Computing Over Ophthalmology Clinical Text From Electronic Health Records: Case Study in Identifying Candidates for Low Vision Rehabilitation Using Neural Word Embeddings

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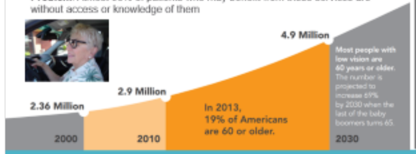
Byers Eye Institute, Department of Ophthalmology, Stanford University

Background

Low Vision and Rehabilitation Services

- **Low Vision**: Visual impairment that cannot be corrected with glasses, contacts, or other treatments. Prevalence increasing
- **Severely impacts activities of daily living**: 3x unemployment, 3x MVC, if they can even drive, 3x depression and anxiety, 2x falls
- **Low vision rehabilitation services**: Palliative care for the eye, maximizing use of remaining vision
- **Problem**: Almost 90% of patients who may benefit from these services are without access or knowledge of them



Ophthalmology Progress Note
HPI: 56 yo F presents with decreased VA...
OcHx:
- Cataracts OU
- Macular Degeneration OU
Gtt:
AREDS2 vitamins
Exam:
Vacc OD: 20/40-2 ph 20/25-2
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SLE:
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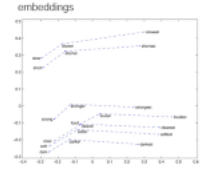
DFE: CDR 0.5 /0.5, macular with drusen OD and GA OS, normal vessels/periphery OU
A/P
1) Dry macular degeneration OU...

Electronic Health Records (EHR)

- So much data in EHR
- How to make use of free text?
- Turn the text into numbers via word embeddings



Problem: General word embeddings don't cover highly domain-specific text

Purpose

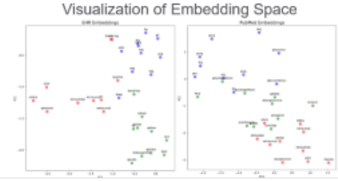
- **To train and evaluate ophthalmology domain-specific word vectors** using corpora from published ophthalmology literature and from electronic health records (EHR), comparing them to pre-trained general embeddings.
- **To predict the prognosis of low vision patients** using clinical free-text from EHR, in order to identify candidates for low vision rehabilitation services

Methods: Ophthalmology Embeddings

Text Corpora Construction

Corpora	Clean	Train	Embeddings
PubMed: MeSH: Eye Diseases, Ocular Physiological Phenomena, Ophthalmology, Ophthalmologic Surgical Procedures N=121,740 EHR: Random ophthalmology progress note from every ophthalmology patient N=89,282 notes	Text Processing: Lowercase; Tokenize (split into words); Remove stopwords (the, a, an, etc.); Remove words that occur less than 5 times in the corpus; PubMed Tokens: N=55,937; EHR Tokens: N=41,630	Word2Vec: Continuous-bag-of-words architecture: Predict the word given the context; Context window size +/-5 words	Output: 300-dimension word vectors where words used in similar contexts (assumed to have similar meaning) appear closely in vector space
Two different ophthalmology domain-specific corpora	Text pre-processed the same way for both corpora	Trained in separate models with the same specifications	Compared to GloVe : 300-d 42B vectors trained on Common Crawl

Visualization of Embedding Space



Intrinsic Evaluation: Creation of 200 Novel Ophthalmology Domain-Specific Analogies

Examples of ophthalmology domain-specific analogies			
dorzolamide	brinzolamide	bromfenac	ketorolac
limbus	limbal	canthus	canthal
ocp	conjunctiva	pseudoexfoliation	lens
left	right	os	od
brinzolamide	glaucoma	bevacizumab	amd
sclera	sclerotomy	iris	iridotomy

Methods: Predicting Low Vision Prognosis

Cohort Construction and Features

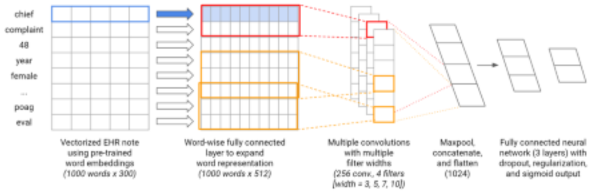
01 STARR with >4 million patients
- Free text notes
- Smartforms (where much of the eye examination information resides)
- Demographics, billing codes, meds, etc.

02 N=553,184 documented VA measurements, belonging to N=88,692 unique patients

03 ~14% of VA measurements were worse than 20/40, belonging to N=13847 unique patients. The first date of low vision was determined for each patient.

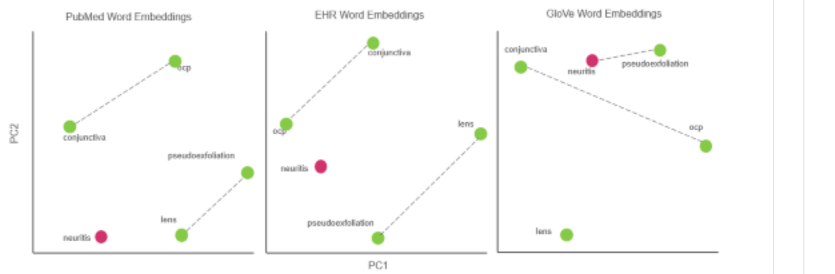
04 N=5612 patients with low vision had at least one year of follow-up, defined as ≥ one visit with documented VA ≥ 365 days from the initial low vision date

Convolutional Neural Network Model Architecture



Classification Target: Patients who did not improve to better than 20/40 in 1 year (40.5% of population)

Results: Evaluation Using Analogies



Example word analogy depicted: ocp:conjunctiva::pseudoexfoliation: ???
Correct answer choice: "lens". **Incorrect answer choice**: "neuritis".
Cosine similarity between (pseudoexfoliation – ocp + conjunctiva) and either lens or neuritis.
PubMed and EHR word embeddings identifies the correct answer while GloVe chooses the wrong answer.
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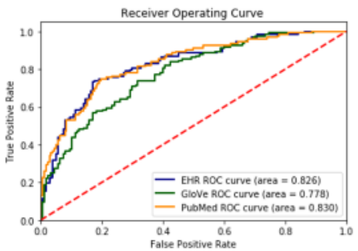

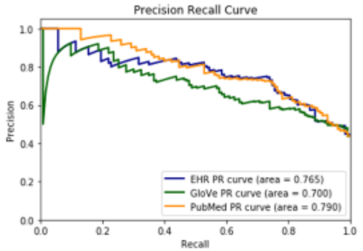

	F1	Sensitivity (Recall)	Specificity	PPV (Precision)	NPV	Accuracy
PubMed	0.73	0.76	0.78	0.7	0.82	0.77
EHR	0.72	0.77	0.76	0.68	0.82	0.76
GloVe	0.65	0.74	0.63	0.58	0.78	0.68

Conclusions

- For predictive tasks using highly domain-specific text, using domain-specific neural word embeddings may yield better performance than general word embeddings.
- **Training word embeddings using domain-specific published literature** abstracts is relatively easy and has good coverage even of text from electronic health records.
- We found that analyzing ophthalmology domain-specific word embeddings using analogies required **creation of ophthalmology domain-specific analogies.**
- Using ophthalmology domain-specific word embeddings, we were able to **predict the prognosis of low vision patients using clinical free text** with good performance.

Email me at **sywang@stanford.edu**

Supported By Research to Prevent Blindness

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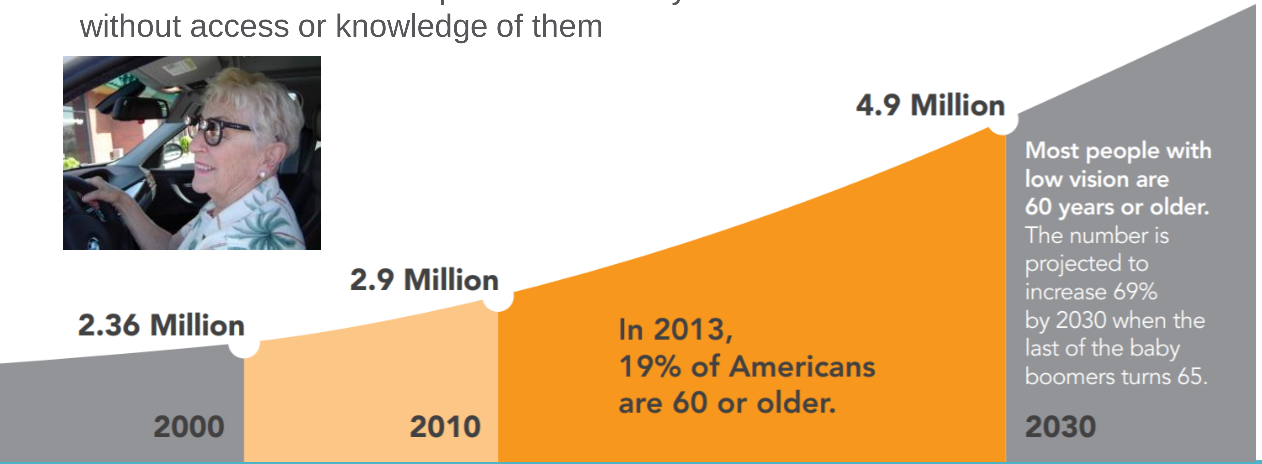

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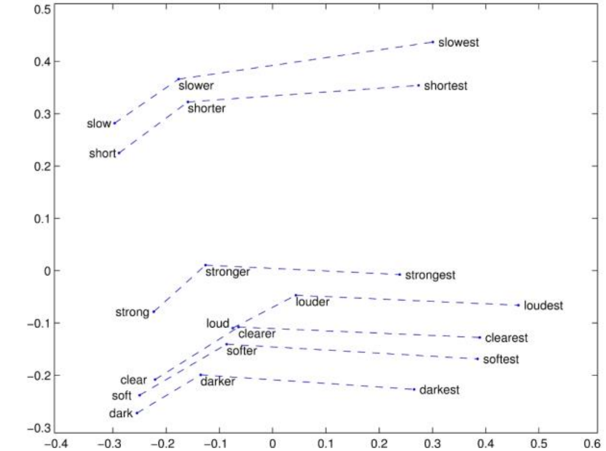

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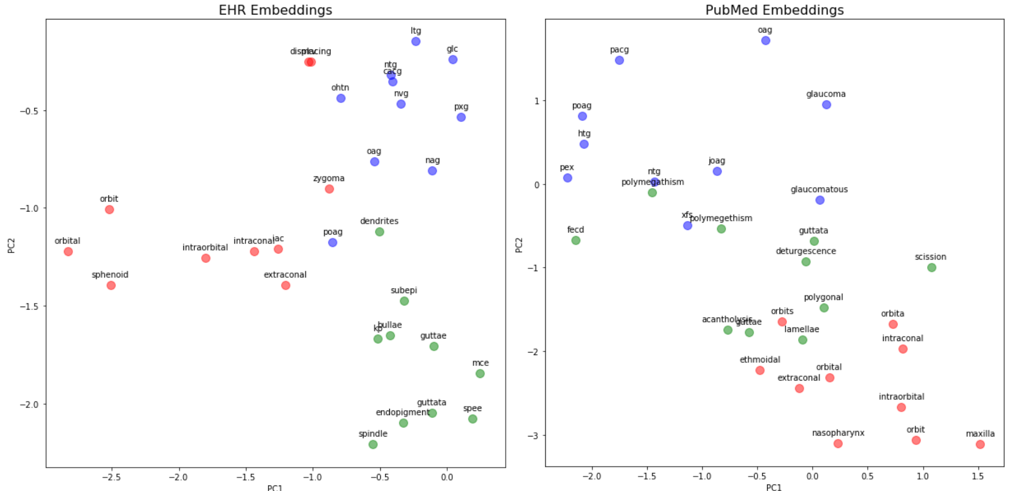

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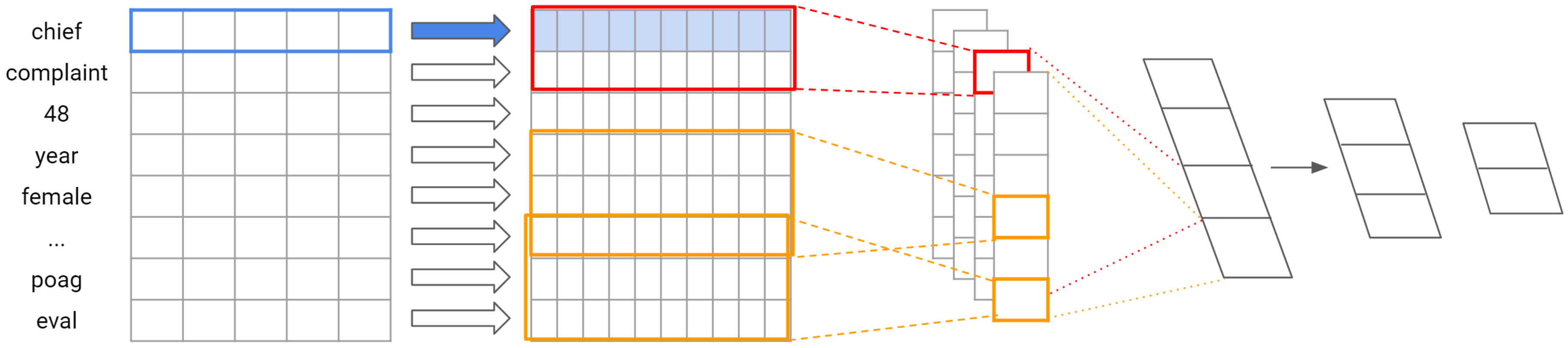

Vectorized EHR note using pre-trained word embeddings *(1000 words x 300)*

Word-wise fully connected layer to expand word representation *(1000 words x 512)*

Multiple convolutions with multiple filter widths *(256 conv., 4 filters [width = 3, 5, 7, 10])*

Maxpool, concatenate, and flatten (1024)

Fully connected neural network (3 layers) with dropout, regularization, and sigmoid output

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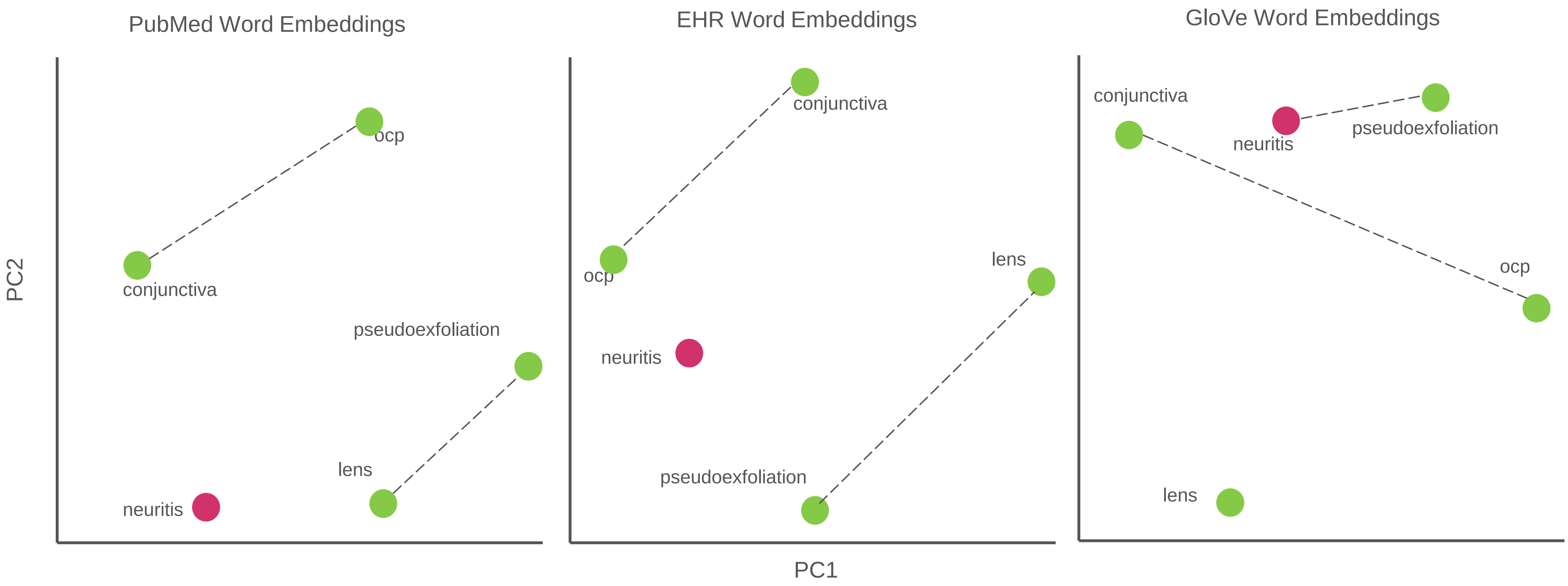

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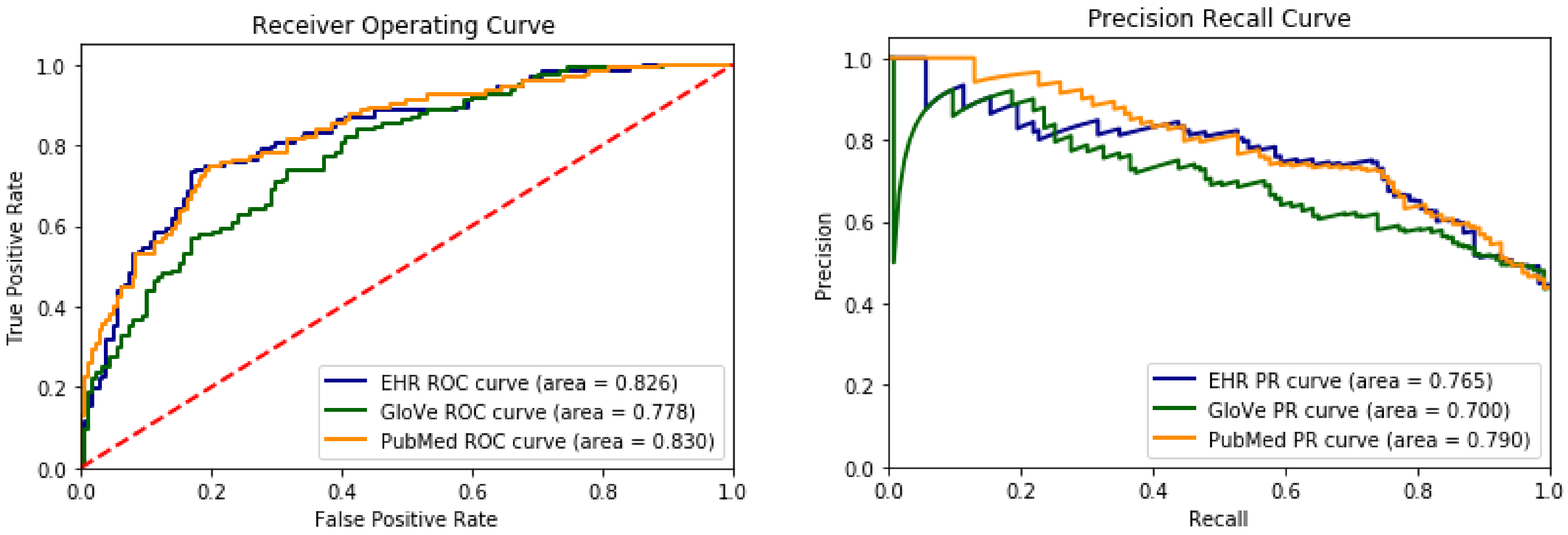

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