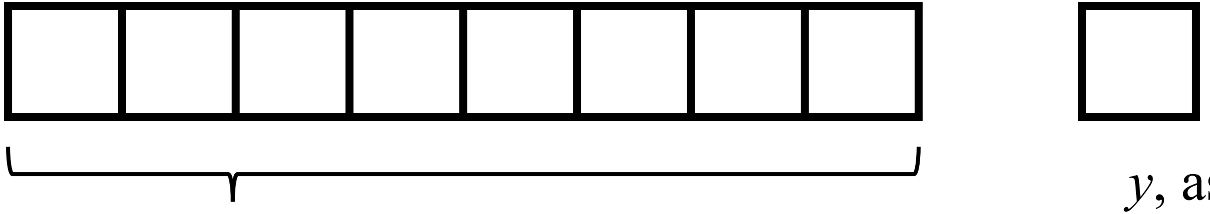
Intro to Natural Language Processing for Clinical Text

Matthew Engelhard

Predictive models for tabular data



End goal: predict y from x

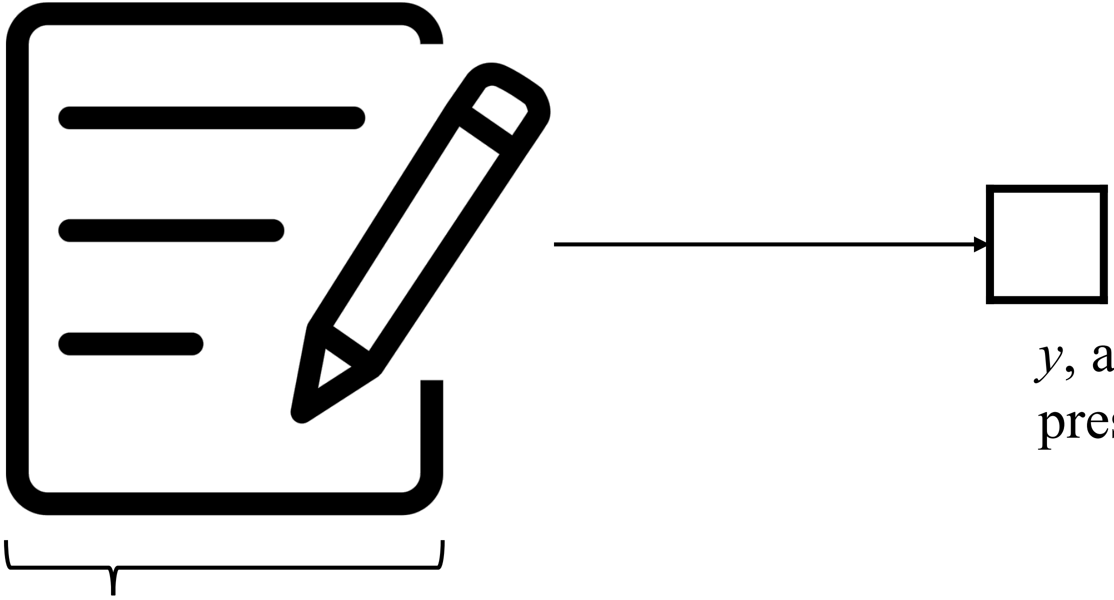
CNNs: predictive models for image data

y, referrable diabetic retinopathy

x, retinal image

End goal: predict y from x

NLP: predictive models for text data



End goal: predict y from x

Today: NLP and Model Interpretability

- What can natural language processing (NLP) do, and how is it relevant to clinical medicine?

- How does NLP work?
  - Methods based on word *counts* (“bag of words”)
  - Methods based on word *vectors* (including deep neural networks)

What can today’s NLP do?

Classification and Regression

psychologist presenting problem NAME is a 3 year, 4 month old female who was referred for a neurodevelopmental assessment due to concerns regarding her overall development, behavior, and social emotional functioning and to

x, clinical note

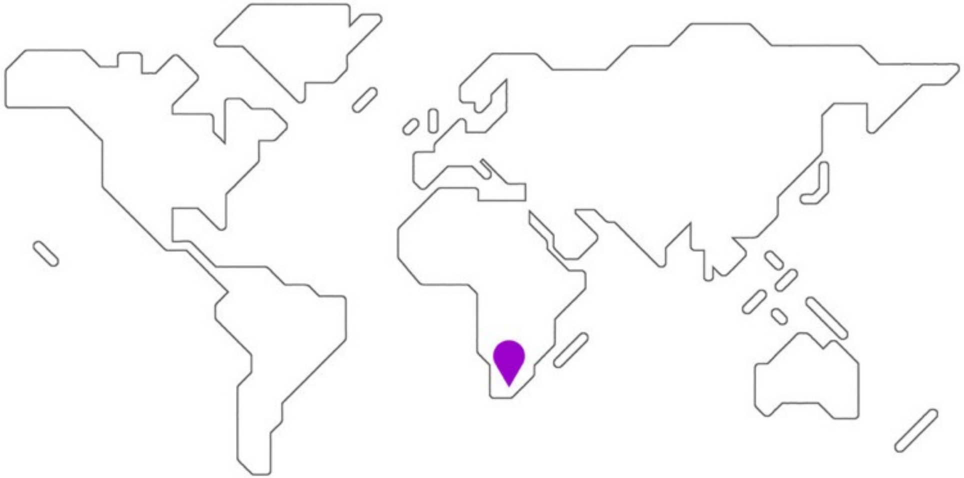
y, autism risk

End goal: predict y from x

Case Study: SMS Triage for Global Maternal Health

Maternal Health HelpDesk:

2 million women connected to NDoH staff via SMS



https://www.praekelt.org

Binary Classification: Urgent Message? (Yes/No)

Why use clinical notes?

Notes >> structured data for identifying diseases, procedures

Journal of the American Medical Informatics Association, 26(11), 2019, 1189–1194
doi: 10.1093/jamia/ocz119
Advance Access Publication Date: 12 August 2019
Research and Applications

AMIA INFORMATICS PROFESSIONALS. LEADING THE WAY.

OXFORD

Research and Applications

Real world evidence in cardiovascular medicine: ensuring data validity in electronic health record-based studies

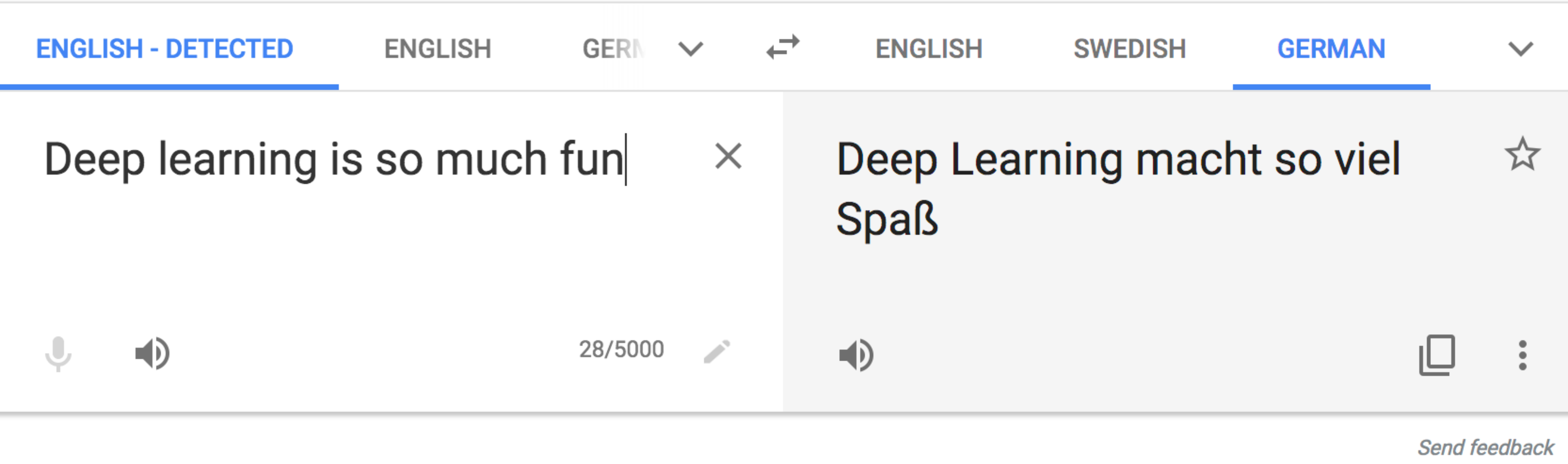
Tina Hernandez-Boussard,[1,2,3] Keri L Monda,[4,5] Blai Coll Crespo,[4] and Dan Riskin[1,3,6]

Table 1. Cohort identification of diseases and procedures stratified by EHR-S and EHR-U data[a]

Cohort	Occurrence		EHR-S			EHR-U		
	Concept	Patient	Recall (%)	Precision (%)	F1-score (%)	Recall (%)	Precision (%)	F1-score (%)
Hyperlipidemia	2471	837	65.2	99.3	78.7	98.2	99.4	98.8
Hypercholesterolemia	1899	478	55.1	98.0	70.5	90.4	98.8	94.4
Coronary artery disease	1427	465	67.5	99.4	80.4	94.6	96.2	95.4
Diabetes mellitus	4502	1377	80.6	97.9	88.4	97.0	92.6	94.8
Myocardial infarction	523	282	29.8	86.2	44.2	90.4	76.5	82.9
Chronic kidney disease	640	101	40.8	97.6	57.6	92.9	97.9	95.3
Stroke	693	307	36.5	97.2	53.0	95.7	79.6	87.0
Dementia	317	103	62.1	100.0	76.6	93.1	90.0	91.5
Cataract	240	85	28.6	100.0	44.4	96.1	94.9	95.5
CABG[b]	194	73	32.2	100.0	48.7	96.6	95.0	95.8

[a]All comparisons were significant at $P < .0001$.
[b]Coronary artery bypass graft.

Text Translation



translate.google.com

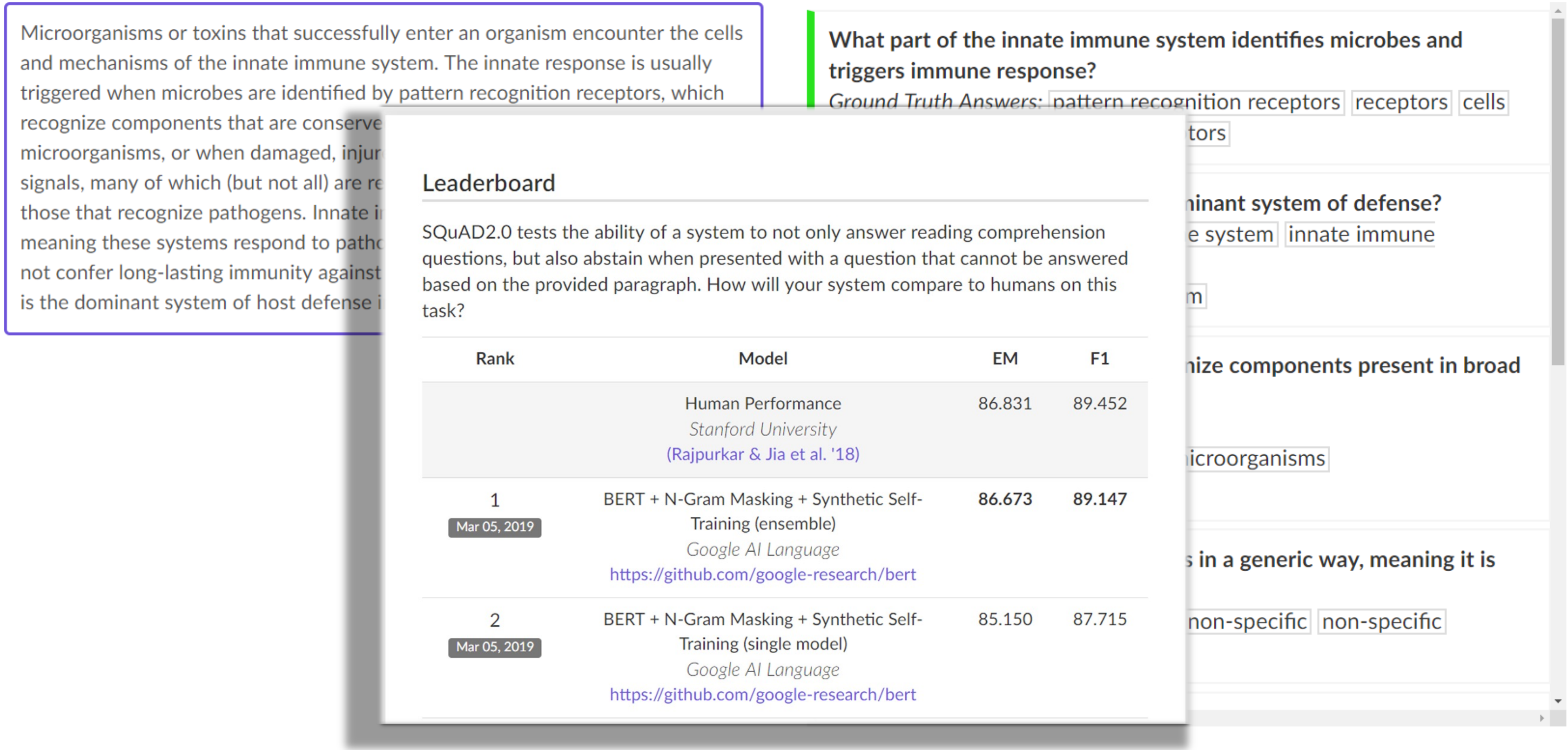
Text Translation --> De-Identify Notes

Table 5. Examples of correctly detected PHI instances (in bold) by the ANN

PHI category	ANN
AGE	Father had a stroke at **80** and died of?another stroke at age Personal data and overall health: Now **63**, despite his FH: Father: Died @ **52** from EtOH abuse (unclear exact etiology) Tobacco: smoked from age 7 to **15**, has not smoked since 15.
CONTACT	History of Present Illness **86F** reports worsening b/l leg pain. by phone, Dr. Ivan Guy. Call w/ questions **86383**. Keith Gilbert, H/O paroxysmal afib VNA **171-311-7974** ======= Medications
DATE	During his **May** hospitalization he had dysphagia Social history: divorced, quit smoking in **08**, sober x 10 yrs, She is to see him on the **29th** of this month at 1:00 p.m. He did have a renal biopsy in teh late **60s** adn thus will look for results, Results**02/20/2087** NA 135, K 3.2 (L), CL 96 (L), CO2 30.6, BUN 1 Jose Church, M.D. /ray DD: 01/18/20 DT: **01/19/:0** DV: 01/18/20

De-identification of patient notes with recurrent neural networks
JAMIA 24(3), 2017, 596–606

Question Answering



Question Answering --> Query the EHR

Microorganisms or toxins that successfully enter an organism encounter the cells and mechanisms of the innate immune system. The innate response is usually triggered when microbes are identified by pattern recognition receptors, which recognize components that are conserved among broad groups of microorganisms, or when damaged, injured or stressed cells send out alarm signals, many of which (but not all) are recognized by the same receptors as those that recognize pathogens. Innate immune defenses are non-specific, meaning these systems respond to pathogens in a generic way. This system does not confer long-lasting immunity against a pathogen. The innate immune system is the dominant system of host defense in most organisms.

What part of the innate immune system identifies microbes and triggers immune response?
Ground Truth Answers: pattern recognition receptors | receptors | cells
Prediction: pattern recognition receptors

For most organisms, what is the dominant system of defense?
Ground Truth Answers: innate immune system | innate immune system | The innate immune
Prediction: The innate immune system

Pattern recognition receptors recognize components present in broad groups of what?
Ground Truth Answers: microorganisms | microorganisms | microorganisms
Prediction: microorganisms

The innate immune system responds in a generic way, meaning it is what?
Ground Truth Answers: non-specific | non-specific | non-specific
Prediction: non-specific

Automatic Image Captioning

a cow is standing in front of a store

a group of elephants standing next to each other

a table that has wooden spoons on it

a cat is eating some kind of food

a bunch of bananas are sitting on a table

a motorcycle is parked next to a window

Automatic Image Captioning --> annotate imaging

a cow is standing in front of a store

a group of elephants standing next to each other

a table that has wooden spoons on it

a cat is eating some kind of food

a bunch of bananas are sitting on a table

a motorcycle is parked next to a window

Classification of radiology reports using neural attention models, *IJCNN 2017*

Text Generation

SYSTEM PROMPT (HUMAN-WRITTEN)

A train carriage containing controlled nuclear materials was stolen in Cincinnati today. Its whereabouts are unknown.

MODEL COMPLETION (MACHINE-WRITTEN, FIRST TRY)

The incident occurred on the downtown train line, which runs from Covington and Ashland stations.

In an email to Ohio news outlets, the U.S. Department of Energy said it is working with the Federal Railroad Administration to find the thief.

“The theft of this nuclear material will have significant negative consequences on public and environmental health, our workforce and the economy of our nation,” said Tom Hicks, the U.S. Energy Secretary, in a statement. “Our top priority is to secure the theft and ensure it doesn’t happen again.”

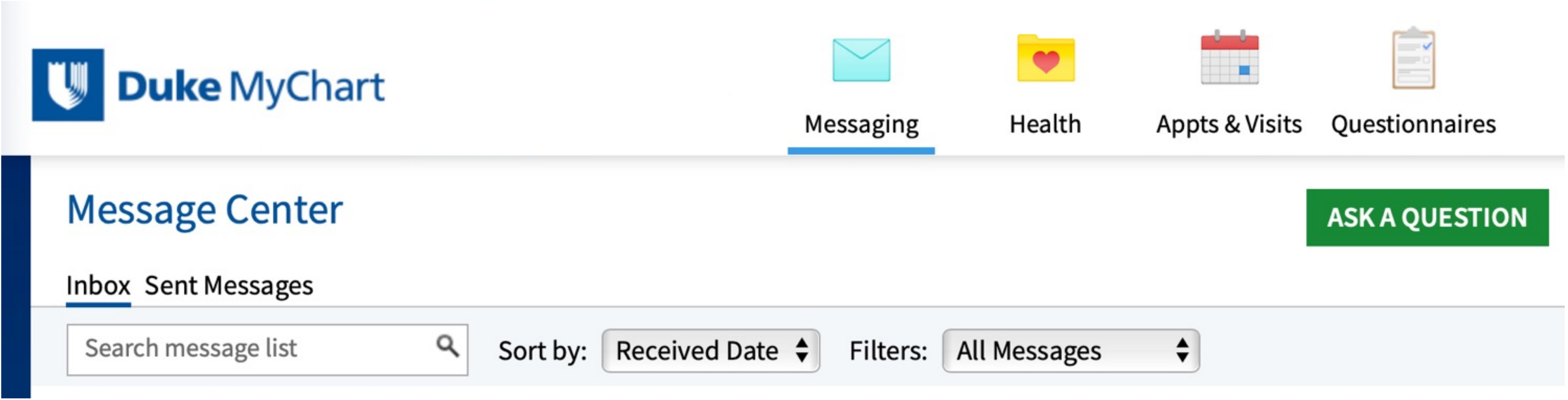
The stolen material was taken from the University of Cincinnati’s Research Triangle Park nuclear research site, according to a news release from Department officials.
The Nuclear Regulatory Commission did not immediately release any information.

According to the release, the U.S. Department of Energy’s Office of Nuclear Material Safety and Security is leading that team’s investigation.

“The safety of people, the environment and the nation’s nuclear stockpile is our highest priority,” Hicks said. “We will get to the bottom of this and make no excuses.

“Better Language Models and Their Implications”
2/14/19
OPENAI

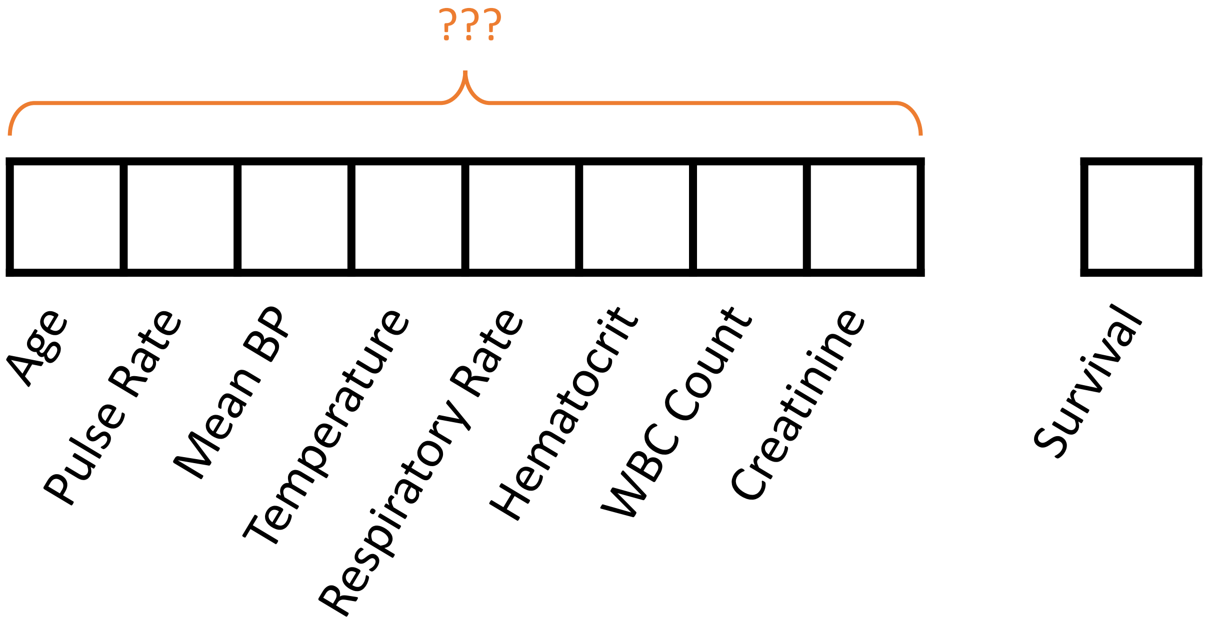
Text Generation -> Suggested Email Responses



How do we make predictions from text?

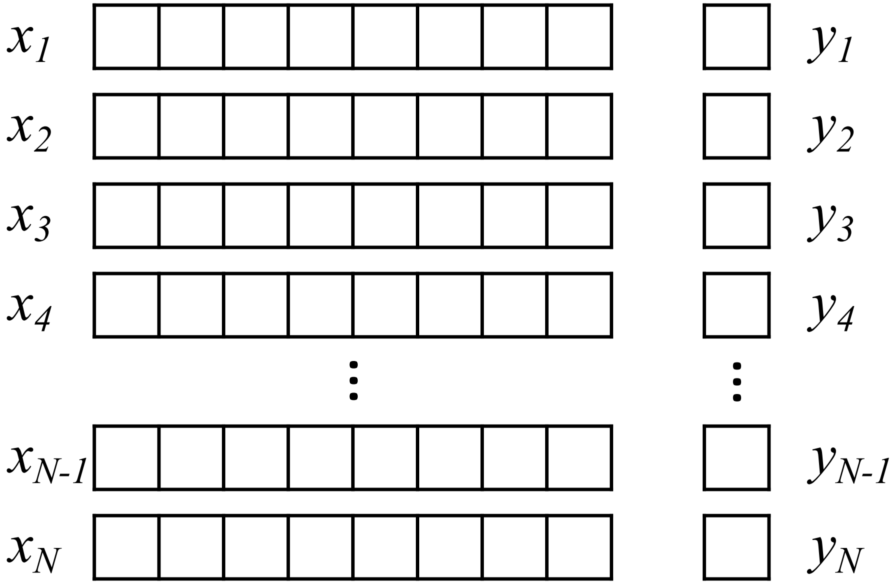
Answer 1: word counts

A Simple Predictive Model: ICU Mortality



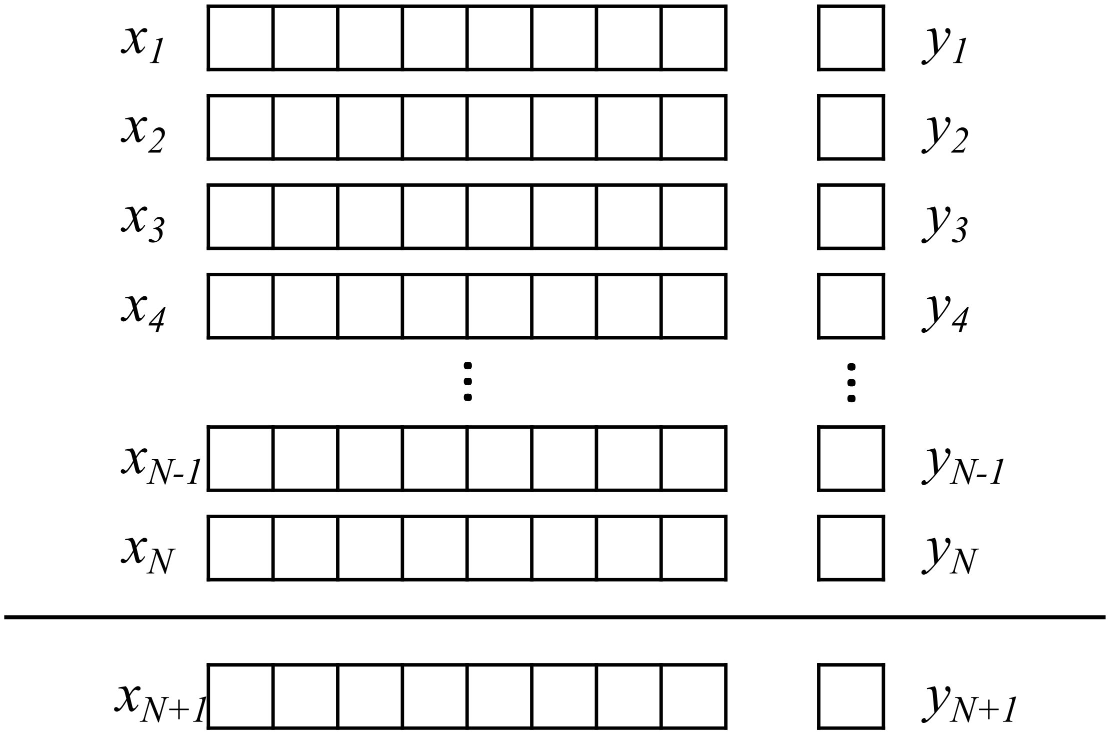
End goal: predict odds of hospital mortality

Training Set (Historical Data)



Find an equation that predicts y based on x across the training set

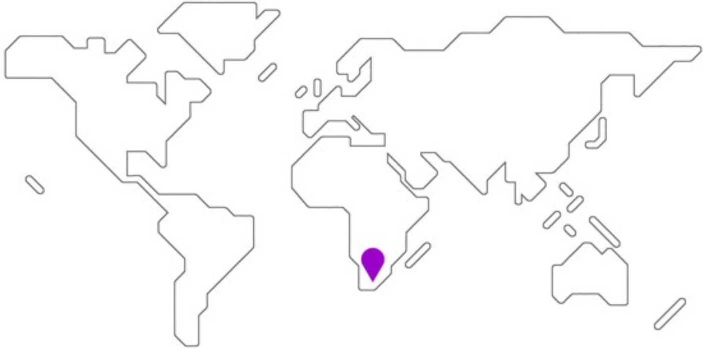
Making Predictions for New x



Find an equation that predicts y based on x across the training set

<- Learn to predict new y

Case Study: SMS Triage for Global Maternal Health



https://www.praekelt.org

Can we use a standard predictive model setup to solve this problem?

This time, our training data is text

x_1	What helps with morning sickness?	y_1
x_2	How many months should I breastfeed?	y_2
x_3	I passed out and Mom said I was shaking	y_3
x_4	Where is the nearest clinic?	y_4
	⋮	⋮
x_{N-1}	I am having heavy bleeding, what should I do?	y_{N-1}
x_N	What foods should I eat while pregnant?	y_N

y_i: Urgent or Not Urgent?

x_{N+1}	My heart is racing and I can’t catch my breath	y_{N+1}

<- Learn to predict new y

We need numbers, not words

- **Can we convert our text to a vector or sequence of numbers?**

- If yes, we can use logistic regression (or any other predictive model)!

First try: count words in each SMS
Step 1: <u>Define a **vocabulary** of words</u>

x_1	What helps with morning sickness?
x_2	How many months should I breastfeed?
x_3	I passed out and Mom said I was shaking
x_4	Where is the nearest clinic?

→ list of all words
(in no particular order) →

shaking	with	and
what	said	I
clinic	months	is
how	the	how
helps	morning	out
was	mom	breastfeed
nearest	should	passed
many	sickness	where

Step 2: count how many times each vocabulary word appears in a given SMS

What helps with morning sickness?

x_1

shaking	what	clinic	how	helps	was	nearest	many	with	said	months	the	morning	mom	should	sickness	and	I	is	how	out	breastfeed	passed	where
0	1	0	0	1	0	0	0	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0

Step 2: count how many times each vocabulary word appears in a given SMS

I passed out and Mom said I was shaking

	shaking	what	clinic	how	helps	was	nearest	many	with	said	months	the	morning	mom	should	sickness	and	I	is	how	out	breastfeed	passed	where
x_3	1	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	2	0	0	1	0	1	0

Note that word order does not matter!

clinic is where nearest the

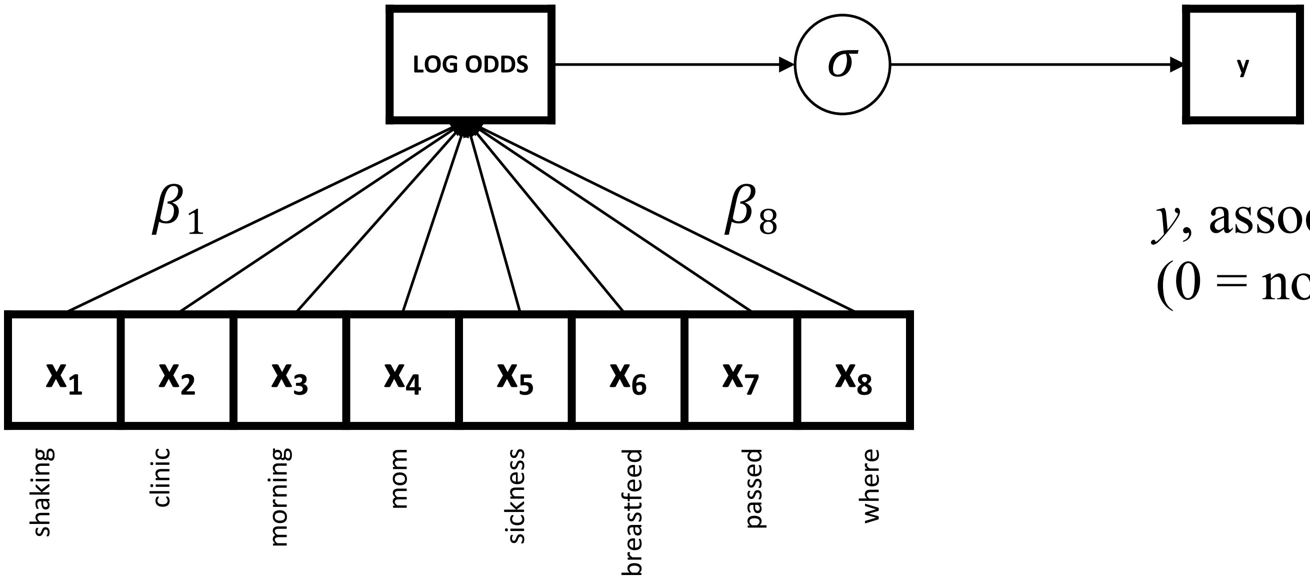
x_4

shaking	what	clinic	how	helps	was	nearest	many	with	said	months	the	morning	mom	should	sickness	and	I	is	how	out	breastfeed	passed	where
0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	1

A “bag of words”

Now we can use logistic regression.

$$\text{URGENCY LOG ODDS} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots$$



y, associated label:
(0 = not urgent, 1 = urgent)

Variations on count-based feature extraction

- Entirely data-driven
  - Vocabulary of words we care about is derived from the training data
  - We then represent text as counts of each vocabulary word
  - We can also count 2- and 3-word phrases; this helps with negation and context
- Knowledge-driven extraction of key words or concepts
  - Rather than creating a vocabulary from the data, we can identify words we (or content experts) believe are important for a given task
  - Concept extraction systems (e.g. cTakes) will identify many alternative phrasings for the same clinical concept (e.g. diagnosis) and group them together as a single feature

Strengths and Weaknesses

- (+) Count-based approaches are simple and work surprisingly well in practice
- (+) Often the best approach with small datasets
- (-) Does not capture word order
- (-) Does not group synonyms together or understand semantic relationships between words

Summary

- A central challenge of NLP lies in converting text documents into feature vectors that can be used in a predictive model
- Bag of words models solve this challenge by constructing a feature vector based on counts of each word of interest
- Even though they ignore word order and semantic relationships, these models are very powerful

Other text processing details

N-grams, tf-idf, pre-processing steps

Count 1- and 2-grams in each SMS
(i.e. extend vocabulary to include 2-word phrases)

x_1	What helps with morning sickness?
x_2	How many months should I breastfeed?
x_3	I passed out and Mom said I was shaking
x_4	Where is the nearest clinic?

1-grams

shaking	was	months	sickness	out
what	nearest	the	and	breastfeed
clinic	many	morning	I	passed
how	with	mom	is	where
helps	said	should	how	

2-grams

what helps	should I	said I
helps with	I breastfeed	I was
with morning	I passed	was shaking
morning sickness	passed out	where is
how many	out and	is the
many months	and mom	the nearest
months should	mom said	nearest clinic

n-grams can be very helpful!

I am not sick and feel great

I am not great and feel sick

Bag of 1-grams: no difference between these sentences

n-grams can be very helpful!

I am not sick and feel great

I am not great and feel sick

Bag of 1- and 2-grams:

not sick, **feel great**

versus

not great, **feel sick**

Variations on counting: term frequency

term count: ‘times’

2	“It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of Light, it was the season of Darkness, it was the spring of hope, it was the winter of despair, we had everything before us, we had nothing before us, we were all going direct to Heaven, we were all going direct the other way—in short, the period was so far like the present period, that some of its noisiest authorities insisted on its being received, for good or for evil, in the superlative degree of comparison only.”
1	“And the first one now Will later be last For the times they are a-changin'.”

Variations on counting: term frequency

term frequency: ‘times’

2/119

“It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of Light, it was the season of Darkness, it was the spring of hope, it was the winter of despair, we had everything before us, we had nothing before us, we were all going direct to Heaven, we were all going direct the other way—in short, the period was so far like the present period, that some of its noisiest authorities insisted on its being received, for good or for evil, in the superlative degree of comparison only.”

1/16

“And the first one now
Will later be last
For the times they are a-changin'.”

-> better measure of the importance of the term within a given text sample

Variations on counting: inverse document frequency

2/2 document frequency: ‘times’

✔ “It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of Light, it was the season of Darkness, it was the spring of hope, it was the winter of despair, we had everything before us, we had nothing before us, we were all going direct to Heaven, we were all going direct the other way—in short, the period was so far like the present period, that some of its noisiest authorities insisted on its being received, for good or for evil, in the superlative degree of comparison only.”

✔ “And the first one now
Will later be last
For the times they are a-changin'.”

Variations on counting: inverse document frequency

1/2 document frequency: ‘evil’

✓ “It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of Light, it was the season of Darkness, it was the spring of hope, it was the winter of despair, we had everything before us, we had nothing before us, we were all going direct to Heaven, we were all going direct the other way—in short, the period was so far like the present period, that some of its noisiest authorities insisted on its being received, for good or for evil, in the superlative degree of comparison only.”

✗ “And the first one now
Will later be last
For the times they are a-changin'.”

term frequency-inverse document frequency (tf-idf)

- What helps with morning sickness?
- How many months should I breastfeed?
- I passed out and Mom said I was shaking
- Where is the nearest clinic?
- I am having heavy bleeding, what should I do?
- What foods should I eat while pregnant?
- My heart is racing and I can't catch my breath

$$\frac{\text{term frequency}}{\text{document frequency}}$$ for 'shaking'

$$\frac{1/9}{1/7} = .78$$

$$\frac{\text{term frequency}}{\text{document frequency}}$$ for 'I'

$$\frac{2/9}{5/7} = .31$$

Preprocessing

```
I passed out, and Mom said I was shaking.
```

- remove punctuation

```
I passed out and Mom said I was shaking
```

- to lowercase

```
i passed out and mom said i was shaking
```

- “tokenization”

```
[i, passed, out, and, mom, said, i, was, shaking]
```

- “stemming”

```
[i, pass, out, and, mom, said, i, wa, shake]
```