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Towards Interactive NLP for Clinical Text: An Intelligent Signout Tool

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NLP for Clinical Text

- Free-text in EMR clinical notes contain rich data that is challenging to analyze
- Natural Language Processing (NLP) methods can facilitate the use of this information to improve clinical care and advance research
- Current methods for building NLP models are expensive and time-consuming:
  - Clinicians provide training data, data scientists build models
- Lack of **user-centered** development is a barrier to NLP for clinical text [1]

Our Solution: Interactive NLP

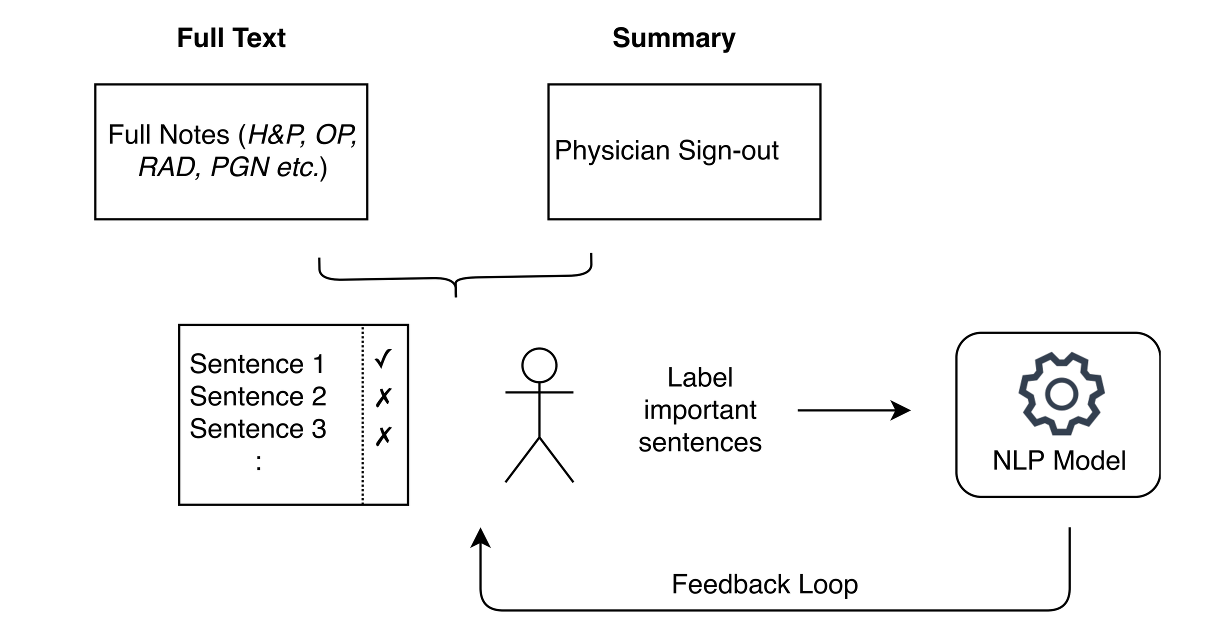
- Increase utility of NLP: decrease expense of creating annotated training data
- Demonstrated in NLPReViz – an interactive tool to train, review, and revise binary models for clinical research (`nlpreviz.github.io`) [2]
  - Guided by work in *InfoVis, Natural Language Processing* and *Interface Design*

Interactive NLP in Clinical Care

- To improve construction of summaries and facilitate location of relevant information; reduce cognitive burden
- Currently, clinicians manually curate summaries from patient records for many tasks
  - Example use-case in preparing *signouts* for care transitions between shifts
- Builds upon prior work in NLPReViz [2]:
  - Extends the problem from classifying documents to also identifying relevant text spans within them
  - Towards interactive NLP for a wide range of problems in processing clinical text

Intelligent Signout Tool

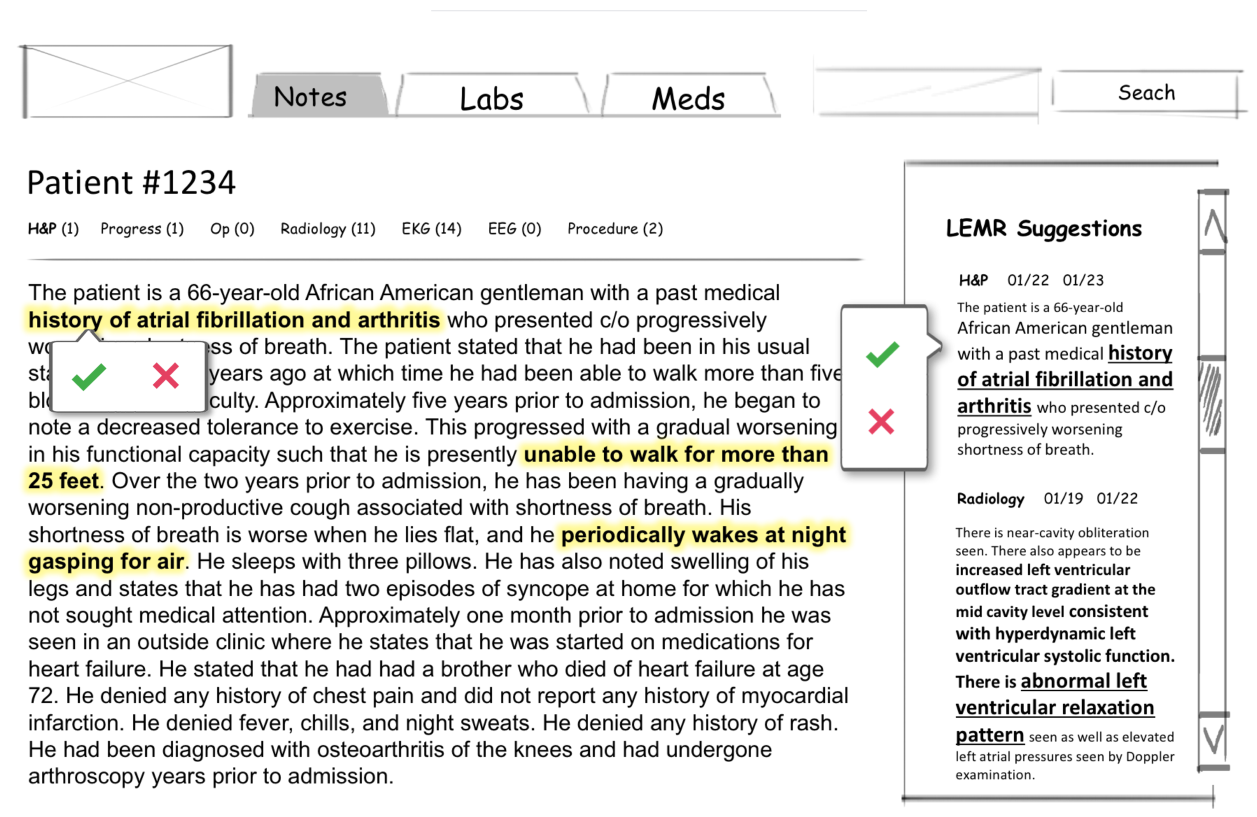
Interactive tool for clinicians to build NLP models for highlighting text (within patient notes) that should go into a 'signout' note



User Interface

Design Requirements:

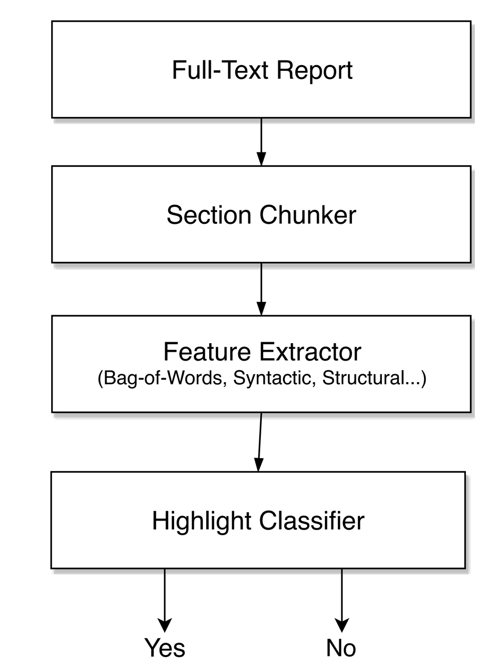
- **Review:** show important highlights, and indicate confidence of NLP predictions
- **Feedback:** users may add spans missed by the model and remove non-useful ones
- **Retrain:** changes between model revisions should be made apparent to the users



Interface Mockup: Full note on left with highlights • Suggestion box on the right emphasizes highlights for easy navigation • Users feedback through contextual menus

Learning Model

- Example NLP Pipeline used in [3]



- Adopt NLPReViz-like retraining process [2]

Evaluation

Dataset: from UPMC Trauma Services. Focus on 'incidentals' section in signouts for evaluation: 235 patients with 1,989 full-text reports

Proposed User Studies:

- **Usability Evaluation** to demonstrate feasibility and overall usefulness
- **Empirical Evaluation** to measure model correctness; a) *Intrinsic:* using annotated gold standard, and b) *Extrinsic:* task completion times, clicks etc.

References

[1] W W Chapman, P M Nadkarni, L Hirschman, L W D'Avolio, G K Savova, O Uzuner. Overcoming barriers to NLP for clinical text: the role of shared tasks and the need for additional creative solutions. *Journal of the American Medical Informatics Association* 18, 5 (2011), 540-543.

[2] Gaurav Trivedi, Phuong Pham, Wendy W Chapman, Rebecca Hwa, Janyce Wiebe, Harry Hochheiser. NLPReViz: an interactive tool for natural language processing on clinical text. *Journal of American Medical Informatics Association* 25, 1 (2018), 81–87.

[3] Meliha Yetisgen-Yildiz, Martin L Gunn, Fei Xia, and Thomas H Payne. Automatic identification of critical follow-up recommendation sentences in radiology reports. *In AMIA Annual Symposium Proceedings*, volume 2011, page 1593. American Medical Informatics Association, 2011.

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