Explainable Prediction of Medical Codes from Clinical Text

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The Clinical Coding Problem

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- They abound with written physician notes
- ICD: taxonomy of diagnoses and procedures
- Human coding laborious, error-prone [Birman-Deych et al., 2005]

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- Testbed for document representations
- Documents are long and loosely structured

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Date of Birth:                    Sex:  F

Service:  MICU and then to [**Doctor Last Name **] Medicine

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Many labels:

```
519.1: 'Other disease…'
491.21: 'Obstructive …'
518.81: 'Acute respir…'
486: 'Pneumonia, orga…'
276.1: 'Hyposmolality…'
244.9: 'Unspecified h…'
31.99: 'Other operati…'
.
.
.
```

Long: Median post-processed document length: 1,341

Median # labels: 14

Prior approaches

- Predict from a subset of labels

This work

- Predict from all labels

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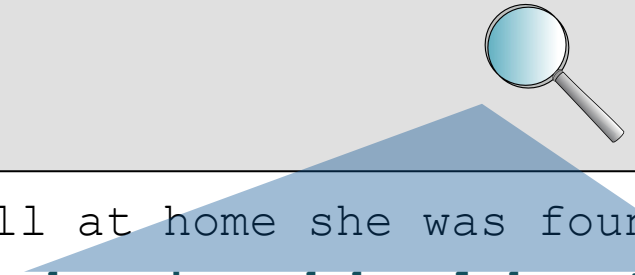
This work

- Predict from all labels
- General ICU setting
- Open-access data

Modeling desiderata

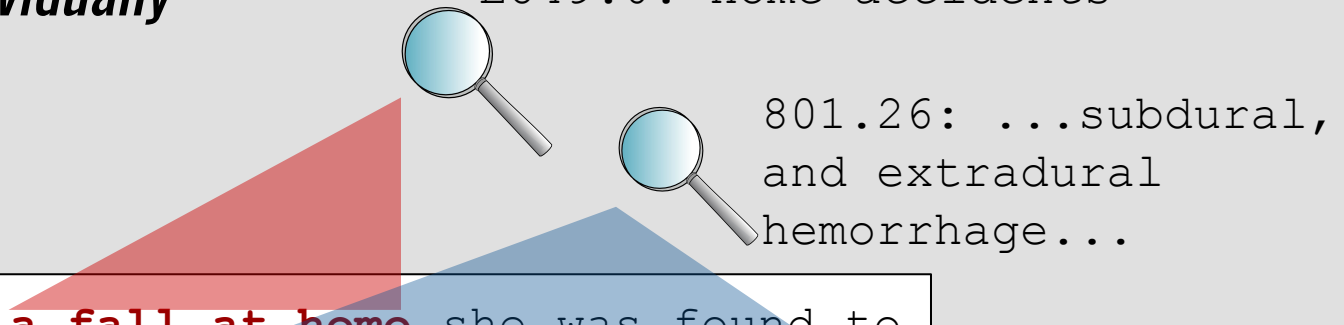
- Focus on the parts that matter



...who sustained a fall at home she was found to have a large acute on **chronic subdural hematoma** with extensive midline shift...

Modeling desiderata

- Focus on the parts that matter
- Treat labels *individually*



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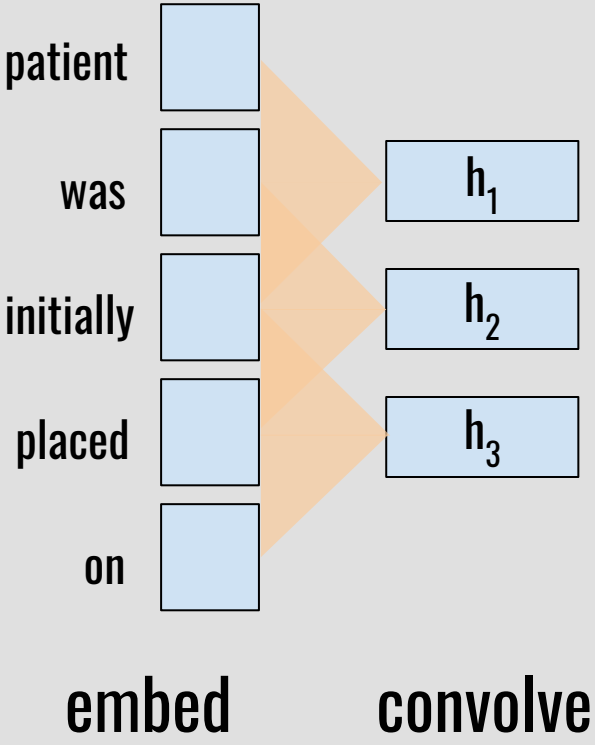
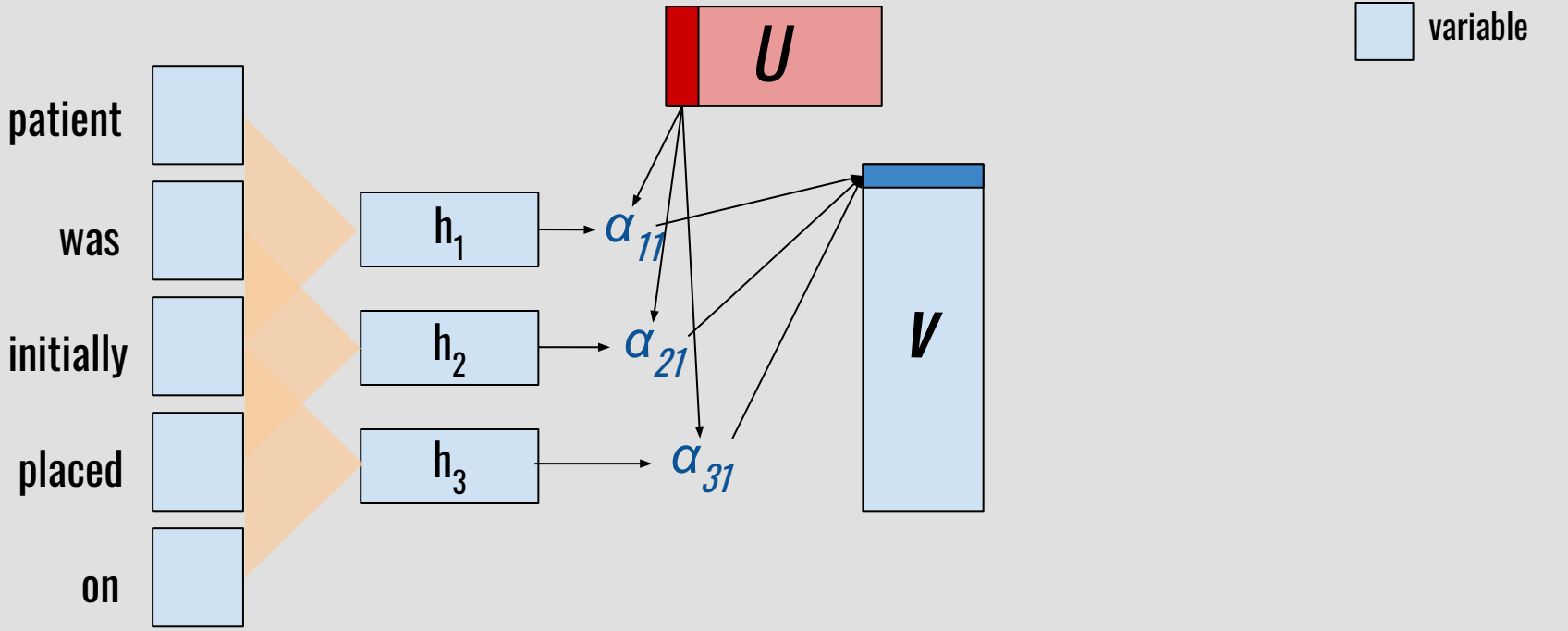
Convolution

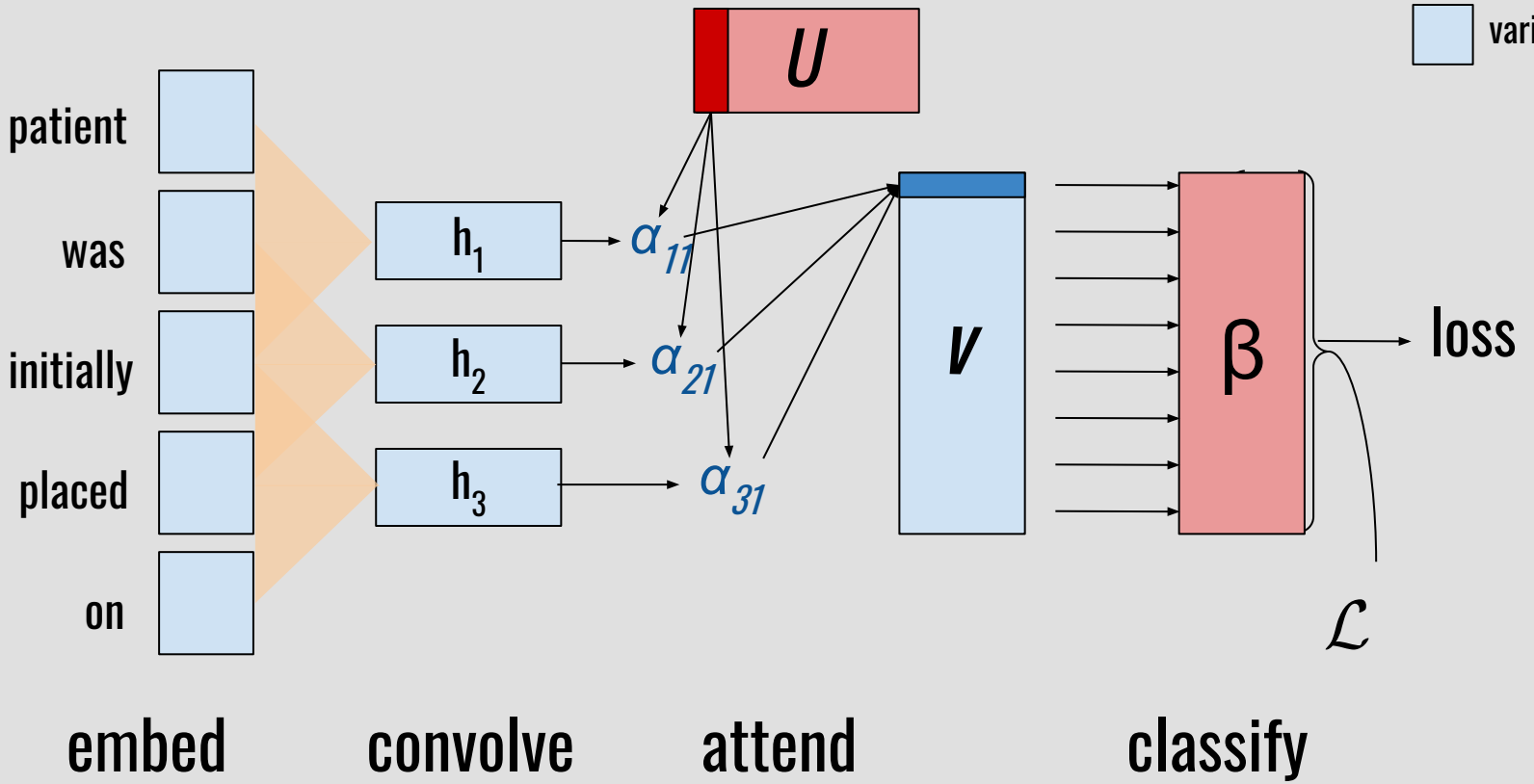


Convolution + Attention



embed convolve attend (separately for each label)

Convolution + Attention = the CAML model



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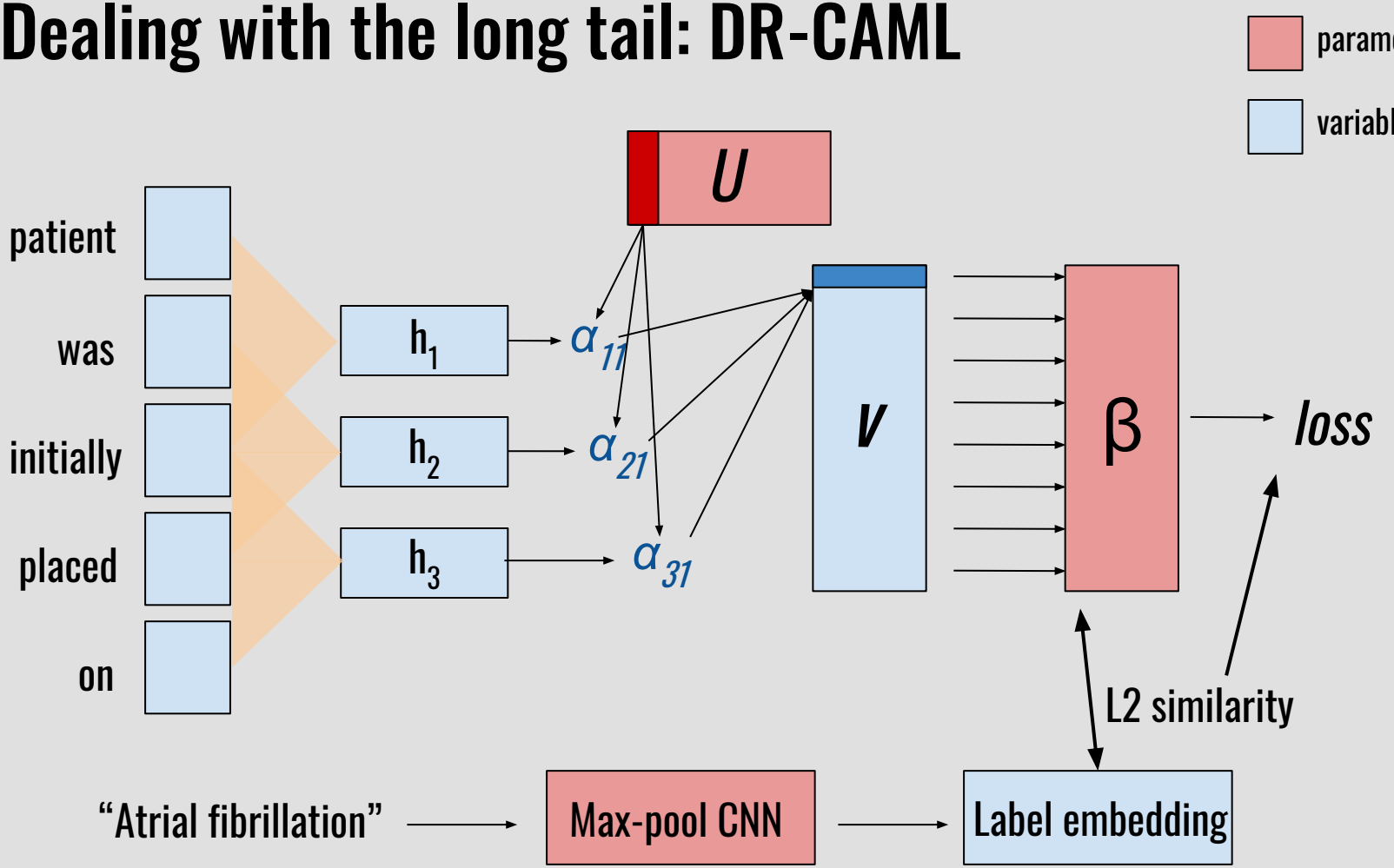
250.00: “Diabetes mellitus without mention of complication, type II or unspecified type, not stated as uncontrolled”

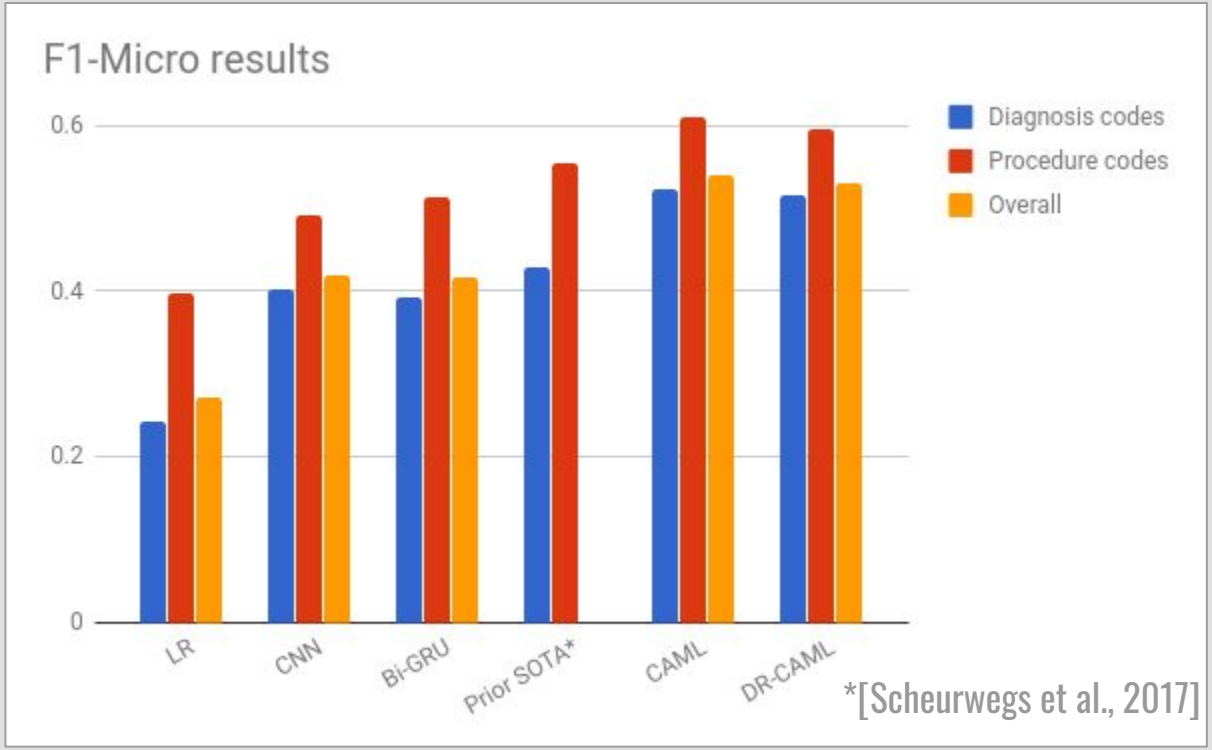
250.02: “Diabetes mellitus without mention of complication, type II or unspecified type, uncontrolled”

Dealing with the long tail: DR-CAML



MIMIC results

- Few works use the whole label space



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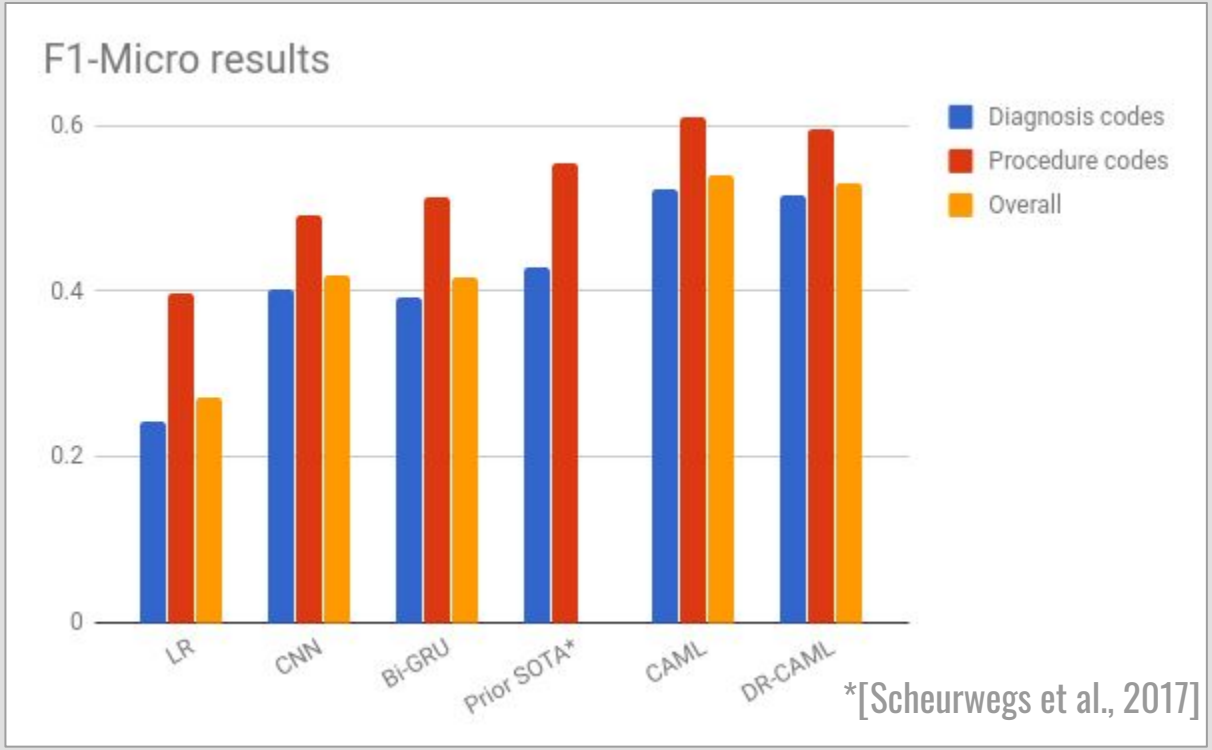
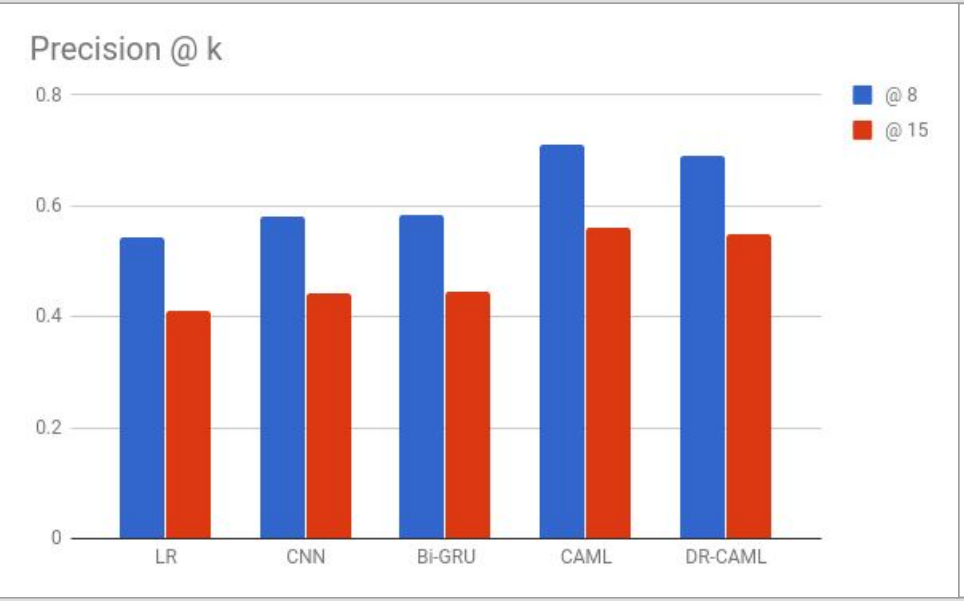
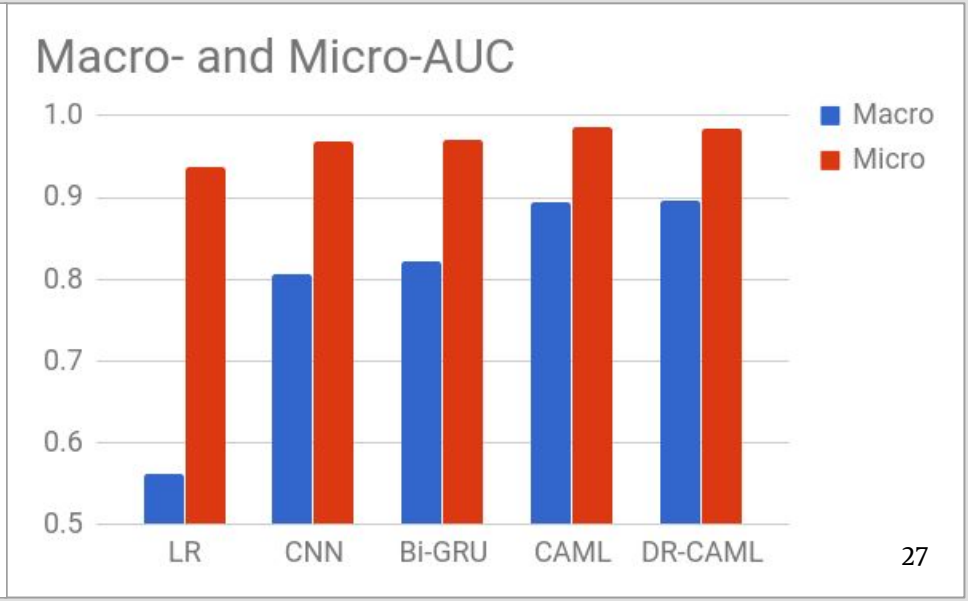
- 20%, 8% relative improvement over prior SotA



More MIMIC metrics

- Enable future comparison
- Precision @ k: decision support use-case





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- “Informative” and “Highly Informative”

Physician evaluation example*

Code: 575.4

Full descriptions: Perforation of gallbladder

“. . in the setting of gallbladder perforation secondary to acute acalculous cholecystitis after . . . . . inhalation hospital1 times a day metronidazole mg tablet sig one tablet po tid times . . . . . to have an infection in your gallbladder requiring iv antibiotics and tube placement for . . .”

*not exact format used

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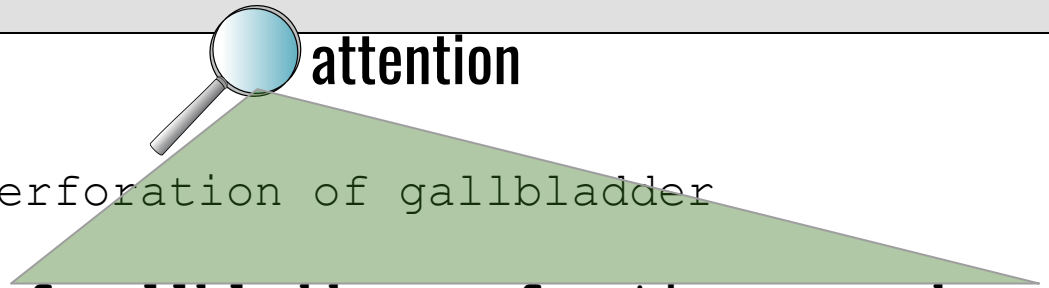

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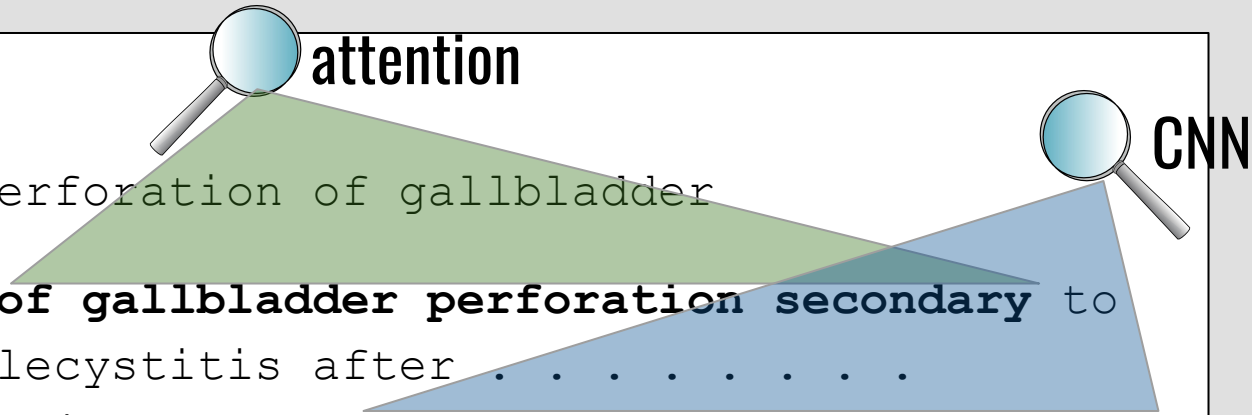

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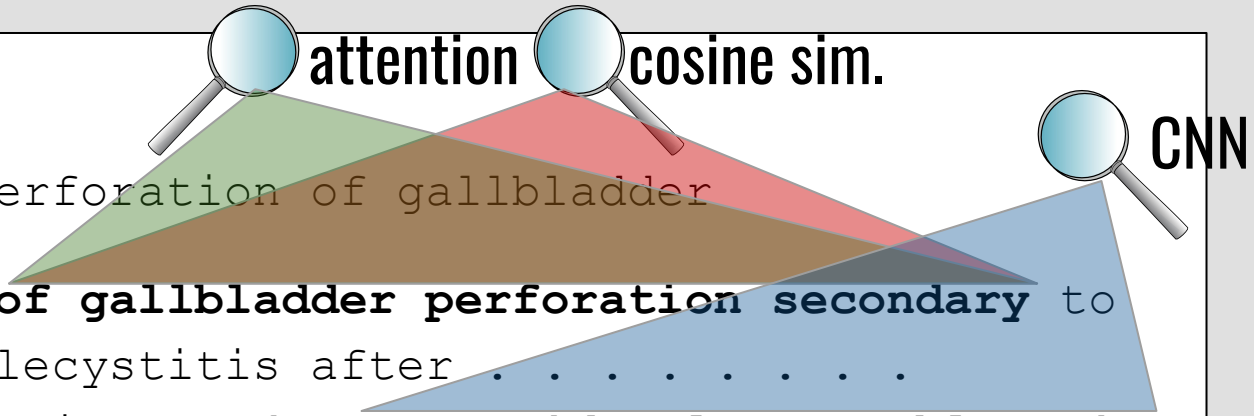

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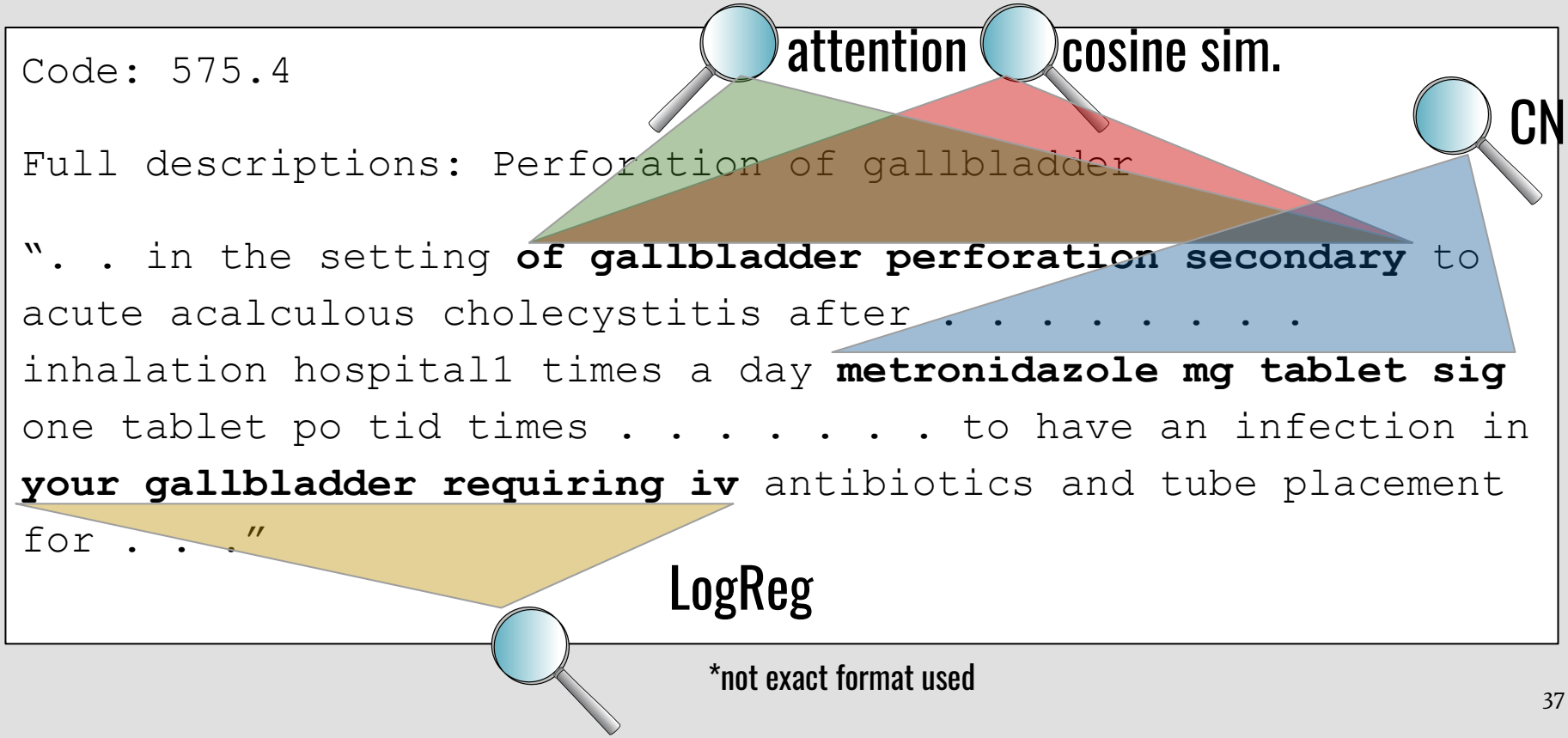

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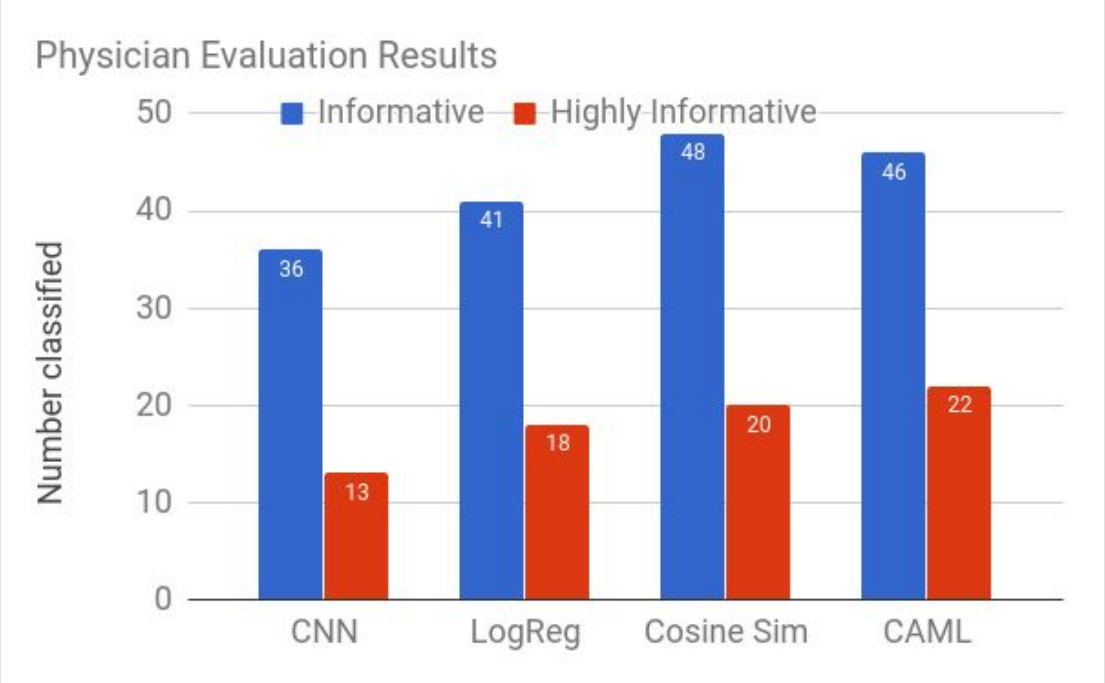
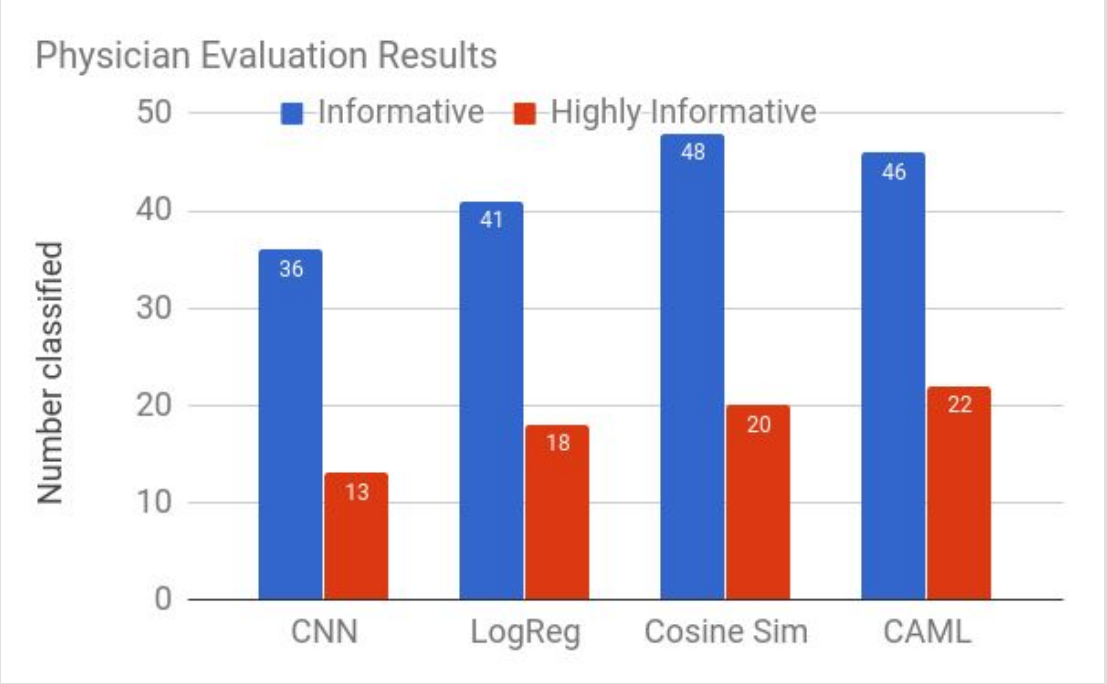


Physician evaluation results

- Improves upon CNN, LogReg
- More experts needed!



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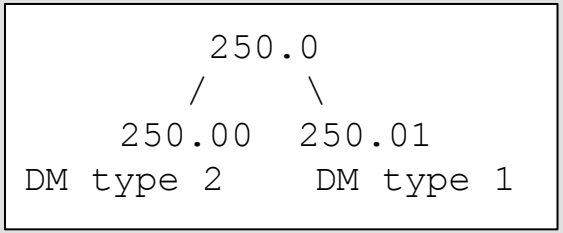
- Develop methods for few-shot or zero-shot classification
- Exploit hierarchy of codes
  - GRAM [Choi et al., 2017]



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Thank you!

Questions?

Code, data splits, pretrained models: github.com/jamesmullenbach/caml-mimic