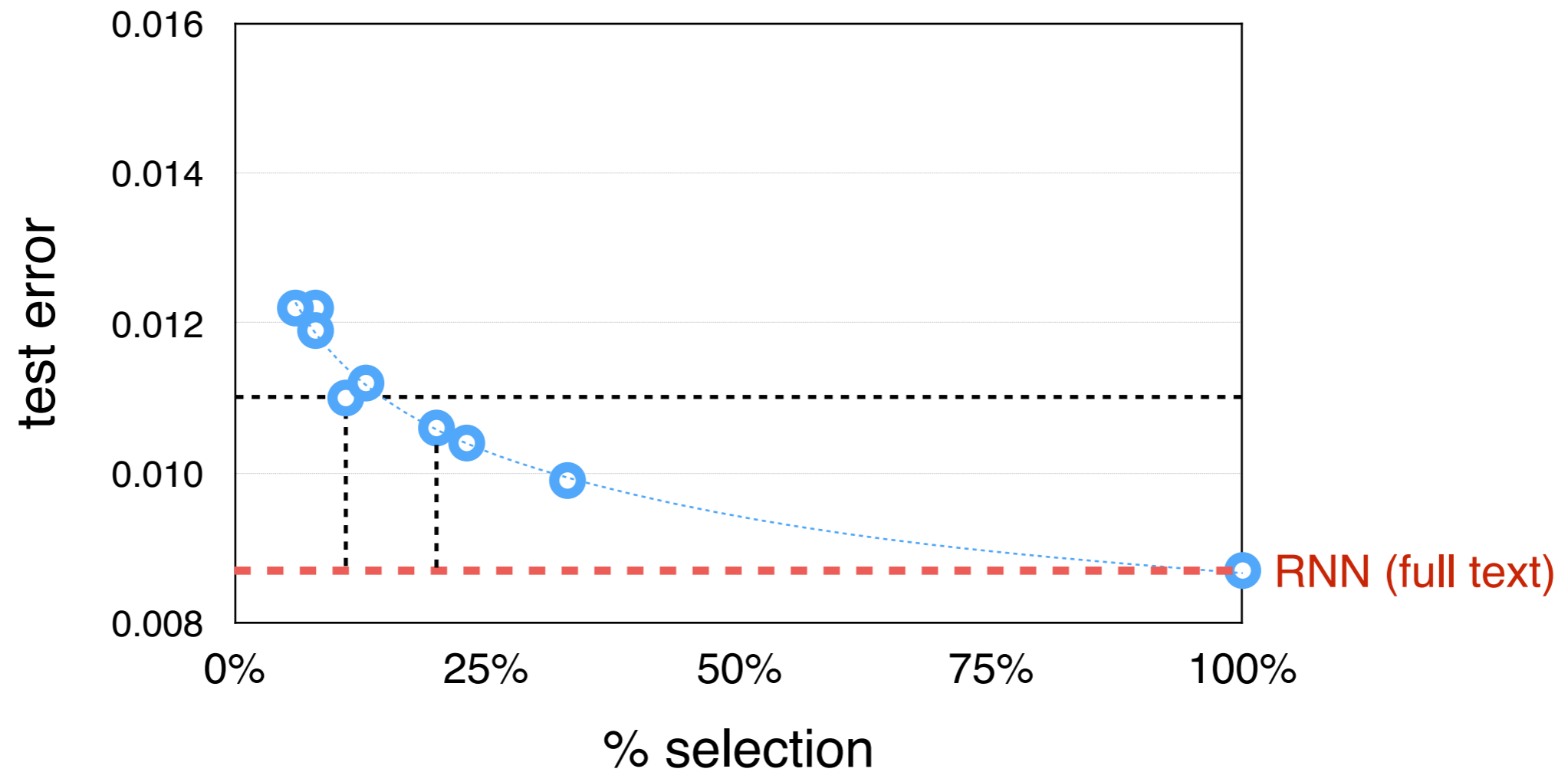
# Evaluation: Product Review

- 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

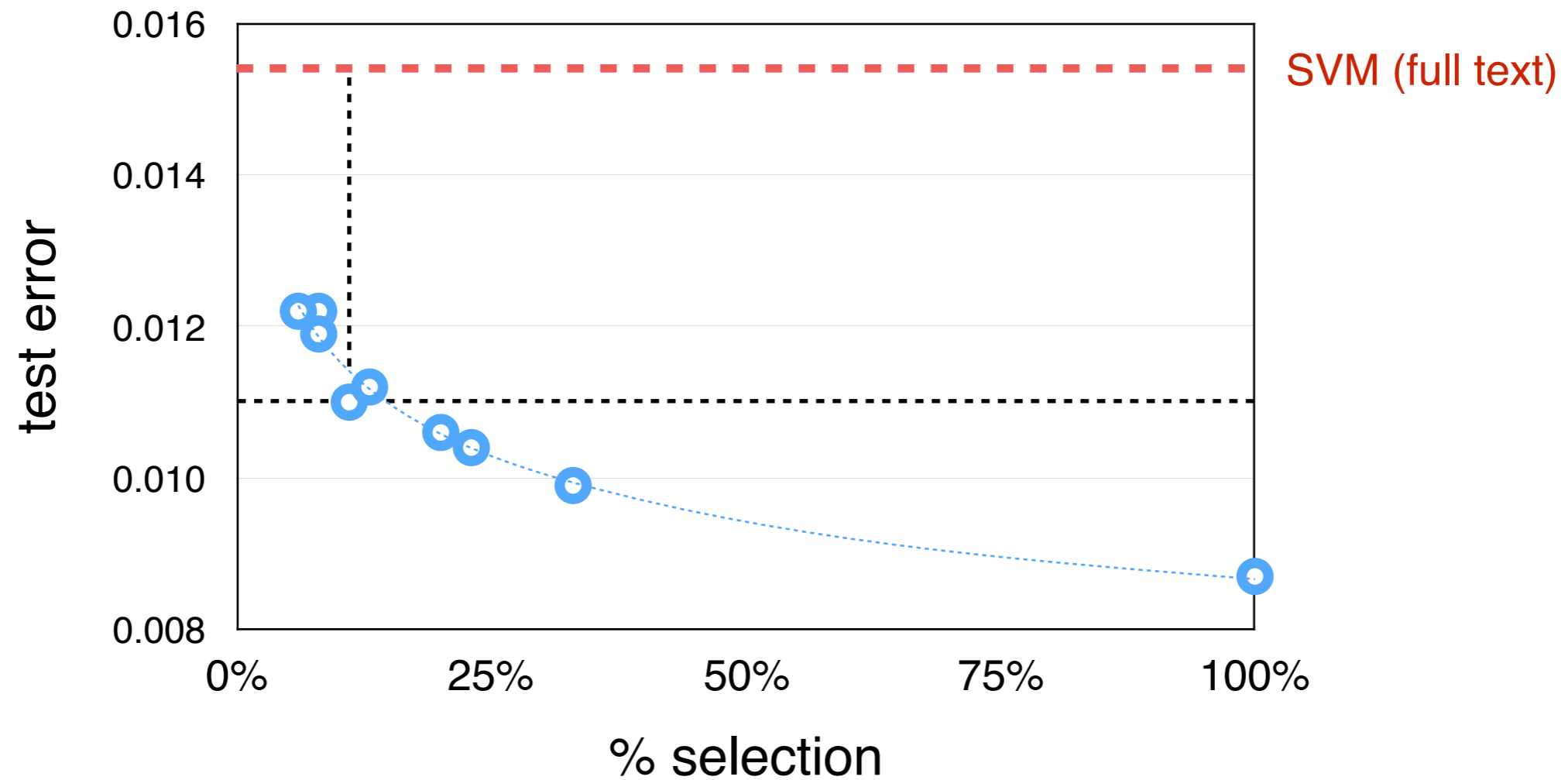


# Sentiment Prediction



rationales getting close performance to full text

# Sentiment Prediction



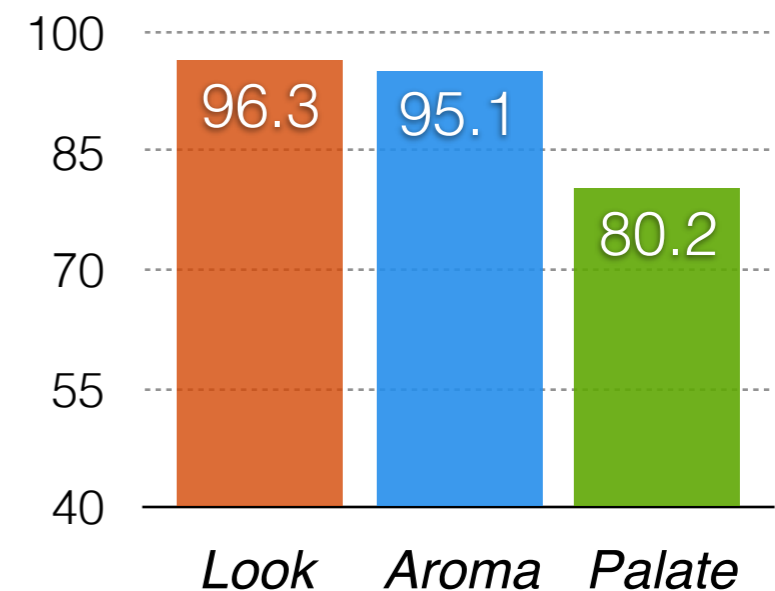
advantage of neural models over linear classifiers still clear

# 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**

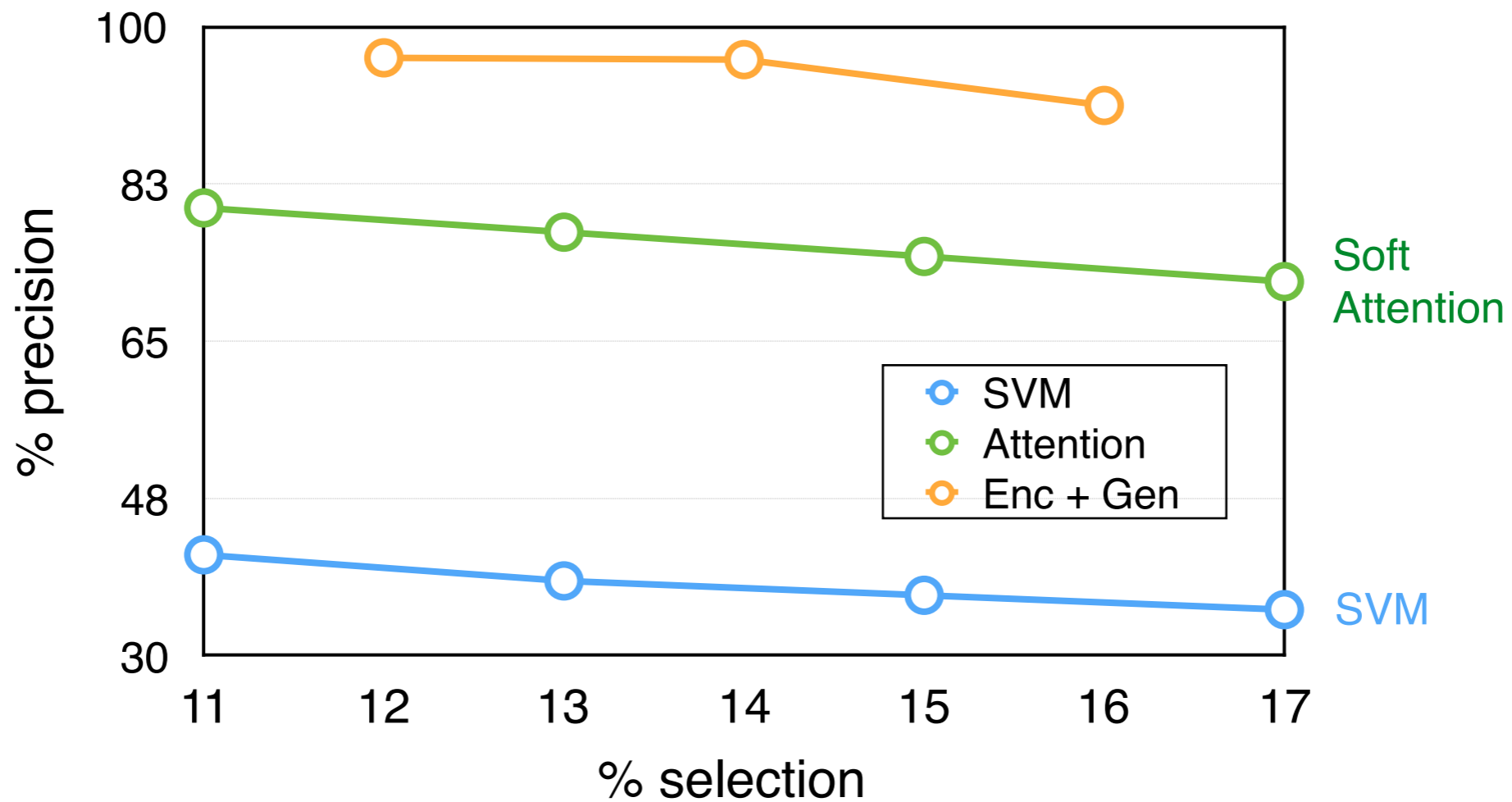
poured into a snifter . **produces a small coffee head that reduces quickly** . **black as night** . pretty typical imp . **roasted malts** hit on the nose . **a little sweet chocolate follows** . big toasty character on the taste . in between i 'm getting plenty of dark chocolate and some bitter espresso . 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

# Evaluation: Parsing Pathology Report

**Dataset:** patients' pathology reports from hospitals such as MGH

**Task:** check if a disease/symptom is positive in text  
binary 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

*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 ...

*F-score:*

98%

LCIS

... **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%

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%



# MIT-MGH Validator

## Pathology Validator



Reviewing *Thomas King*  
5 remaining



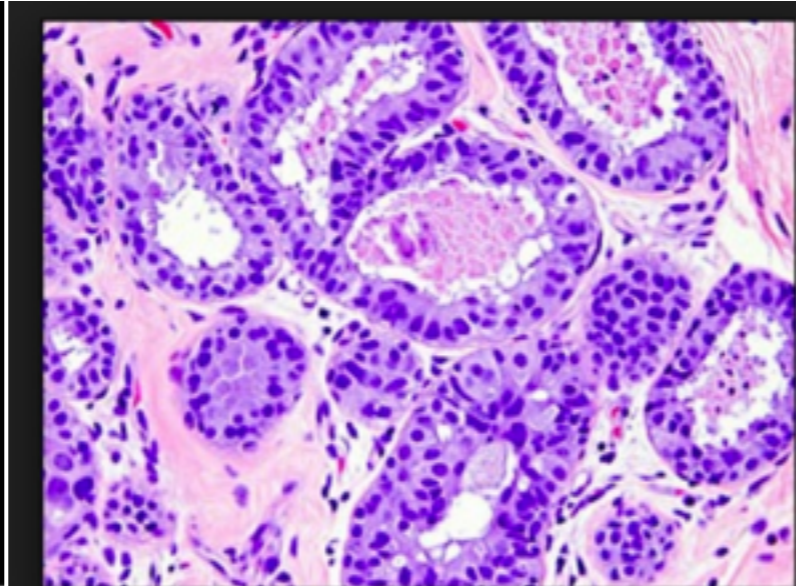
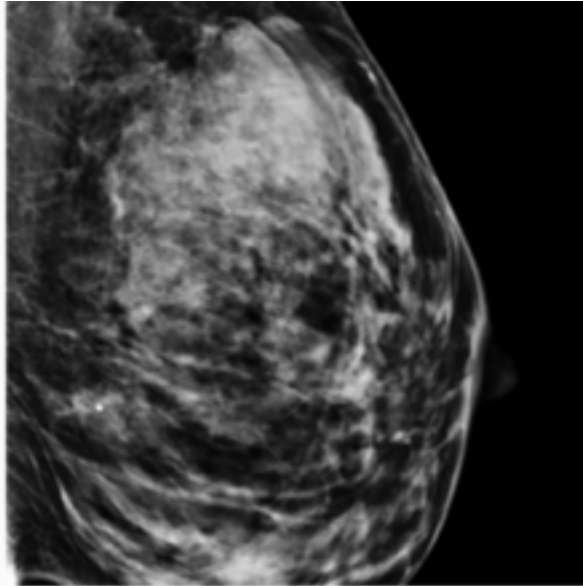
### Text

Accession Number: REMOVED\_ACCESSION\_ID Report Status: Final  
Type: Surgical Pathology  
Pathology Report REMOVED\_ACCESSION\_ID LYMPH NODES REGIONAL RESECTION  
Accessioned On: REMOVED\_DATE  
LESTER, SUSAN, M.D.~PH.D.  
DIAGNOSIS: by LESTER,SUSAN,M.D.,PH.D.  
RIGHT BREAST, QUADRANCTECTOMY:  
Atypical lobular hyperplasia with pagetoid spread.  
Atypical ductal hyperplasia with pagetoid spread (single focus; block 4), not present at a margin.  
Biopsy site with repair reaction.  
Nine (9) axillary lymph nodes, no tumor identified.  
NOTE: Diagnostic features of **DCIS** or invasive carcinoma are not seen.  
AXILLARY LYMPH NODE (INCLUDING FSA):  
One lymph node with no tumor seen.  
CLINICAL DATA:  
History: None given.  
Clinical Diagnosis: Right breast mass  
TISSUE SUBMITTED: #1) Axillary lymph node  
#2) Quadrantectomy with axillary node dissection  
O.R. CONSULTATION:  
SPECIMEN LABELED "#1. AXILLARY LYMPH NODE" (FROZEN SECTION):  
Lymph node with no tumor seen on representative frozen section.  
GROSS DESCRIPTION: by IAFRATE,ANTHONY JOHN,M.D.,PH.D.  
The specimen is received fresh in two parts, each labeled  
REMOVE\_PATIENT\_NAME patient's name and unit number.  
Part one, labeled "#1. axillary lymph node", consists of a single fragment of soft tissue (2.5 x REMOVED\_DATE x 0.6cm ) with a single lymph node (1.3 x REMOVED\_DATE x 0.8cm ).  
Half of the lymph node is frozen as FSA  
Micro 1: FSA remnant, 1 frag, ESS  
Micro 2: non frozen tissue, 2 frag, ESS

### Extractions

BreastSide:	Right ▾
DCIS:	Present ▾
ILC:	Absent ▾
IDC:	Absent ▾
PositiveLN:	Absent ▾
EIC:	Present ▾
ER:	NA ▾
Her2:	NA ▾
ITC:	No ▾
PR:	NA ▾
LVI:	Absent ▾
BVI:	Absent ▾
LCIS:	Absent ▾
ALH:	Present ▾

# Modeling Disease Progression

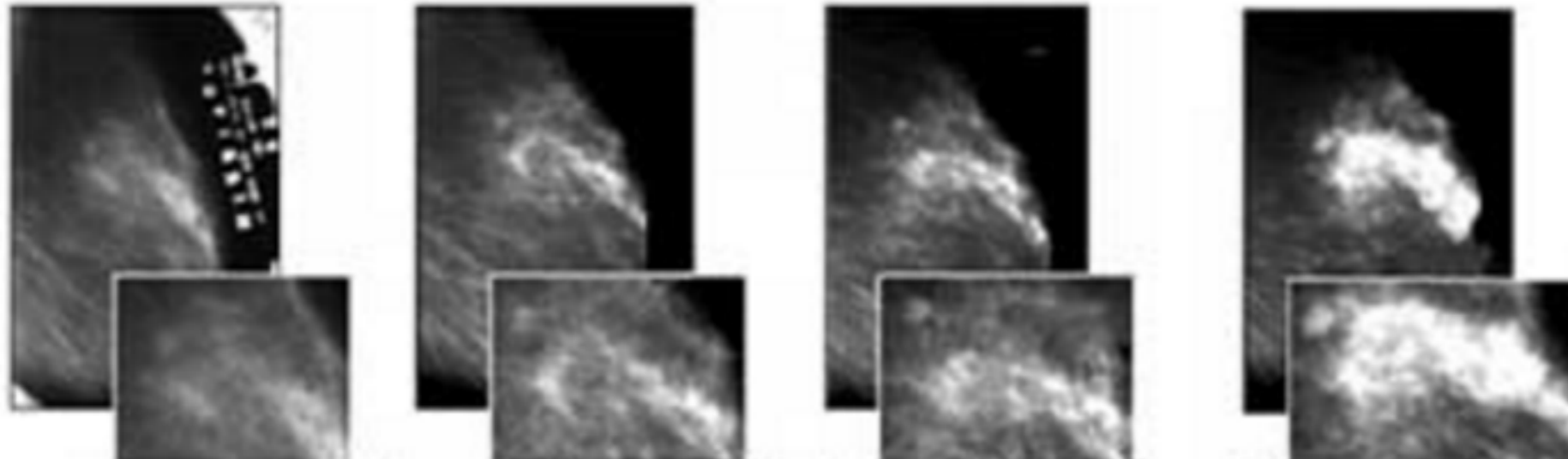


AST	8~ 40 U/L
ALT	5~ 40 U/L
LDH	50~400 U/L
ALP	80~280 U/L
γ-GTP	0~ 50 U/L
ZTT	4~ 12 KU
TTT	0~ 5 KU
Total bilirubin	0.4~0.9 mg/dℓ
Direct bilirubin	0~0.4 mg/dℓ
Indirect bilirubin	0.4~0.5 mg/dℓ
Total protein	6.0~9.0 g/dℓ



Predict Recurrence

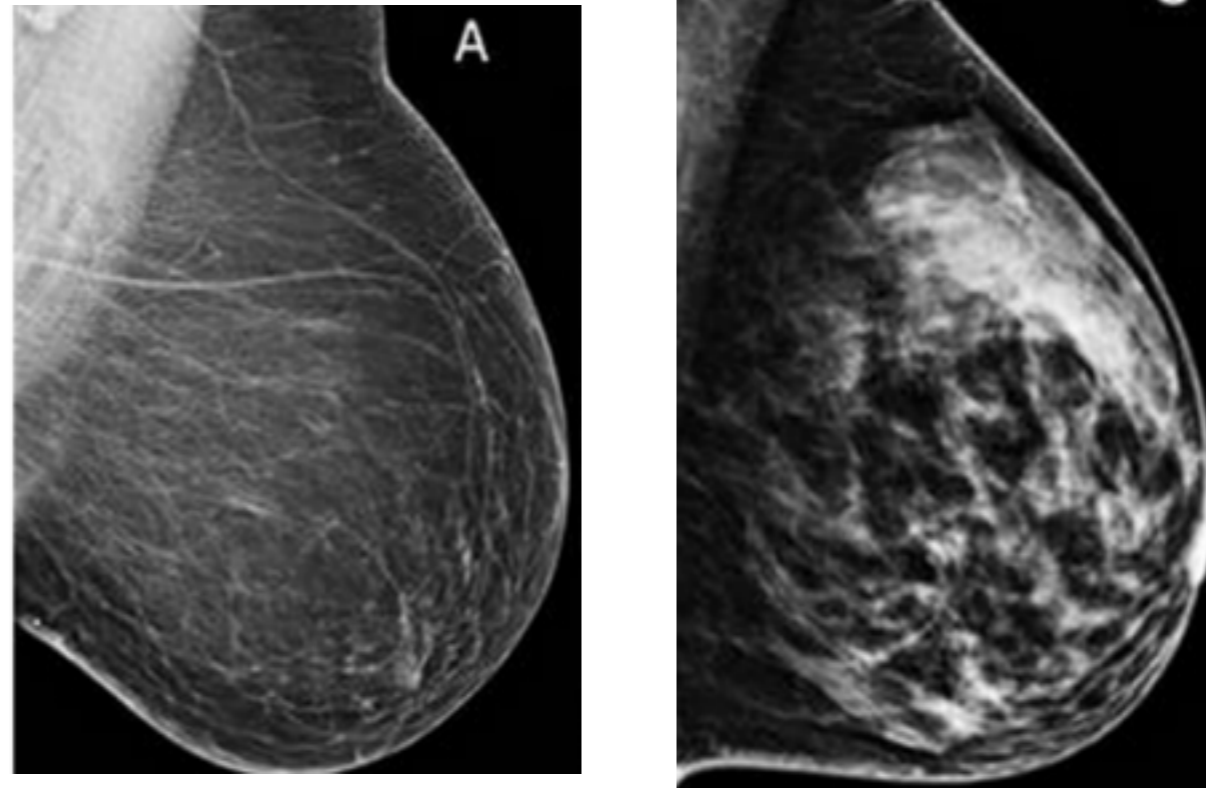
# Early Cancer Detection



Hypothesis: changes in tissue are early cancer precursors

- support in clinical studies
- currently is not utilized in practice

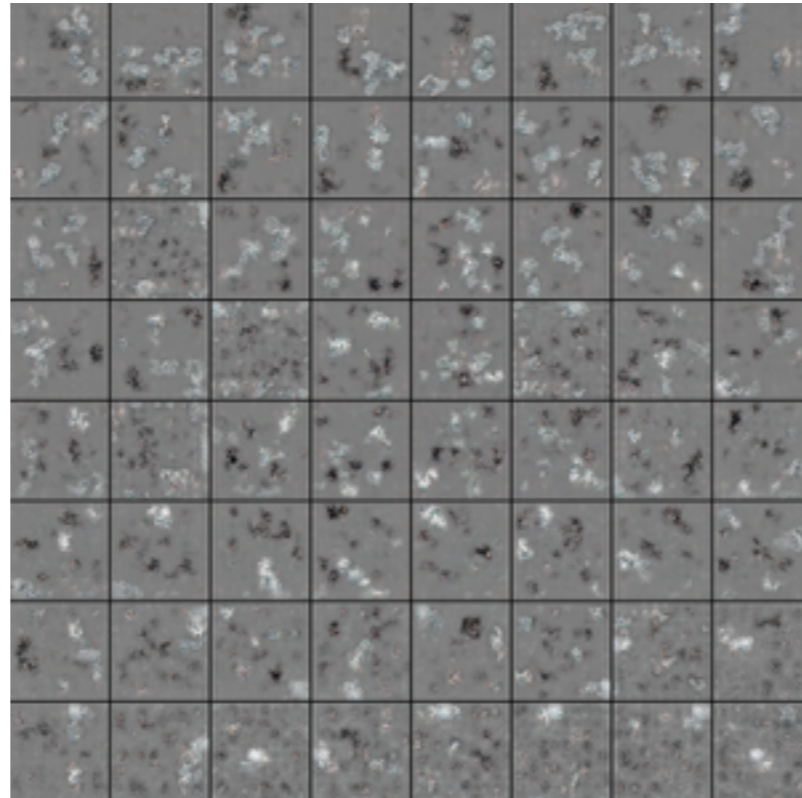
# Predicting Density



**Density: ratio of fatty and fibrous tissue**

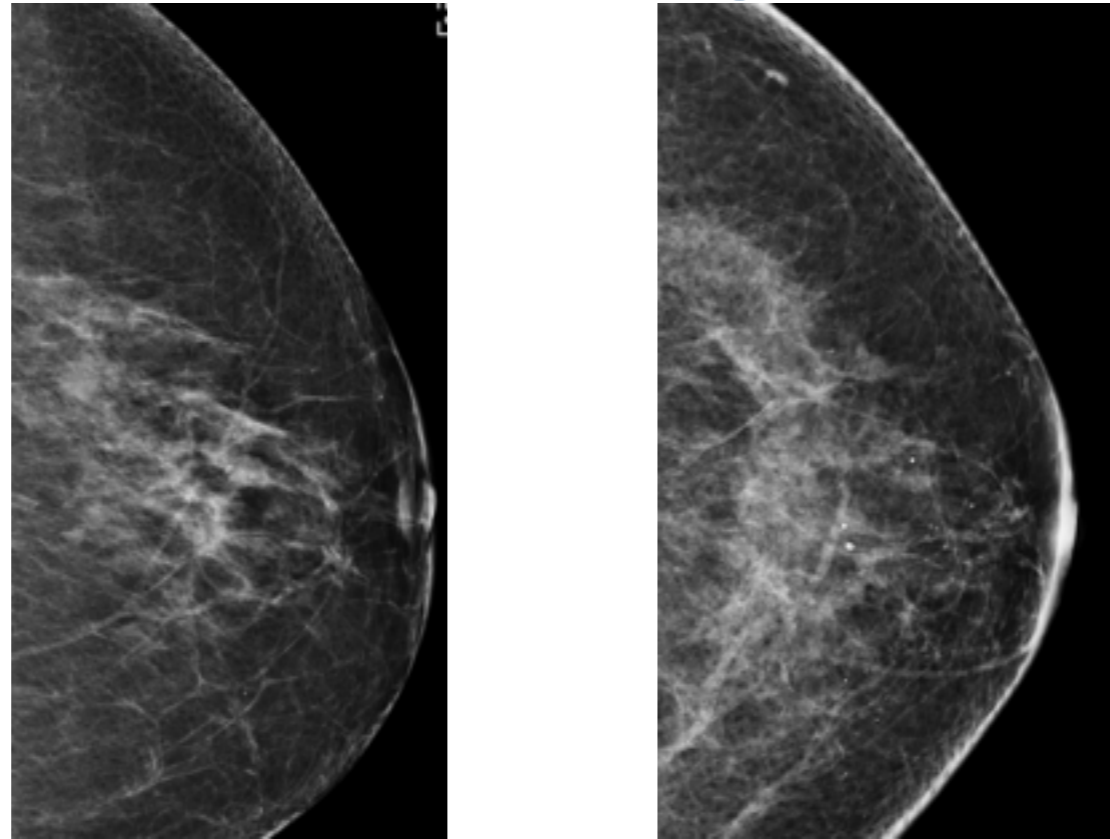
- increases lifetime breast cancer risk
- assessment is subjective

# Predicting Density



- Training: 20K , Test: 5K
- Original 3K\*3K images are downsampled to 256\*256
- AlexNet Accuracy: 88%
- Human Agreement: 86%

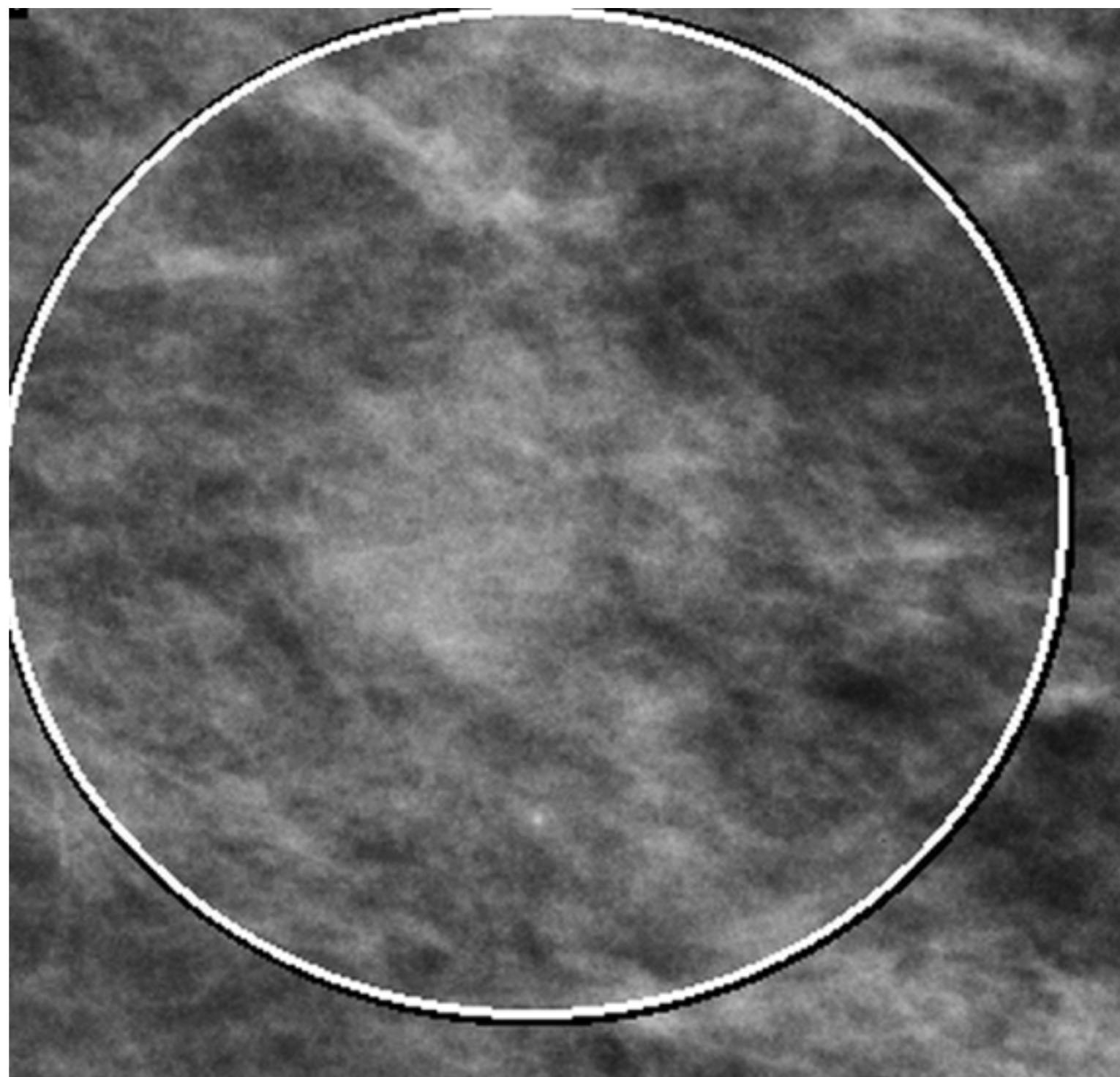
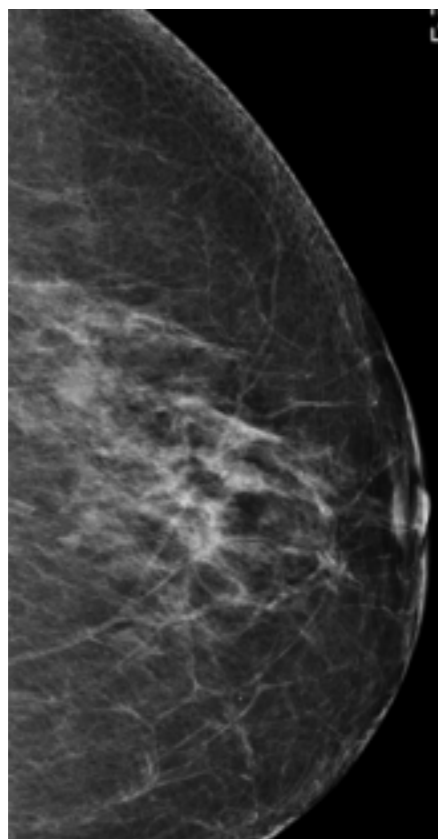
# Predicting BI-RAD



**BI-RAD:** quantifies the need in additional testing due to abnormality

- reasons: mass, asymmetry, distortion of tissue, ...
- radiologists can assess BI-RAD with high accuracy

# ZOOMED IN MAMMO



# Predicting BI-RAD

- Train: 28K, Test: 1K
- Methods: AlexNet, Inception, Resnet, VGGNet, ...
- F-measure: AUC 61%, F1 51%

Consistent with other reported results!

## High-Resolution Breast Cancer Screening with Multi-View Deep Convolutional Neural Networks

Krzysztof J. Geras<sup>a</sup>, Stacey Wolfson<sup>c</sup>, S. Gene Kim<sup>c,d</sup>, Linda Moy<sup>c,d</sup>, and Kyunghyun Cho<sup>a,b,1</sup>

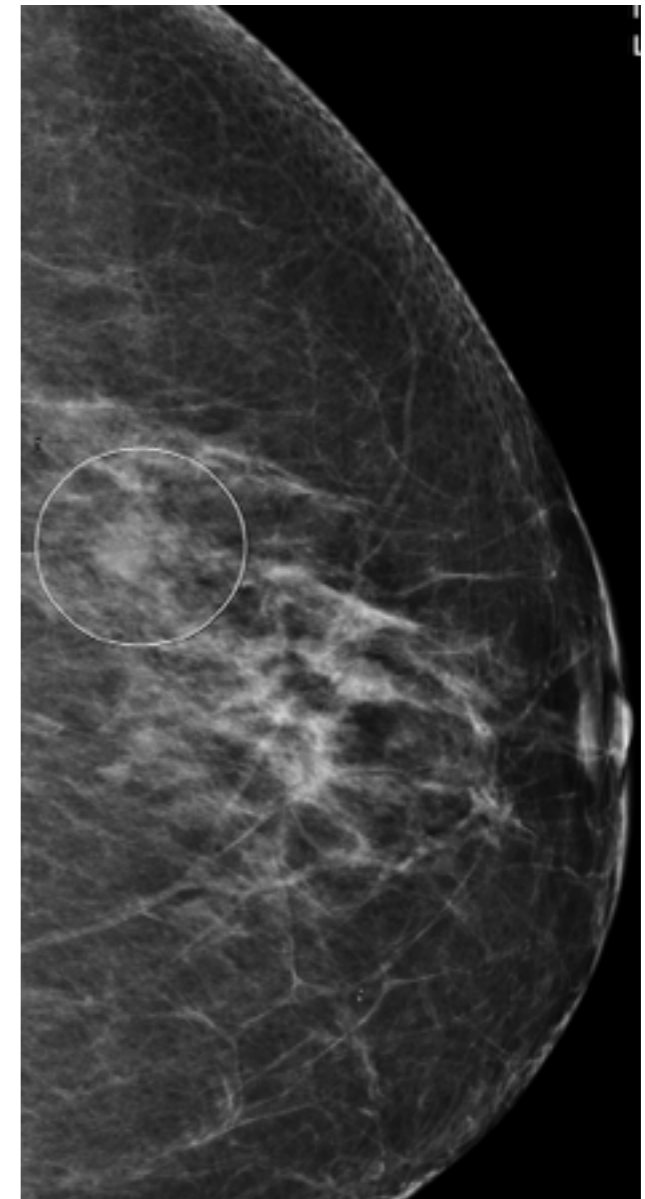
<sup>a</sup>Center for Data Science, New York University; <sup>b</sup>Courant Institute of Mathematical Sciences, New York University; <sup>c</sup>Center for Biomedical Imaging, Radiology, NYU School of Medicine; <sup>d</sup>Perlmutter Cancer Center, NYU Langone Medical Center



# Can Text Help to Focus Attention?

Finding 1: There is a focal asymmetry in the upper outer quadrant of the left breast. Finding 2: There are two asymmetries in the lateral aspect of the left breast. Finding 3: There are post lumpectomy changes in the right breast.

**IMPRESSION:** Finding 1: Focal asymmetry in the upper outer quadrant of the left breast requires additional evaluation. Recommend additional mammographic views and ultrasound if warranted. Finding 2: Asymmetries in the lateral aspect of the left breast require additional evaluation.



# Infinite thanks to my students and collaborators who helped to cure me

