Machine Learning for Healthcare

6.871, HST.956

Lecture 15: Weak supervision

David Sontag

HEALTH SCIENCES
& TECHNOLOGY

Outline for today's class

1. **Learning with noisy labels**
   - Consistent estimation under class-conditional noise (Natarajan et al., NeurIPS '13)
   - Application in health care (Halpern et al., JAMIA '16)
2. Weak supervision

Labels may be noisy

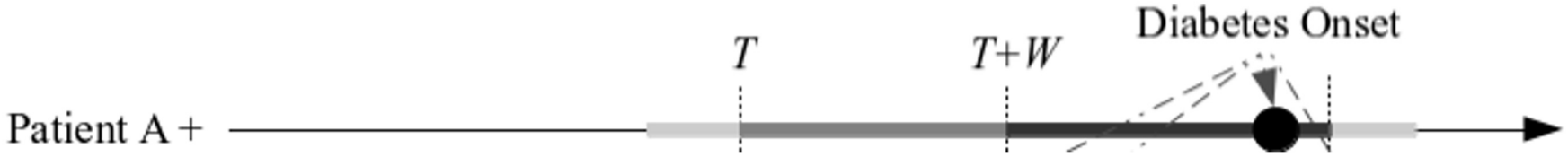
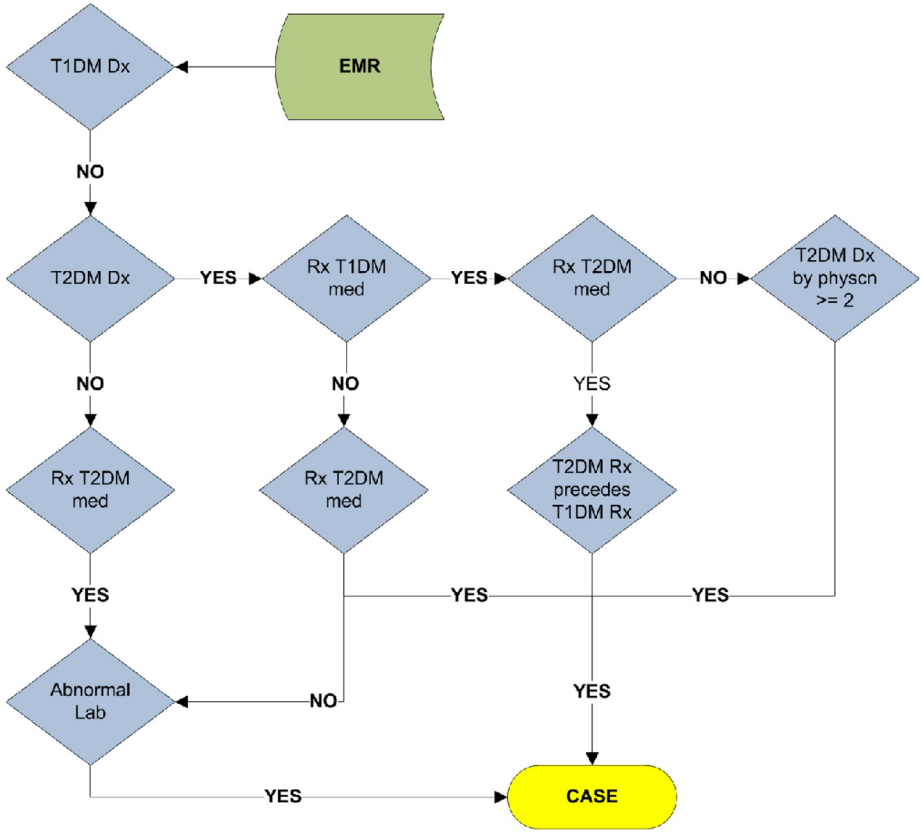


Figure 1: Algorithm for identifying T2DM cases in the EMR.

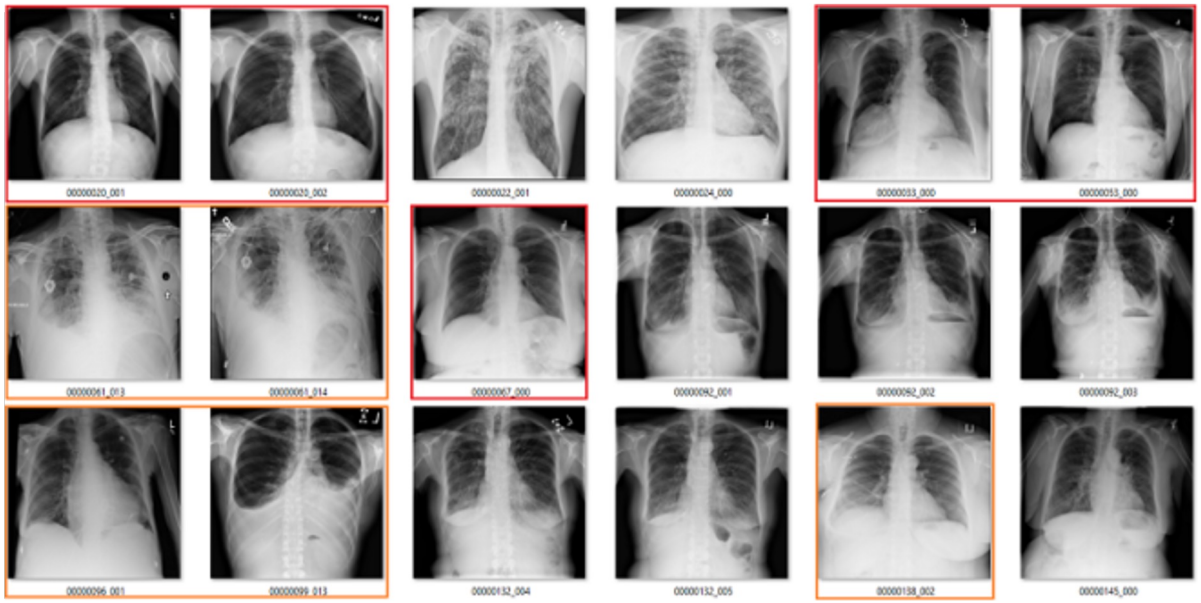
If the derived label is noisy, how does it affect learning?



Source: https://phekb.org/sites/phenotype/files/T2DM-algorithm.pdf

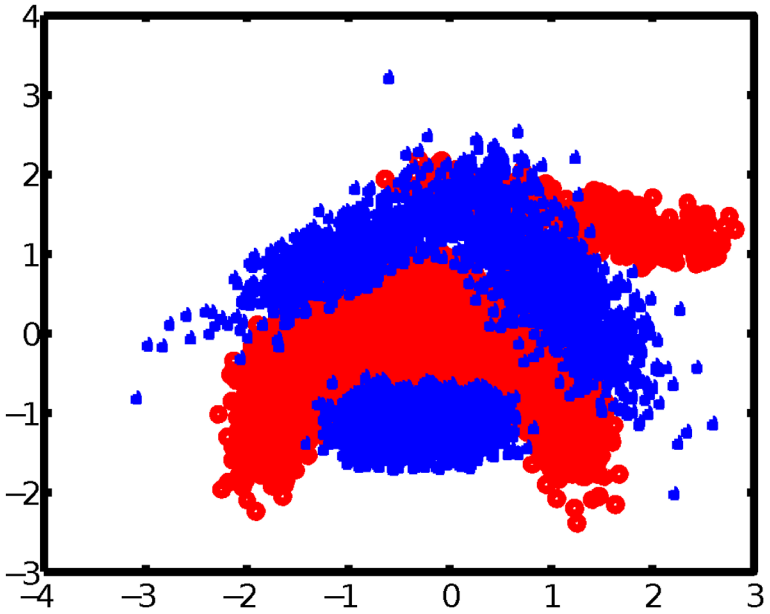
Labels may be noisy

Fibrosis

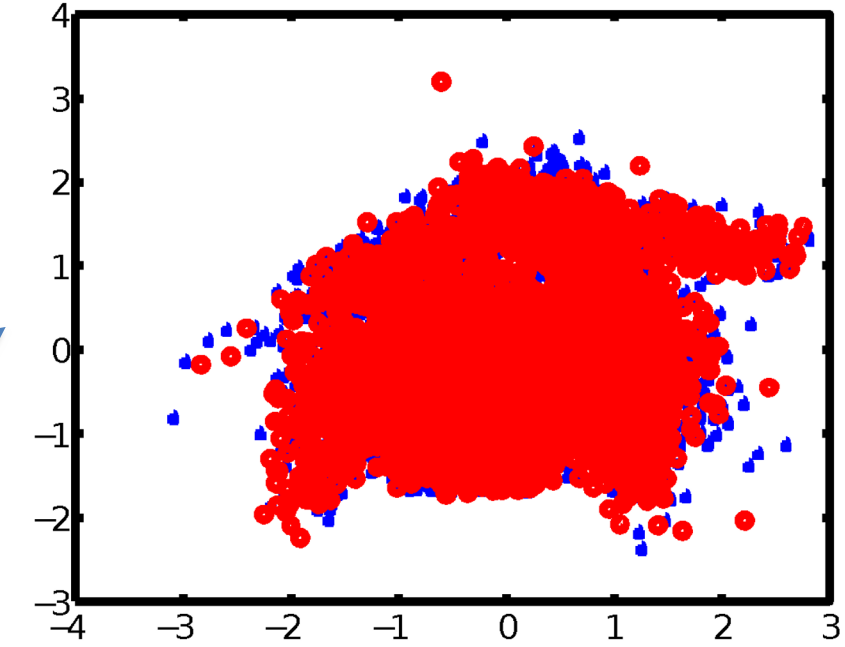


red = mislabeled
orange = maybe mislabeled

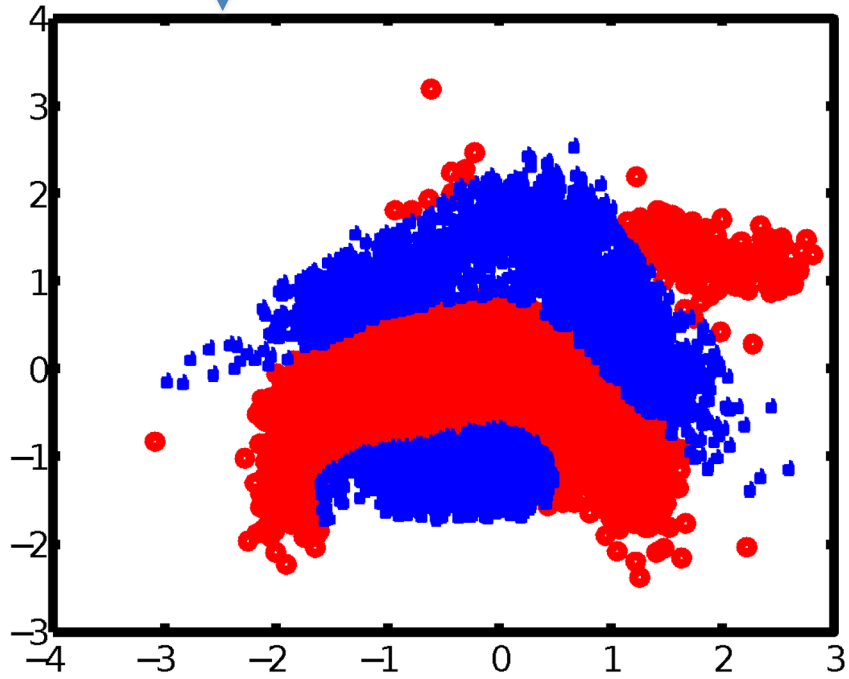
[Wang et al., “Chest X-ray8”]
figure credit: https://lukeoakdenrayner.wordpress.com/2017/12/18/the-chestxray14-dataset-problems/



40% label noise



Machine learning



[Natarajan et al., NeurIPS ’13. Figure 2]

Learning with noisy labels

We will show that if we have

a) ***class-conditional*** label noise and

b) ***lots*** of training data,

learning as usual, substituting noisy labels, works!

This opens the door to using noisy labels for training, and coming up with clever ways of deriving these for free

(Natarajan et al., *Learning with Noisy Labels.* NeurIPS '13)

Natarajan et al: Introduction

- Features X
- True unobserved labels $Y \in \{-1, 1\}$
- Noisy observed labels $\tilde{Y} \in \{-1, 1\}$
- True distribution $P(X, Y, \tilde{Y})$

$\boldsymbol{X}$ (age)	$\boldsymbol{Y}$ (diabetic)	$\widetilde{\boldsymbol{Y}}$ (noisy version)
30	-1	
64	1	
75	1	

Natarajan et al: Introduction

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- True unobserved labels $Y \in \{-1, 1\}$
- Noisy observed labels $\tilde{Y} \in \{-1, 1\}$
- True distribution $P(X, Y, \tilde{Y})$

X (age)	Y (diabetic)	$\tilde{Y}$ (noisy version)
30	-1	-1
64	1	1
75	1	-1

- Data sampled from $P(X, \tilde{Y}) = \sum_y P(X, Y = y, \tilde{Y})$

Y *exists*, but it is hidden during training

X (age)	$\tilde{Y}$ (noisy version)
30	-1
64	1
75	-1

Assumption: class-conditional label noise

- Assume that $\tilde{Y} \perp X|Y$:

$$P(X, Y, \tilde{Y}) = P(X, Y)P(\tilde{Y}|Y)$$

$\tilde{Y}$ only depends on Y: label noise is independent of input features

- Since Y is binary, need two parameters to fully define $P(\tilde{Y}|Y)$: $\rho_+ = P(\tilde{Y} = -1|Y = 1)$ & $\rho_- = P(\tilde{Y} = 1|Y = -1)$

- Assume that $\rho_+ + \rho- < 1$ and that ρ_+, ρ_- are known

(Natarajan et al., *Learning with Noisy Labels.* NeurIPS '13)

Learning with class-conditional noise

- If we could learn $\eta(X) = P(Y = 1|X)$, then we would be able to predict optimally.

(Natarajan et al., *Learning with Noisy Labels.* NeurIPS '13)

Learning with class-conditional noise

- If we could learn $\eta(X) = P(Y = 1|X)$, then we would be able to predict optimally.

$$\tilde{\eta}(X) = P(\tilde{Y} = 1|X)$$

(Natarajan et al., *Learning with Noisy Labels.* NeurIPS '13)

Learning with class-conditional noise

- If we could learn $\eta(X) = P(Y = 1|X)$, then we would be able to predict optimally.

$$\begin{aligned}\tilde{\eta}(X) &= P(\tilde{Y} = 1|X) \\ &= P(\tilde{Y} = 1, Y = 1|X) + P(\tilde{Y} = 1, Y = -1|X)\end{aligned}$$

(Natarajan et al., *Learning with Noisy Labels.* NeurIPS '13)

Learning with class-conditional noise

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(Natarajan et al., *Learning with Noisy Labels.* NeurIPS '13)

Learning with class-conditional noise

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(Natarajan et al., *Learning with Noisy Labels.* NeurIPS '13)

Learning with class-conditional noise

- If we could learn $\eta(X) = P(Y = 1|X)$, then we would be able to predict optimally.

$$\begin{aligned}
\tilde{\eta}(X) &= P(\tilde{Y} = 1|X) \\
&= P(\tilde{Y} = 1, Y = 1|X) + P(\tilde{Y} = 1, Y = -1|X) \\
&= P(Y = 1|X)P(\tilde{Y} = 1|Y = 1) \\
&\quad + P(Y = -1|X)P(\tilde{Y} = 1|Y = -1) \\
&= \eta(X)(1 - \rho_+) + (1 - \eta(X))\rho_- \\
&= \eta(X)(1 - \rho_+ - \rho_-) + \rho_-
\end{aligned}$$

(Natarajan et al., *Learning with Noisy Labels.* NeurIPS '13)

Learning with class-conditional noise

$$\rightarrow \eta(X) = \frac{\tilde{\eta}(X) - \rho_-}{1 - \rho_+ - \rho_-}$$

$\eta(X)$ is monotonically increasing in $\tilde{\eta}(X)$

- Learn $\tilde{\eta}(X)$ using any ML algorithm which returns calibrated classifiers. Substitute $\tilde{\eta}(X)$ in the above equation to get $\eta(X)$!

- When might noise be helpful?

(Natarajan et al., *Learning with Noisy Labels.* NeurIPS '13)

Outline for today's class

1. Learning with noisy labels
   - Consistent estimation under class-conditional noise (Natarajan et al., NeurIPS '13)
   - **Application in health care (Halpern et al., JAMIA '16)**
2. Weak supervision

Application to electronic phenotyping

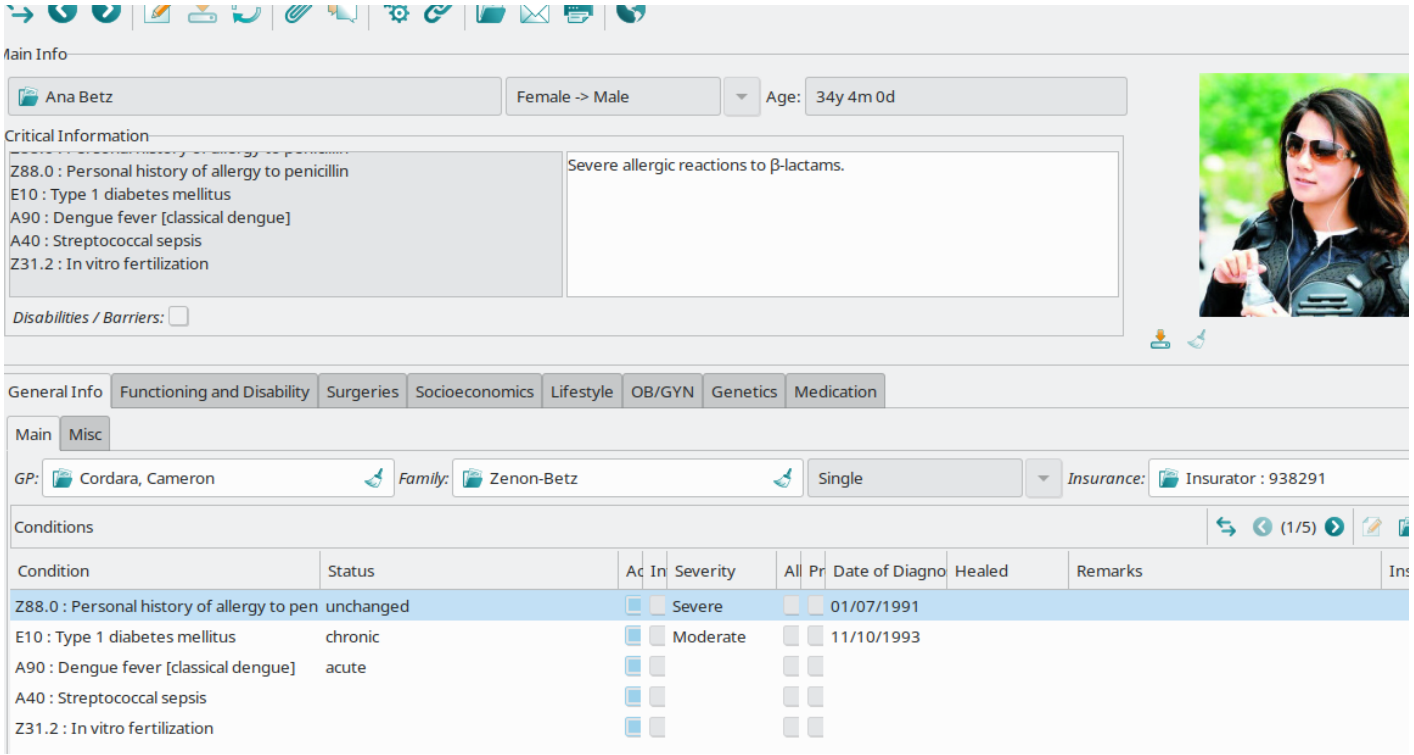


Figure source:
https://commons.wikimedia.org/wiki/File:GNU_Health_patient_main_screen.png

Hundreds of relevant clinical variables

Abdominal pain
Active malignancy
Altered mental status
Cardiac etiology
Renal failure
Infection
Urinary tract infection
Shock
Smoker
Pregnant
Lower back pain
Motor Vehicle accident
Psychosis
Anticoagulated
Type II diabetes
…

[Halpern, Horng, Choi, Sontag, AMIA ’14; Halpern, Horng, Choi, Sontag, JAMIA ‘16]

Simplest approach: rules

- We would like to estimate, for every patient, which phenotypes apply to them (at some point in time)
- Common practice is to derive manual rules:

Need to include:
nursing facility
nursing care
facility nursing / rehab
nsg facility
nsg faclty
…

text contains: *"nursing home"*

Nursing home? physician response (gold standard)

	T	F
T	297	129
F	1,319	34511

PPV 0.70

297/(297+129)

Sensitivity 0.18

Slow, expensive, poor sensitivity.

Often we can find noisy labels WITHIN the data!

Phenotype	Example of noisy label (“anchor”) ⚓
Diabetic (type I)	gsn:016313 (insulin) in **Medications**
Strep Throat	Positive strep test in **Lab results**
Nursing home	“from nursing home” in **Text**
Pneumonia	“pna” in **Text**
Heart attack	ICD10 I21 in **Billing codes**

How can we use these for machine learning?

Often we can find noisy labels WITHIN the data!

Phenotype	Example of noisy label (anchor) ⚓
Heart attack	ICD10 I21 in **Billing codes**

- Suppose we want to know, was a patient admitted to the emergency department for a heart attack?
- Billing codes not available at prediction time, but can be used for labels
- Reasonable to assume that $\rho_- = P\left(\tilde{Y} = 1 \middle| Y = -1\right) \approx 0$, but because of noisy nature of billing codes, $\rho_+ = P\left(\tilde{Y} = -1 \middle| Y = 1\right)$ likely non-zero

Called "positive only" noise since it implies $P\left(Y = 1 \middle| \tilde{Y} = 1\right) = 1$

Anchor & Learn Algorithm

(special case for anchors derived from future data)

Training

1. Treat the anchors as "true" labels
2. Learn a classifier to predict whether the ***anchor*** $\tilde{Y}$ appears
3. Calibration step: divide by $\frac{1}{|P|}\sum_P P(\tilde{Y}=1|X)$

P = data points with $\tilde{Y}=1$

Test time

1. Predict using the learned classifier (with calibration)

Often we can find noisy labels WITHIN the data!

Phenotype	Example of noisy label (anchor) ⚓
Nursing home	"from nursing home" in **Triage note**

- We again assume that $\rho_- = P(\tilde{Y} = 1 | Y = -1) \approx 0$, but because many ways to write "from nursing home" in text, we have $\rho_+ = P(\tilde{Y} = -1 | Y = 1)$ likely non-zero
- If we simply learn to predict $\tilde{Y}$ using the notes, we will learn a trivial classifier! It will simply extract mentions of this phrase!
- This is a clear violation of the assumption $\tilde{Y} \perp X | Y$, since $\tilde{Y}$ is derived from X

Anchor & Learn Algorithm

Training

1. Treat the anchors as “true” labels
2. Learn a classifier to predict whether the ***anchor*** appears based on ***all other features***
3. Calibration step: divide by $\frac{1}{|P|}\sum_P P(\tilde{Y}=1|X)$

P = data points with $\tilde{Y}=1$

Test time

1. If the anchor is present: Predict 1
2. Else: Predict using the learned classifier (with calibration)

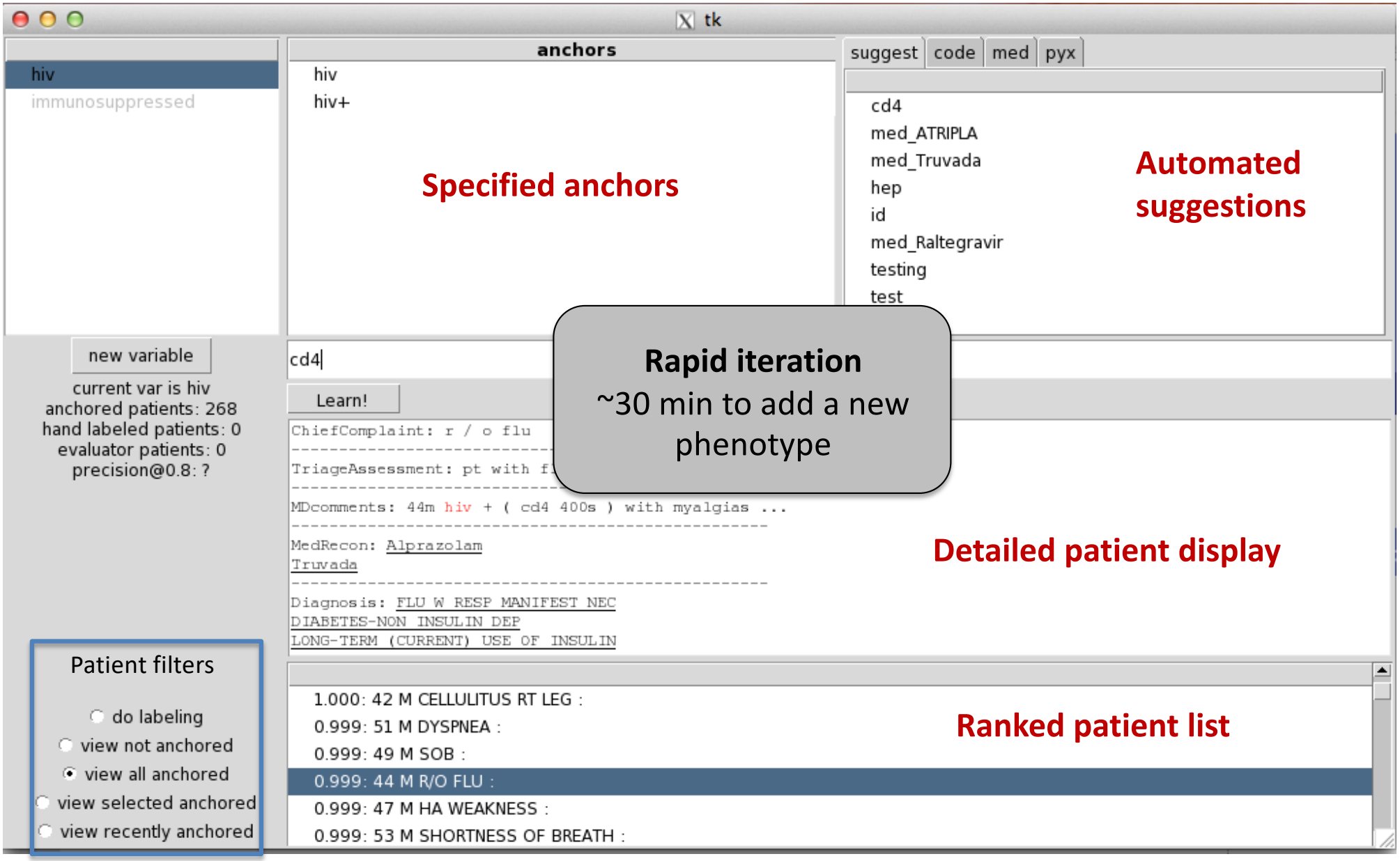
Evaluating phenotypes

- Derived anchors and learned phenotypes using 270,000 patients' emergency department medical records

History
Alcoholism
Anticoagulated
Asthma/COPD
Cancer
Congestive heart failure
Diabetes
HIV+
Immunosuppressed
Liver malfunction

Acute		
Abdominal pain	Deep vein thrombosis	Laceration
Allergic reaction	Employee exposure	Motor vehicle accident
Ankle fracture	Epistaxis	Pancreatitis
Back pain	Gastroenteritis	Pneumonia
Bicycle accident	Gastrointestinal bleed	Psych
Cardiac etiology	Geriatric fall	Obstruction
Cellulitis	Headache	Septic shock
Chest pain	Hematuria	Severe sepsis
Cholecystitis	Intracerebral hemorrhage	Sexual assault
Cerebrovascular accident	Infection	Suicidal ideation
	Kidney stone	Syncope
		Urinary tract infection

[Halpern, Horng, Choi, Sontag, AMIA '14]
[Halpern, Horng, Choi, Sontag, JAMIA '16]

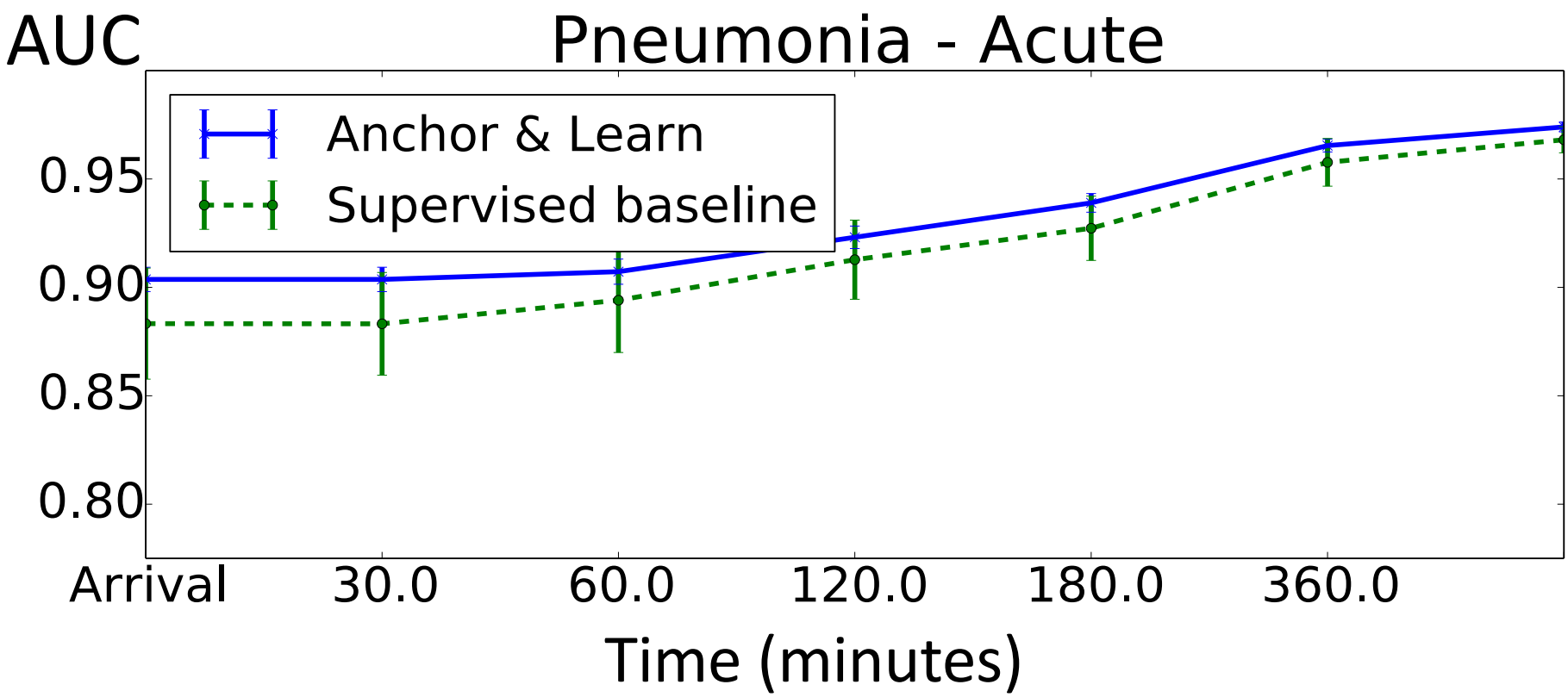

tk
hiv
immunosuppressed
anchors
hiv
hiv+
Specified anchors
suggest
code
med
pyx
cd4
med_ATRIPLA
med_Truvada
hep
id
med_Raltegravir
testing
test
Automated suggestions
new variable
current var is hiv
anchored patients: 268
hand labeled patients: 0
evaluator patients: 0
precision@0.8: ?
cd4
Learn!
Rapid iteration
~30 min to add a new phenotype
ChiefComplaint: r / o flu
TriageAssessment: pt with f
MDcomments: 44m hiv + (cd4 400s) with myalgias ...
MedRecon: Alprazolam
Truvada
Diagnosis: FLU W RESP MANIFEST NEC
DIABETES-NON INSULIN DEP
LONG-TERM (CURRENT) USE OF INSULIN
Detailed patient display
Patient filters
do labeling
view not anchored
view all anchored
view selected anchored
view recently anchored
1.000: 42 M CELLULITUS RT LEG :
0.999: 51 M DYSPNEA :
0.999: 49 M SOB :
0.999: 44 M R/O FLU :
0.999: 47 M HA WEAKNESS :
0.999: 53 M SHORTNESS OF BREATH :
Ranked patient list

Evaluating phenotypes

- Derived anchors and learned phenotypes using 270,000 patients' emergency department medical records
- To obtain ground truth, added a small number of questions to patient discharge procedure, rotated randomly

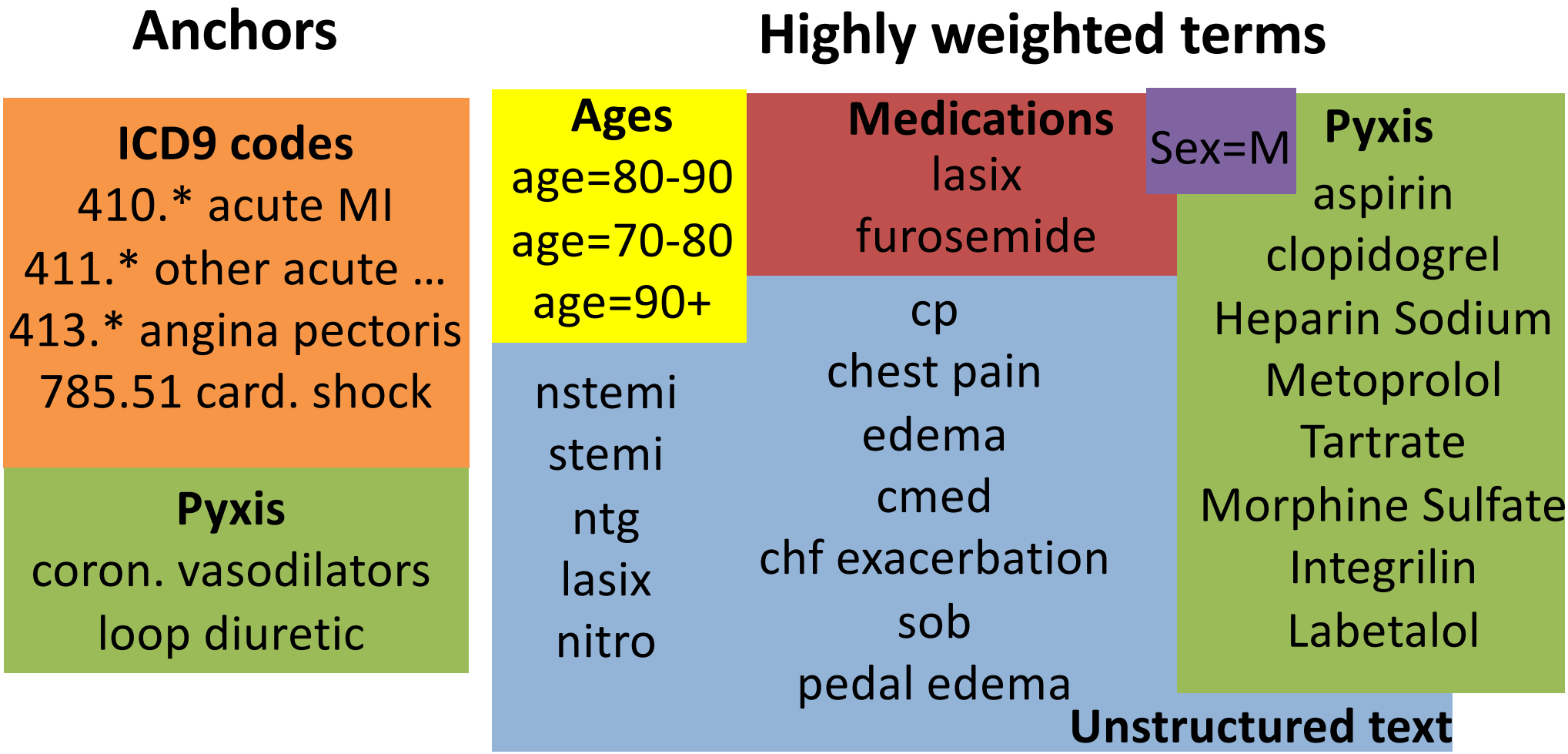
[Halpern, Horng, Choi, Sontag, AMIA '14]
[Halpern, Horng, Choi, Sontag, JAMIA '16]

Evaluating phenotypes



Comparison to supervised learning using labels for 5000 patients

Evaluating phenotypes – example model (cardiac etiology)



[Halpern, Horng, Choi, Sontag, AMIA '14]
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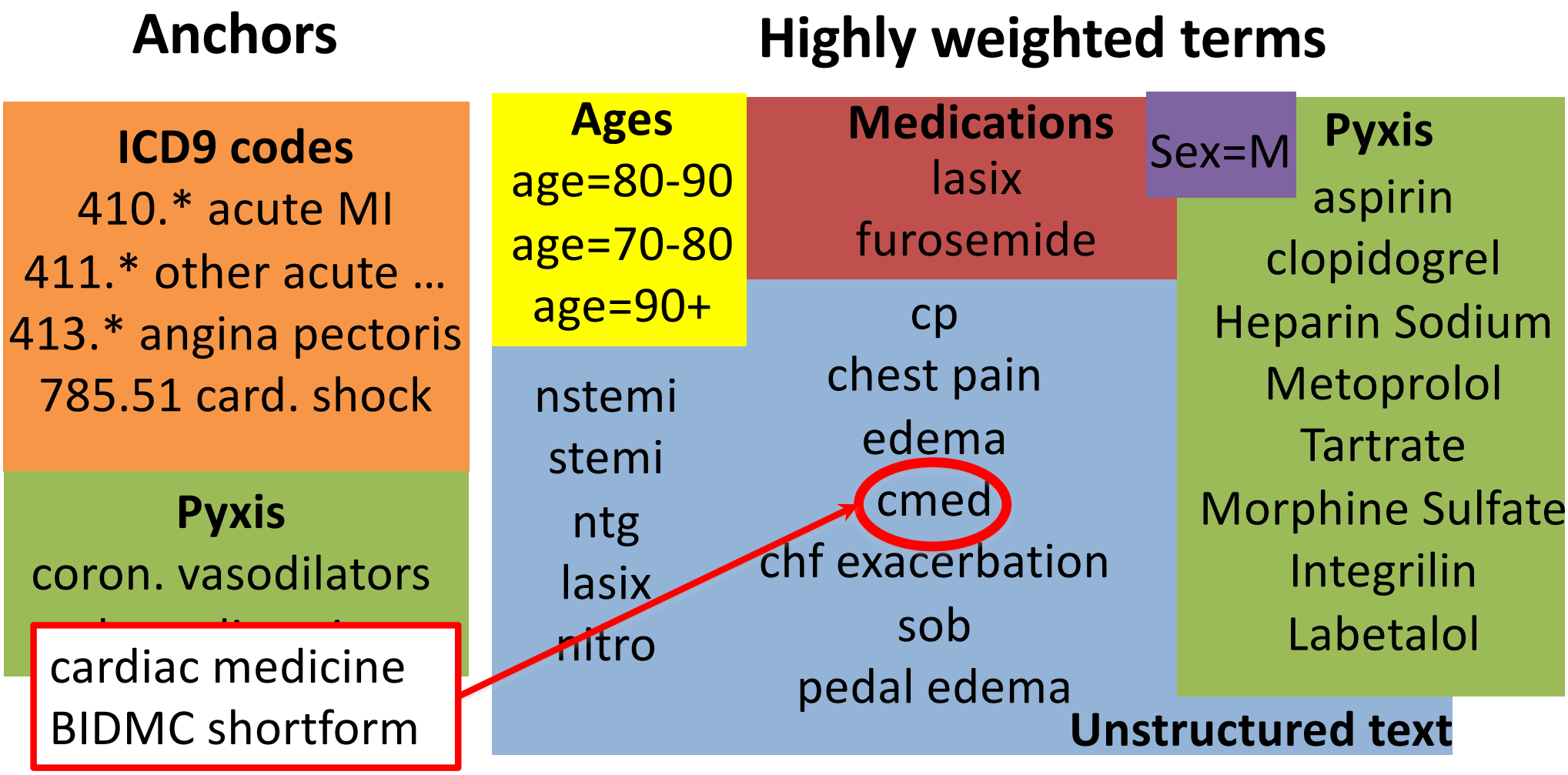
Evaluating phenotypes – example model (cardiac etiology)



[Halpern, Horng, Choi, Sontag, AMIA '14]
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Outline for today's class

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   - Consistent estimation under class-conditional noise (Natarajan et al., NeurIPS '13)
   - Application in health care (Halpern et al., JAMIA '16)
2. **Weak supervision**

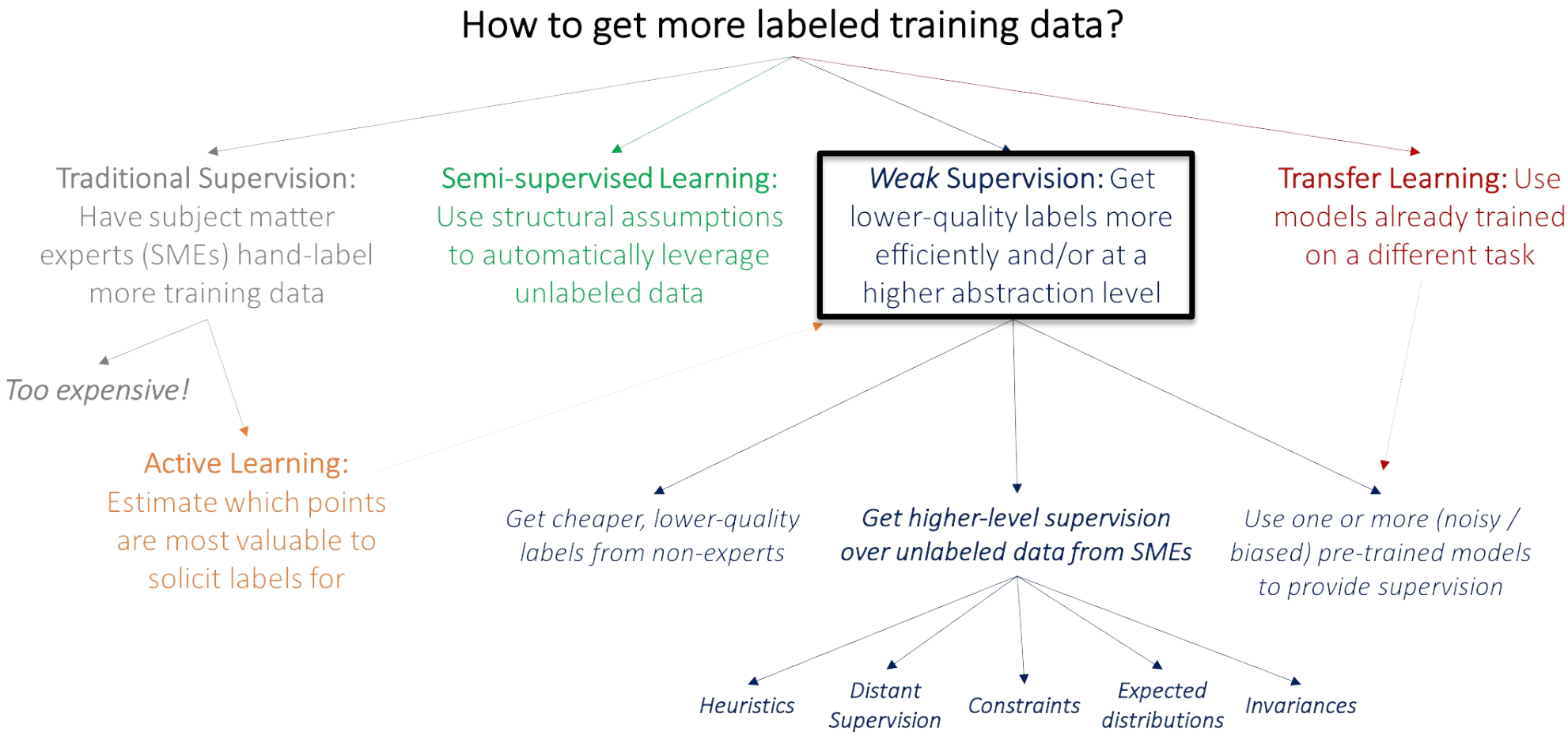
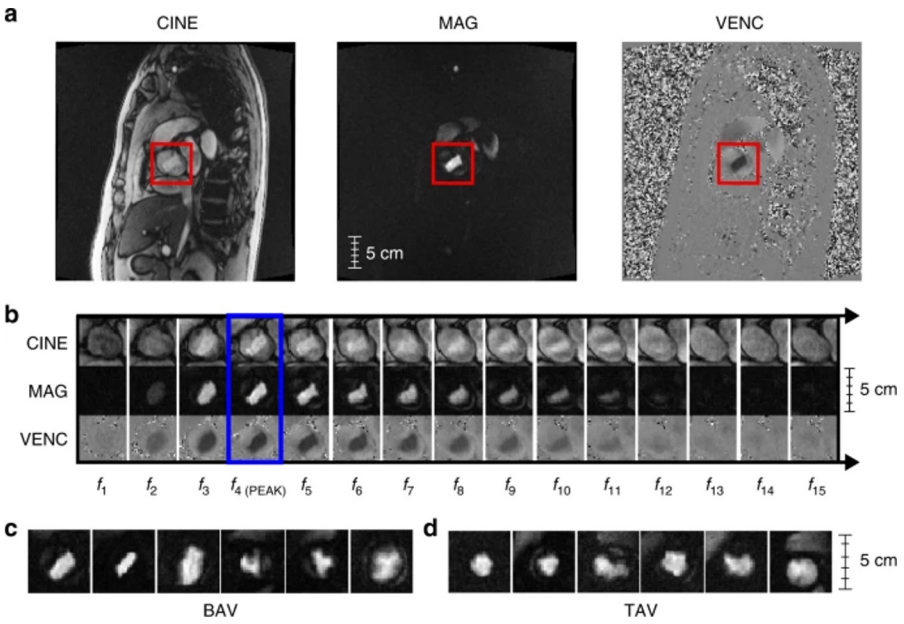


Figure from: https://www.snorkel.org/blog/weak-supervision

Weak supervision

- Define one or more labeling functions l(x) that outputs a label (or no label) for each example
- E.g., for sentiment analysis
  “good” -> +1
  “bad” -> -1
- Reconcile conflicting labels; ignore data points that are unlabeled
- Learn a model on the labeled data points

Classifying Aortic Valve Malformations



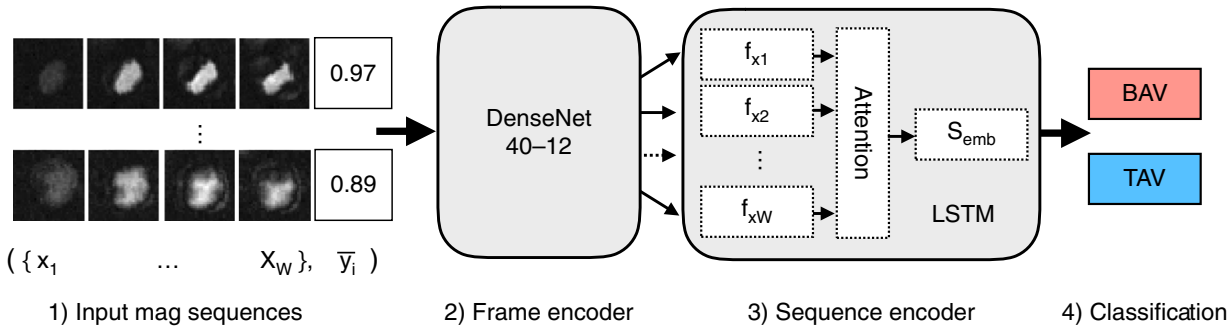
- Data: MRI sequences for 14,328 subjects from the UK Biobank
- True gold standard labels for *aortic valve malformations* (BAV) derived for 412 subjects
- Goal: Train a model which can classify BAV (positive or negative) when given a new MRI sequence

[Fries et al. *Weakly supervised classification of aortic valve malformations using unlabeled cardiac MRI sequences.* Nature Communications 2019]

Classifying Aortic Valve Malformations

Methodology:

1. Train a factor graph-based model to predict noisy labels for all unlabeled examples
2. Train a hybrid convolutional NN / LSTM using the derived noisy labels



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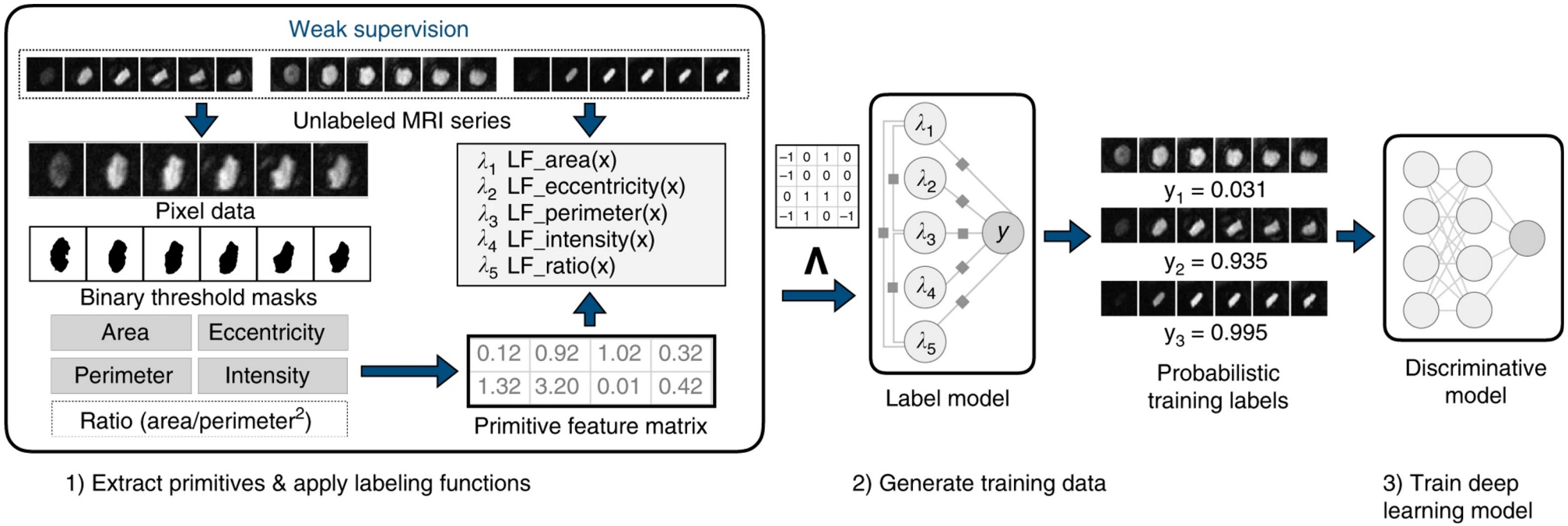
Classifying Aortic Valve Malformations



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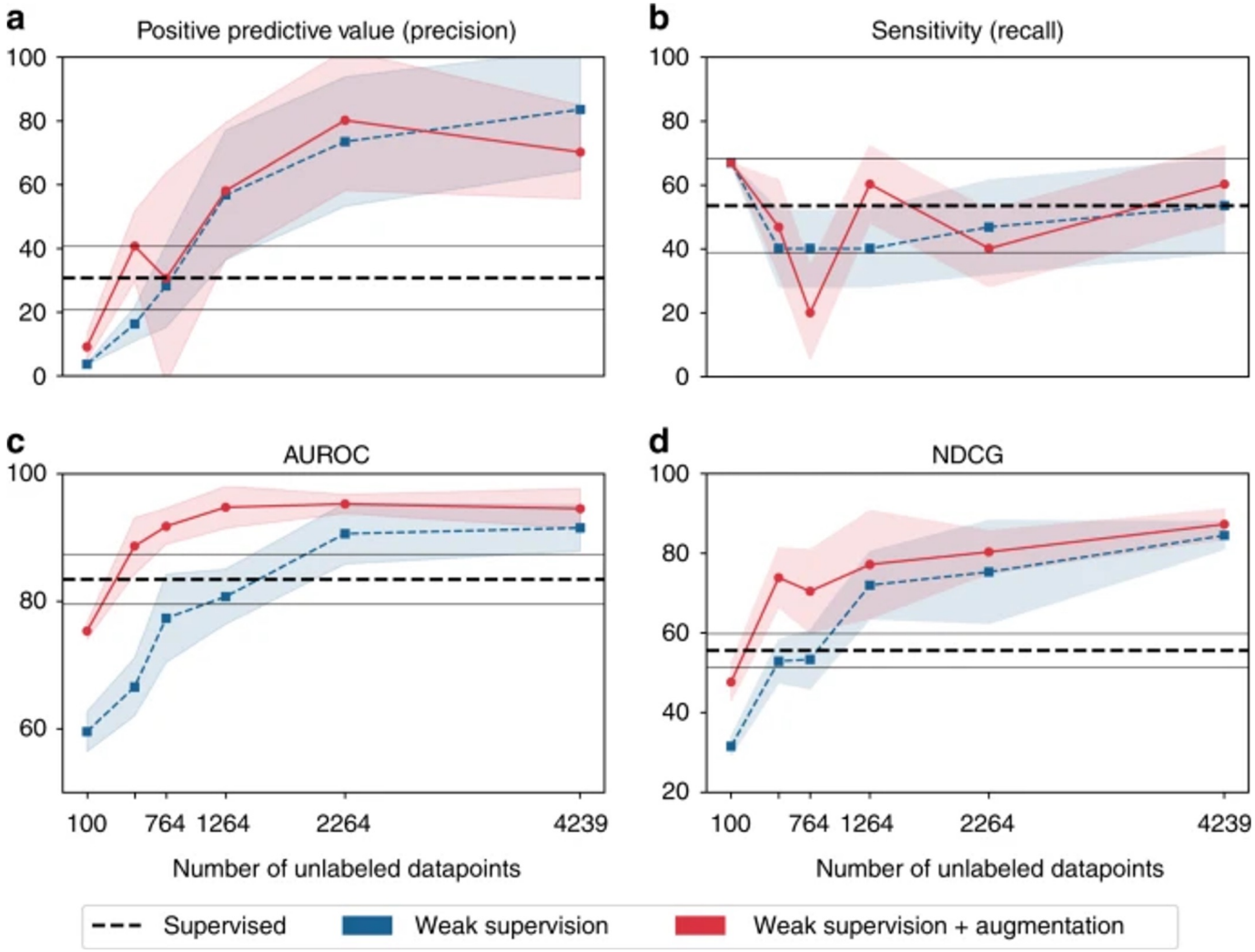
Classifying Aortic Valve Malformations



[Fries et al. *Weakly supervised classification of aortic valve malformations using unlabeled cardiac MRI sequences.* Nature Communications 2019]

Weak supervision for text classification

- Example labeling functions:

```
3   # Setting LF output values
4   ABSTAIN_VAL = 0
5   HEMORRHAGE_VAL = 1
6   NO_HEMORRHAGE_VAL = -1

63  def LF_positive_hematoma(report):
64      """
65      Checking for words indicating hematoma
66      """
67      r1 = re.compile('(No|without|resolution|scalp|subgaleal)\\s([\S]*\\s){0,10}(hematoma)',re.IGNORECASE)
68      r = re.compile('hematoma',re.IGNORECASE)
69      for s in report.report.sentences:
70          if r.search(s.text) and (not r1.search(s.text)):
71              return HEMORRHAGE_VAL
72      return ABSTAIN_VAL
73
74  def LF_hemorrhage_hi_cover(report):
75      """
76      Checking for both hemorrhage and hematoma
77      """
78      if LF_positive_hemorrhage(report) == 0 and LF_positive_hematoma(report) == 0:
79          return NO_HEMORRHAGE_VAL
80      return HEMORRHAGE_VAL
```

Reference: https://github.com/HazyResearch/cross-modal-ws-demo/blob/master/lfs/lfs_hct.py

Weak supervision for text classification

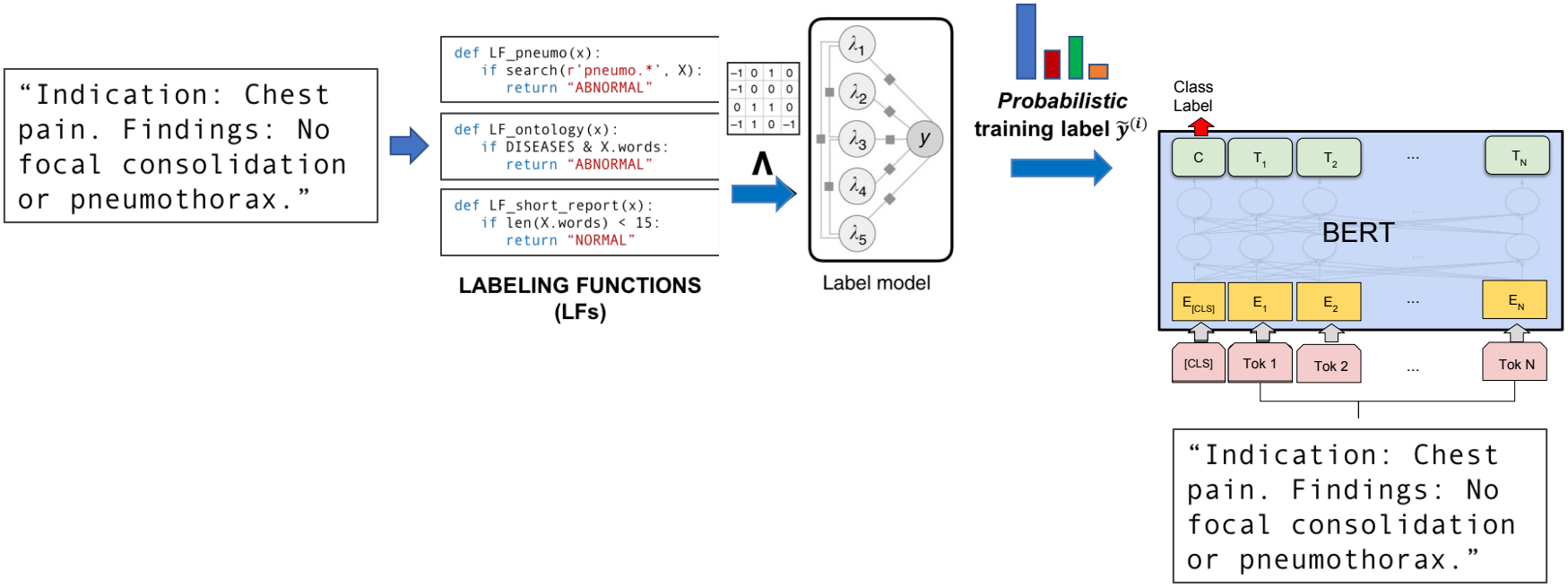
- Example labeling functions:

```
3   # Setting LF output values
4   ABSTAIN_VAL = 0
5   HEMORRHAGE_VAL = 1
6   NO_HEMORRHAGE_VAL = -1
12  def LF_normal_V01(report):
13      """
14      Checking for specific normal phrase
15      """
16      r = re.compile('Normal CT of the Head',re.IGNORECASE)
17      for s in report.report.sentences:
18          if r.search(s.text):
19              return NO_HEMORRHAGE_VAL
20      return ABSTAIN_VAL
21
22  def LF_normal_V02(report):
23      """
24      Checking for specific normal phrase
25      """
26      r = re.compile('No acute intracranial abnormality',re.IGNORECASE)
27      for s in report.report.sentences:
28          if r.search(s.text):
29              return NO_HEMORRHAGE_VAL
30      return ABSTAIN_VAL
```

Reference: https://github.com/HazyResearch/cross-modal-ws-demo/blob/master/lfs/lfs_hct.py

Weak supervision for text classification

- Use BERT as “end model”



- Why does this not simply learn to reproduce the labeling functions?

Weak supervision for text classification

Table 1: Statistics of all the tasks, domains and datasets included in WRENCH.

Task (↓)	Domain (↓)	Dataset (↓)	#Label	#LF	Train #Data	Dev #Data	Test #Data
Sentiment Class.	Movie	IMDb [61, 79]	2	5	20,000	2,500	2,500
	Review	Yelp [107, 79]	2	8	30,400	3,800	3,800
Spam Class.	Review	Youtube [1]	2	10	1,586	120	250
	Text Message	SMS [2, 3]	2	73	4,571	500	500
Topic Class.	News	AGNews [107, 79]	4	9	96,000	12,000	12,000
Question Class.	Web Query	TREC [49, 3]	6	68	4,965	500	500
Relation Class.	News	Spouse [11, 77]	2	9	22,254	2,811	2,701
	Biomedical	CDR [13, 77]	2	33	8,430	920	4,673
	Web Text	SemEval [31, 109]	9	164	1,749	200	692
	Chemical	ChemProt [41, 102]	10	26	12,861	1,607	1,607

[Zhang et al. WRENCH: A Comprehensive Benchmark for Weak Supervision. NeurIPS Track on Datasets and Benchmarks, 2021]

Weak supervision for text classification

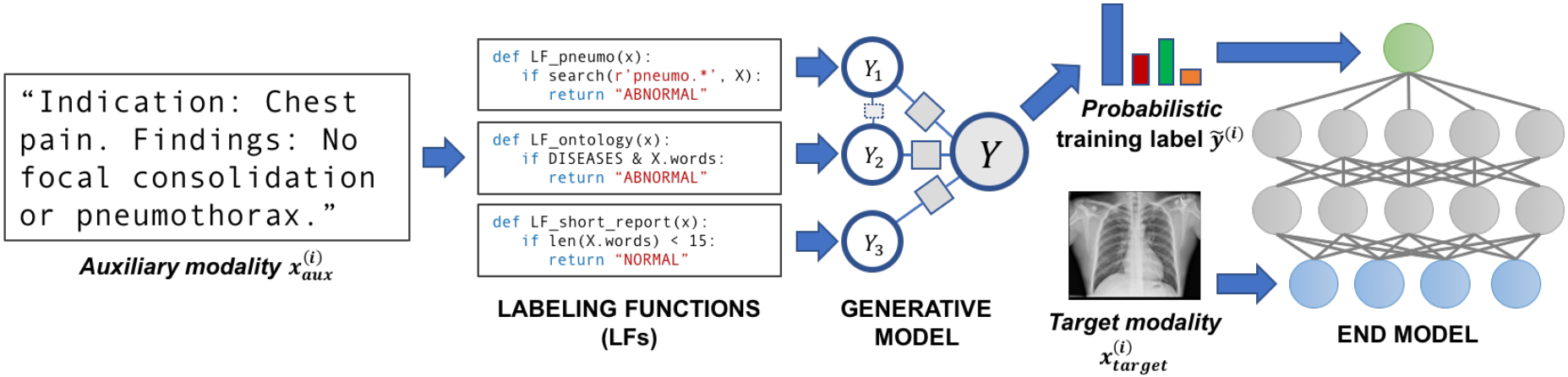
EM: end model (R=RoBERTa, RC=COSINE-RoBERTa, BC=COSINE-BERT)
LM: label model (MV="majority vote", WMC="weighted majority vote")

		Best Gold		Top 1			Top 2			Top 3		
Dataset	**Metric**	**EM**	**Value**	**EM**	**LM**	**Value**	**EM**	**LM**	**Value**	**EM**	**LM**	**Value**
IMDb	Acc.	R	93.25	RC	MeTaL	88.86	RC	FS	88.48	RC	MV	88.48
Yelp	Acc.	R	97.13	RC	FS	95.45	RC	FS	95.33	RC	DS	95.01
Youtube	Acc.	B	97.52	BC	MV	98.00	RC	MV	97.60	RC	MV	97.60
SMS	F1	B	96.96	RC	WMV	98.02	RC	MeTaL	97.71	RC	WMV	97.27
AGNews	Acc.	R	91.39	RC	DS	88.20	RC	MV	88.15	RC	WMV	88.11
TREC	Acc.	R	96.68	RC	DP	82.36	RC	MeTaL	79.84	BC	DP	78.72
Spouse	F1	–	–	BC	FS	56.52	–	MeTaL	46.62	RC	MV	46.28
CDR	F1	R	65.86	–	MeTaL	69.61	–	DP	63.51	RC	DP	61.40
SemEval	Acc.	B	95.43	BC	DP	88.77	BC	MV	86.80	RC	DP	86.73
ChemProt	Acc.	B	89.76	BC	DP	61.56	RC	MV	59.43	RC	MV	59.32

[Zhang et al. WRENCH: A Comprehensive Benchmark for Weak Supervision. NeurIPS Track on Datasets and Benchmarks, 2021]

Weak supervision with multiple views

- Alternatively, one could just use the noisy labels from the label model to directly train the downstream model:



- Co-training (Blum & Mitchell, '98) can be used to improve performance further

[Dunnmon et al., Cross-Modal Data Programming Enables Rapid Medical Machine Learning. arXiv:1903.1101, 2019.]

Conclusion

- Can be difficult to get labeled data for machine learning in health care
- Often possible to quickly derive *noisy* labels (i.e., anchors or labeling functions)
- With conditionally independent noise, ML as usual can be used (with recalibration)
  - $x \perp \tilde{Y} | Y$ (noise rate constant for all examples)
  - Can sometimes *censor* the features to make this assumption more realistic (the anchor & learn method)
  - Alternatively, use pretrained representations