

UNSUPERVISED PATIENT REPRESENTATIONS FROM CLINICAL NOTES

WITH INTERPRETABLE CLASSIFICATION DECISIONS



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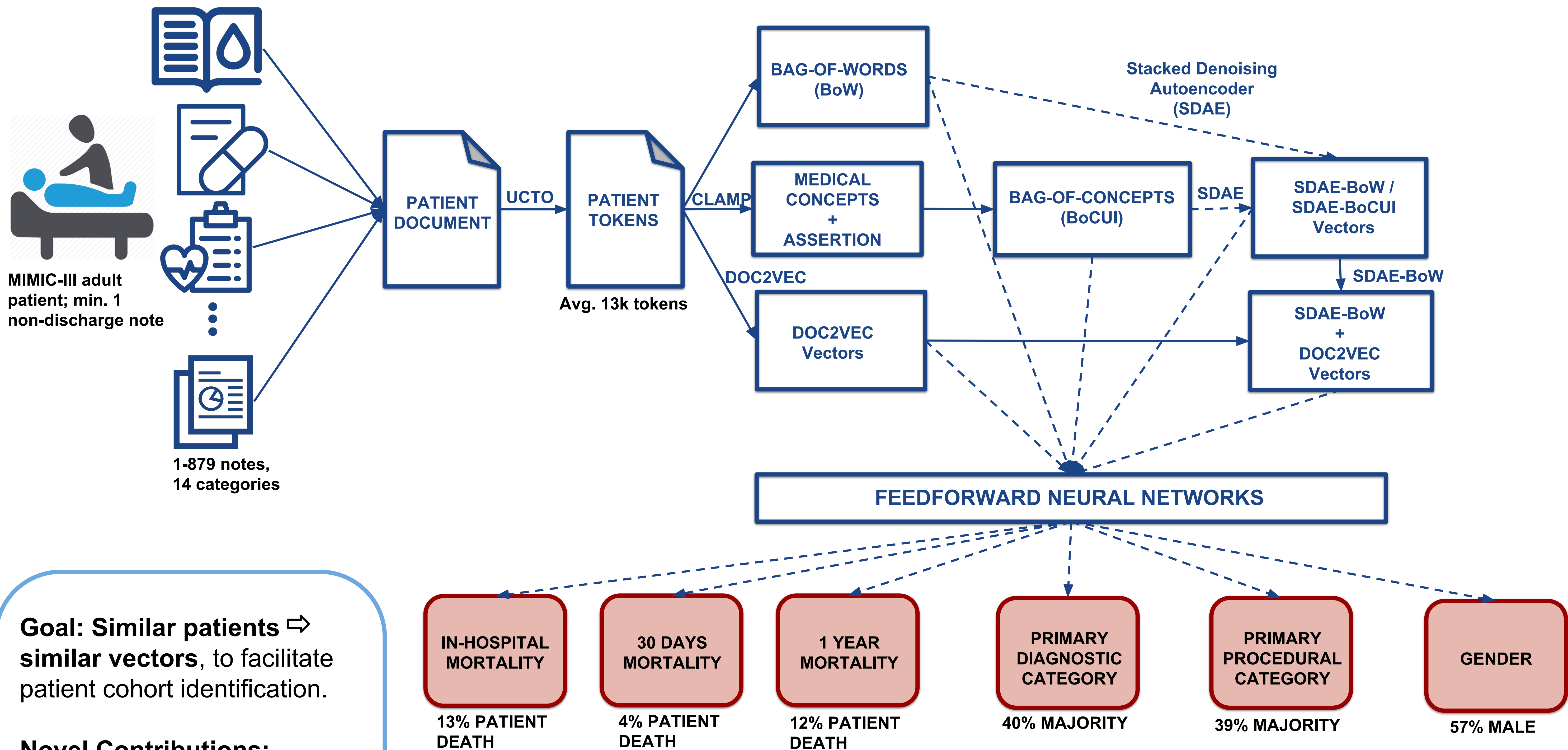


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LEARNING TASK-INDEPENDENT PATIENT REPRESENTATIONS

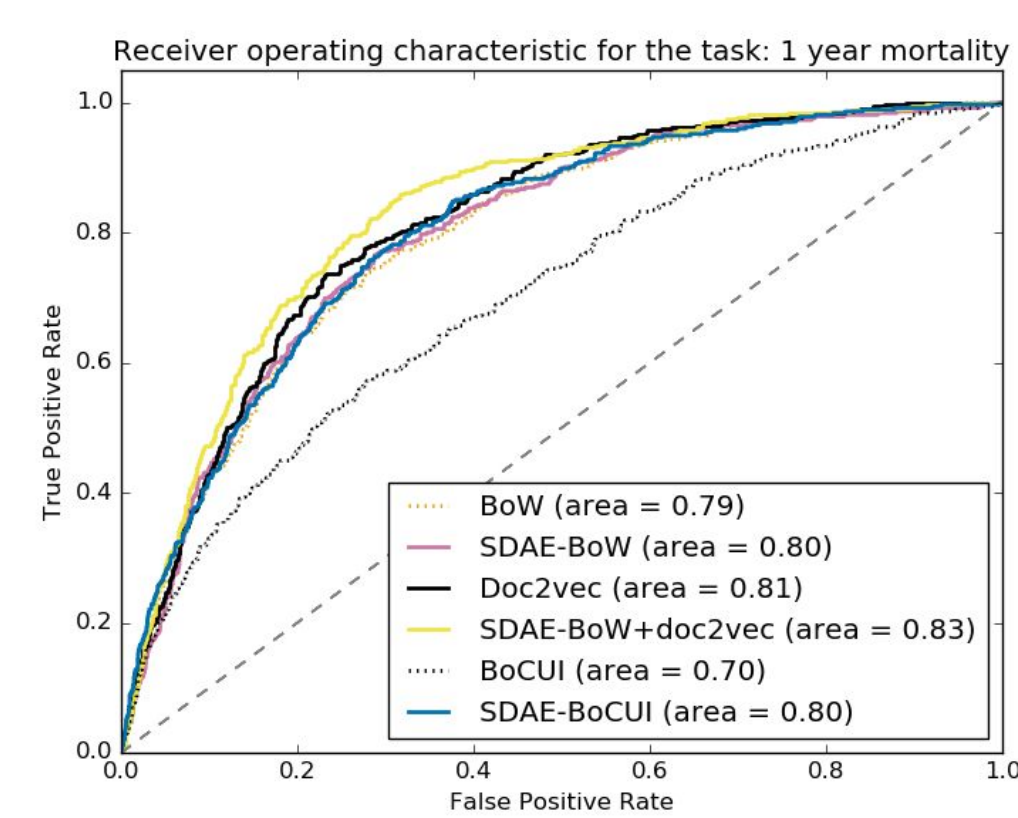
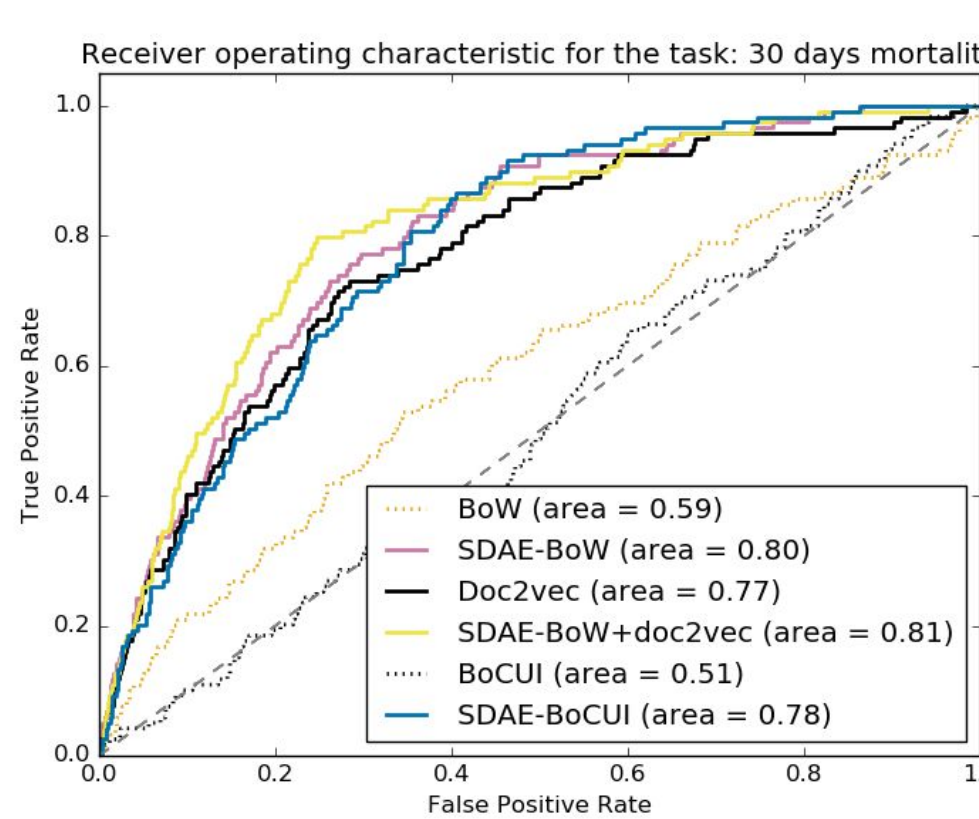
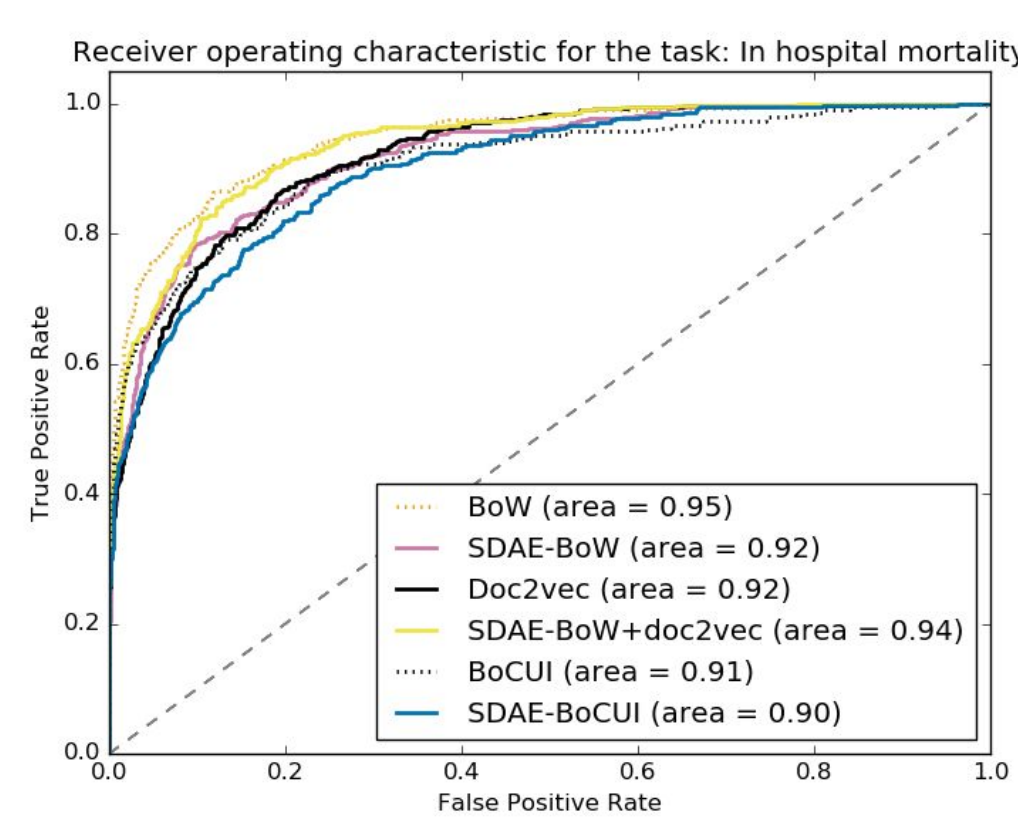


Goal: Similar patients \Rightarrow similar vectors, to facilitate patient cohort identification.

Novel Contributions:

- Evaluating if patient representation models are successful with only clinical notes as input.
- Analyzing if such models are transferable across tasks.
- Understanding the best and the worst encoded features in the SDAE representations.
- Extracting the most influential features for classification decisions.

REPRESENTATION EVALUATION



| Approach | Pri_diag_cat (F-score-wt) | Pri_proc_cat (F-score-wt) | Gender (F-score-wt) |
|--------------------|---------------------------|---------------------------|---------------------|
| BoW | 70.16 | 73.66 | 98.47 |
| SDAE-BoW | 65.00 | 67.46 | 87.75 |
| Doc2vec | 68.07 | 65.83 | 97.70 |
| SDAE-BoW + Doc2vec | 67.88 | 70.30 | 97.47 |
| BoCUI | 71.04 | 72.65 | 75.04 |
| SDAE-BoCUI | 66.47 | 67.77 | 62.45 |

Conclusions:

- BoW model is a strong baseline for all tasks except distant patient mortality due to the presence of strong lexical features.
- Generalized dense representation models significantly outperform sparse models when no. of positive instances is low (30 days mortality).
- Recommended to combine SDAE and doc2vec representations for unknown tasks.

FEATURE EXTRACTION

After **PRETRAINING** SDAE representations:

Compute **squared feature reconstruction error** after training the first SDAE layer, averaged across instances.

Finding: **High error correlation with frequency.**

CLASSIFICATION phase (input: SDAE representations):

Gradient of classification output w.r.t. original input, calculated using chain rule across networks.

Enables feature extraction for an arbitrary set of instances and output classes.

Finding: **Sensible, distinct features extracted for most tasks.**

| In_hosp | 30_days | 1_year | Pri_diag_cat | Pri_proc_cat | Gender |
|-------------|-----------------|-----------------|--------------|--------------|--------|
| vasopressin | leaflet | magnevist | numeric_val | numeric_val | woman |
| pressors | structurally | signal | previous | no | female |
| focused | pacemaker | decisions | rhythm | of | she |
| dnr | sda | periventricular | no | enzymes | man |
| dopamine | periventricular | embolus | flexure | extubated | he |
| acidosis | excursion | underestimated | dementia | rhythm | male |
| levophed | non-coronary | calcified | brbpr | and | her |
| pressor | dosages | screws | of | the | his |
| cvvh | microvascular | rib | sinus | vent | wife |
| cvvh | left-sided | shadowing | for | uncal | uterus |
| emergency | chronic | gadolinium | to | mso | him |

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