Smoking Status Detection with a Pre-Trained Transformer and Weak Supervision in Dutch Electronic Patient Files

CLIN Talk, 9 July 2021

Myrthe Reuver, Iris Hendrickx, Jeroen Kuijpers

Radboud University

topicus

Introduction: what is smoking status, and why extract it?

- Smoking status:
  - clinically relevant, often written in free text of GP (SOEP-text);
  - roughly 20% of Dutch adults smoke (CBS);
  - in NLP/clinical information science usually a task with 3 classes (smoker, ex-smoker, non-smoker) (Uzuner et. al., 2006)
  - or 5 classes (never, past, current, smoker temporally unknown, and unknown smoking status) (Wang et. al. 2019).
  - **high documentation load GPs**

- ‘Care Standard’ Tobacco Addiction 2019 (Trimbos Institute):

Onderdeel 1 – Adviseren

Stel vast of de patiënt rookt door middel van de vraag: “Rookt u wel eens? Doet u dit dagelijks of af en toe?”

Adviseer elke patiënt die (weleens) rookt om te stoppen met roken, waarbij u het advies toespitst op de situatie van de patiënt en informatie geeft over effectieve behandelmogelijkheden

"How can we best automatically detect and classify the smoking status in primary care patients' EMR on the basis of the free text in GP doctor's notes, and overcome the sparsely labelled data problem?"

Important ethical and methodological concerns

Finding all unknown smoking statuses in EMRs?

However:

We are classifying DOCUMENTS, not people.
These documents ≠ consistent or reliable representation of real-world people.

Also, some inherent biases leads to imperfect detection;

- a positive smoking status will more often be recorded, leading to less detection of non or ex-smokers;
- doctors will record the smoking status of certain patient groups more (e.g. chronic illness), leading to any model's bias towards detecting smoking status in this group;
- **absence of any mention of smoking in EMR does not automatically mean non-smoking for a patient!**

LITERATURE ON PROBLEM AND METHODS

Smoking status extraction & classification → working with sparsely labelled data

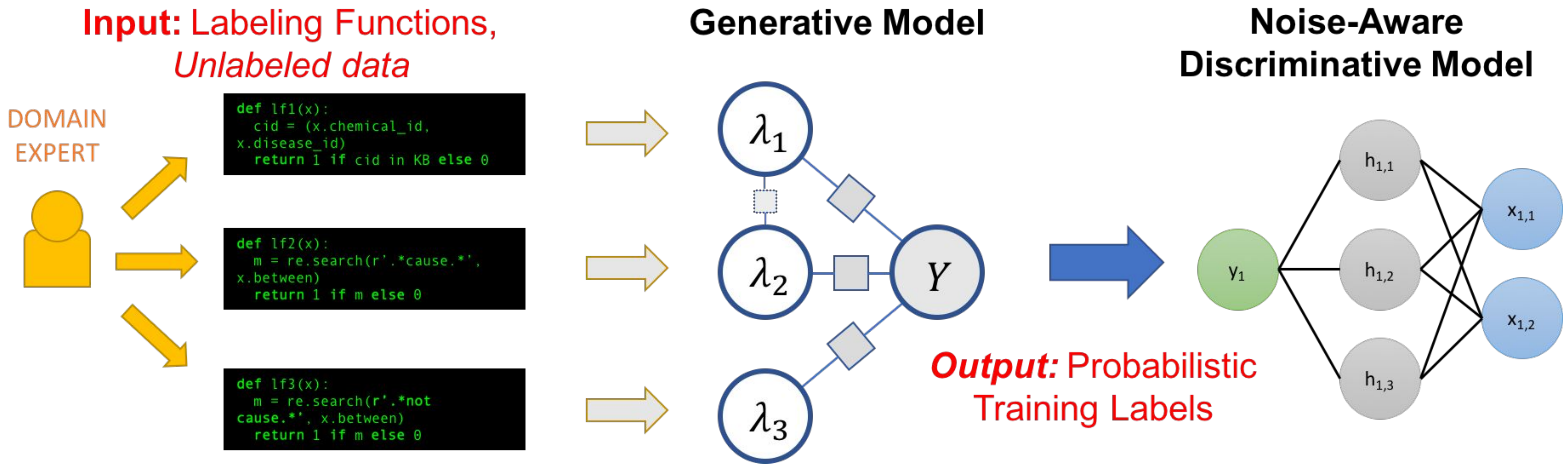
- Kreimeyer (2019), systematic literature review: **46% of clinical NLP projects** aiming to identify and extract elements from unstructured text in EMRs still **use rule-based systems**,

- **A. Rule-based → regular expressions** → used before in Weng 2019, Palmer 2019, Uzuner 2006, reporting over **90% accuracy (!)**
  - **pro:** works because this problem has relatively fixed vocabulary (“tabak”, “nicotin*”)
  - **con:** not very flexible, **cannot detect patterns not noted by rule designers**

- **B. Increasing training data → weak supervision → SNORKEL**
  - **pro:** works with rules, which works well with this problem, while also able to use training data in a machine learning model
  - Wang et. al. (2019) claims to use it, but their paper only gives evidence of simple rule-based labelling (?)

- **C. Transfer learning → BERT → fine-tuning**
  - **pro:** language model already retains semantic information useful for classification.

SNORKEL (Ratner et. al. 2017)



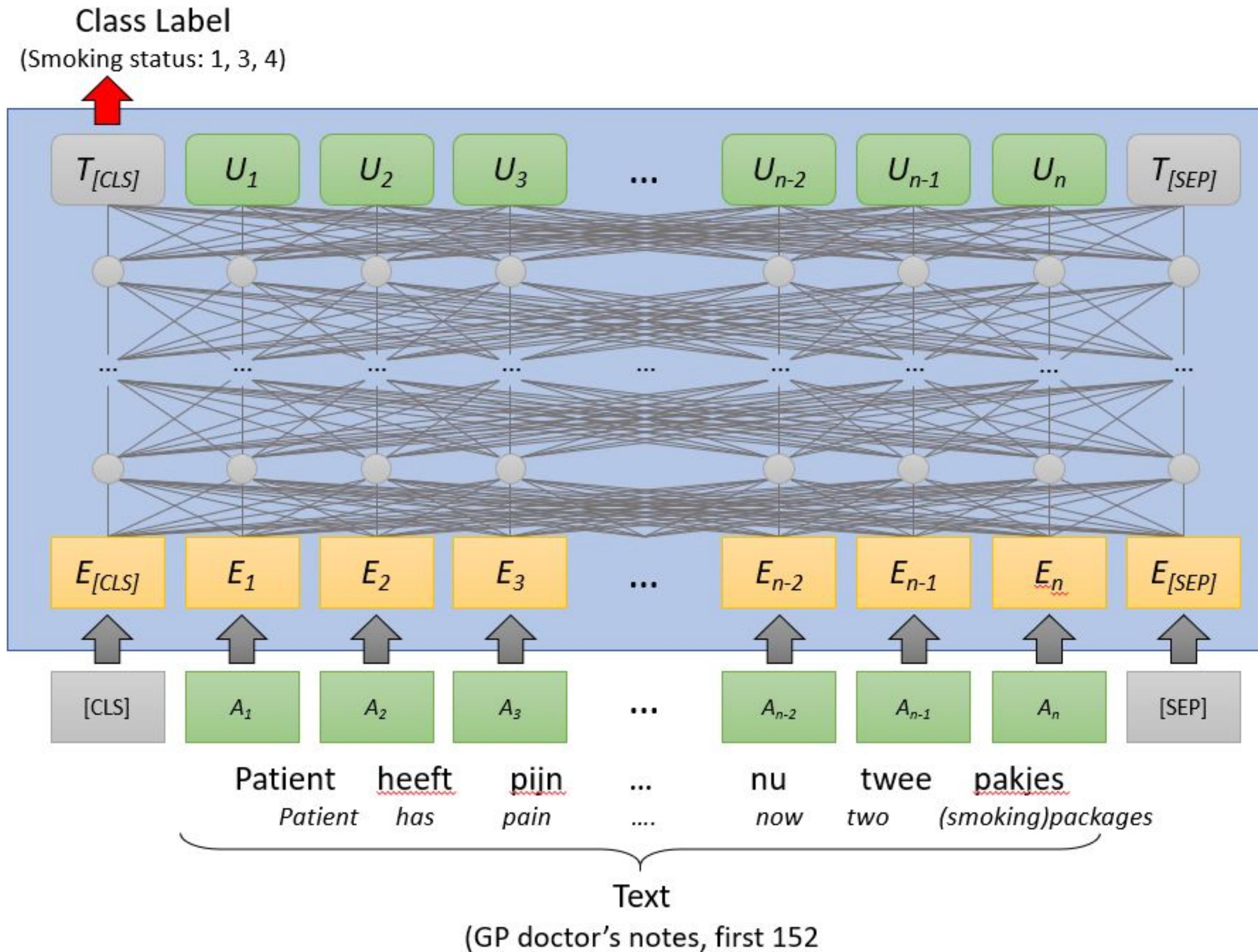
- works with Labelling Functions (LFs), heuristics or rule-based labellers
- These can be optimized on a small labelled **development set**

- LFs are **weighted** in a LabelModel
- exploiting (dis)agreements between LFs → each LF as an independent labeller ("Wisdom of the crowds")

BERT & BERTje

- BERT (Devlin et. al. 2019): large-scale, pre-trained transformer trained on a **masking** task: predicting context from words.
- In this manner, **semantic information can be retained,** useful for newer tasks

- We use BERTje (de Vries 2019), 12 layer Transformer model trained on Dutch Wikipedia, SoNaR, and other data in a masking and next sentence prediction task.



DATA

Data & Preprocessing of EMRs:

- 6 GP offices in the Netherlands.
- Each GP office has 4 datafiles: **PATIENTS, EPISODES, MEASUREMENTS** (many different smoking variables), **CONSULTATIONS (**SOEP-text).
- 943.757 **consultations** in 24 data files

Our preprocessing:
1. combining and **filtering** these 24 datafiles into one datafile

2. Normalization of EMR: only the **last** consultation for each patient.
Smoking status: P1739 → 3 classes: EX-SMOKER, SMOKER, NEVER.

3. Filtering out duplicates and minors

Final dataset: **17.873 EMR representations**

4. Data split: train (80%), dev (10%), and test (10%) split

Dataset: size and labelled sub-set

	Training set	Development	Test
EMR representations	14.298	1.788	1.787

Table 6: The **labelled** datapoints in values used for the smoking status variable '1739' ("smoking"), as defined by the NHG (National GP Association)

	Training	Dev	Test
"smoker"	794	115	103
"never smoked"	2081	268	274
"ex-smoker"	2103	268	251
total labelled EMR representations	4.978	651	628

EMR representation

patient ID_GP ID	Sex	Age at consult	Age in 2020	SOEP text	date	smoking (1739)	Ketenzorg
9999_777	F	40	43	Mevrouw heeft buikpijn Translation: Mrs. has stomach pain	23-04-2017	4	0
8888_666	M	63	62	Is gestopt met pasta eten, is afgevallen. Has stopped eating pasta, has lost weight	05-07-2019	1	1

METHODS

Our comparison in smoking status classification

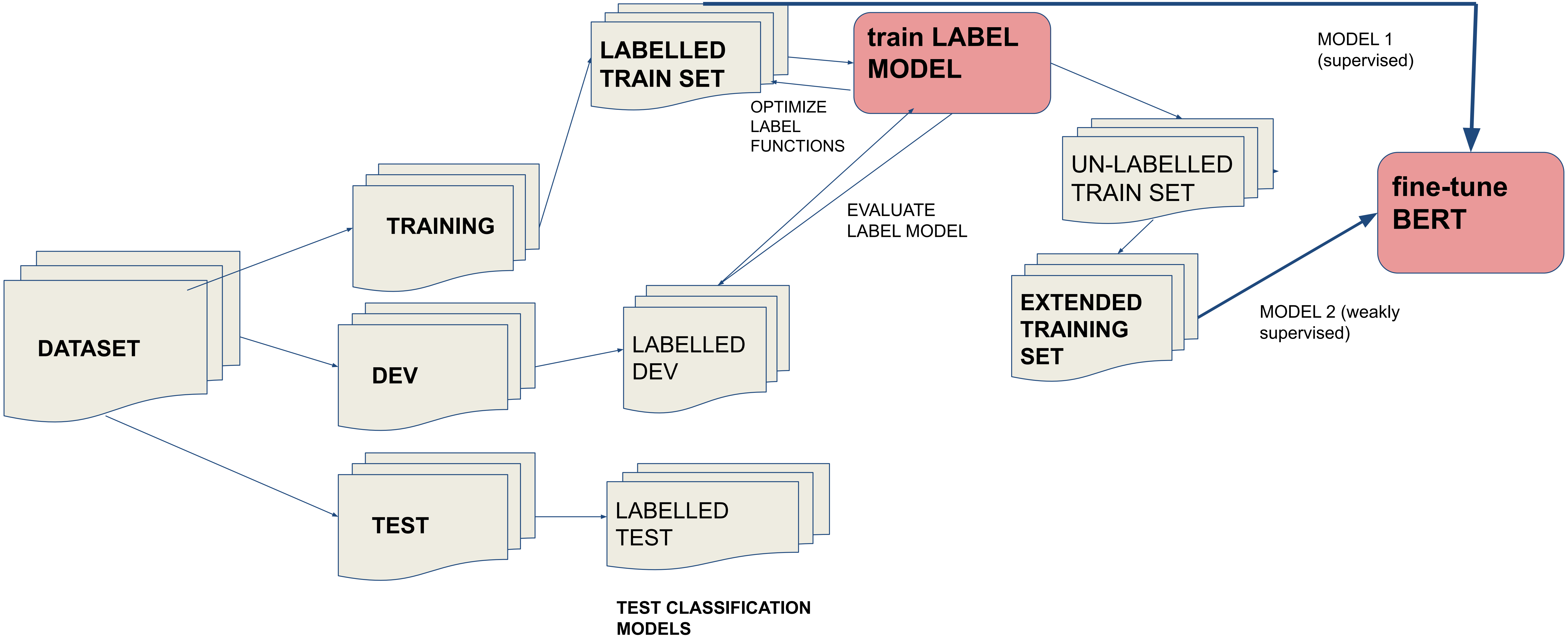
Compare:

- rule-based baselines (based on earlier work + Care Standard);
- BERTje;
- SNORKEL + BERTje (larger training set).

Evaluation:

- precision, recall, F1 → do we correctly predict smoking status?
- confusion matrices → When we incorrectly predict, what does the model predict?

Our pipeline



Transfer Learning with BERTje: fine-tuning

Training process:

- first: tokenize dataset with BERTje tokenizer;
- add one linear layer to BERTje, predicting 3 classes (smoker, non-smoker, ex-smoker)
- training: 3 epochs, learning rate: 0.00005
  → more epochs = overfitting (training loss lower than development loss)

Weak Supervision with SNORKEL - LFs

- Started with 32 heuristics, mostly based on keywords based on earlier literature and the Zorgstandaard:

```
"""rookt --> third person present."""
keyword_rookt = make_keyword_lf(keywords=["rookt"], label=SMOKER)

"""roker --> noun smoker."""
keyword_roker = make_keyword_lf(keywords=["roker"], label=SMOKER)

"""was smoker --> past."""
keyword_roker_was = make_keyword_lf(keywords=["was roker"], label=EX)
```

- LabelModel trained with 500 epochs, learning rate 0.01

RESULTS

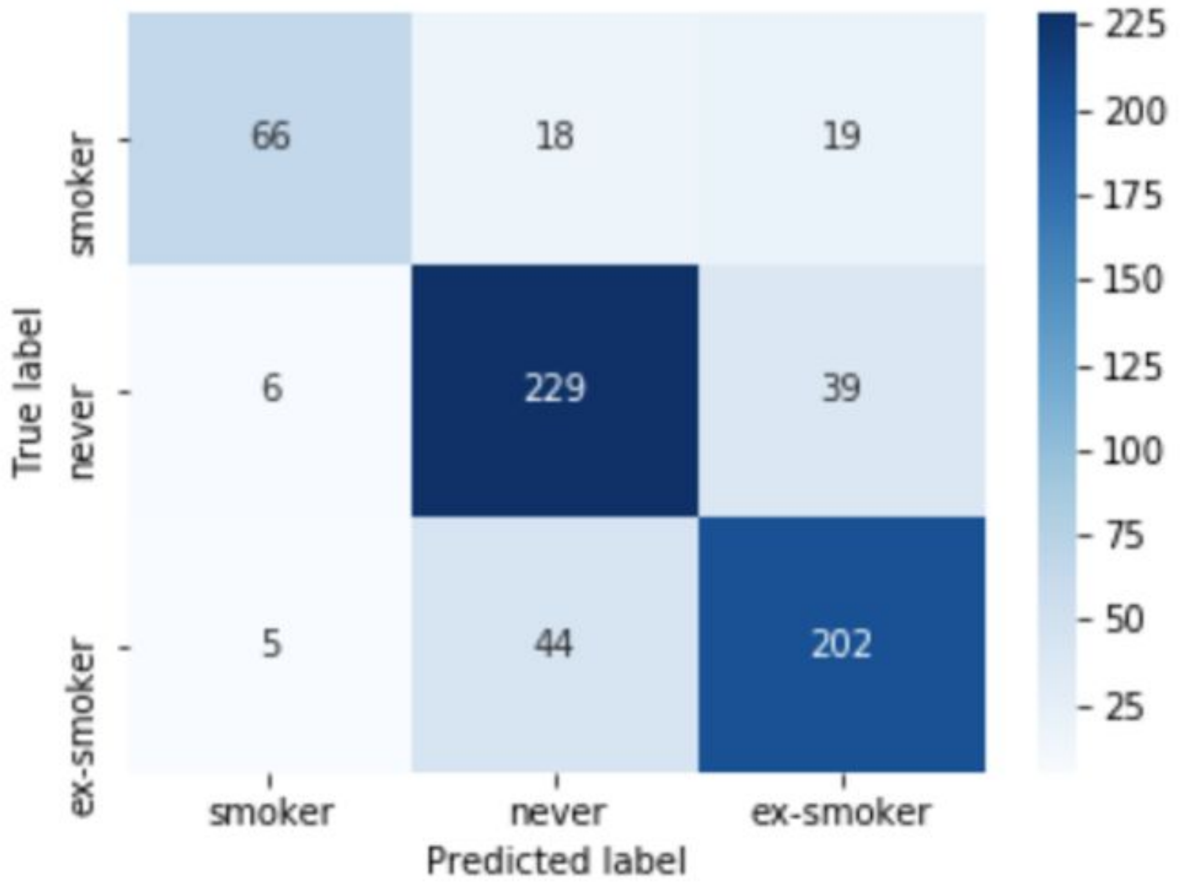
Results on the test set: overall and in-class

	Rule-Based	BERTje	SNORKEL + BERTje
precision (micro)	0.49	**0.79**	**0.79**
recall (micro)	0.43	**0.79**	**0.79**
F1 (micro)	0.55	**0.79**	**0.79**

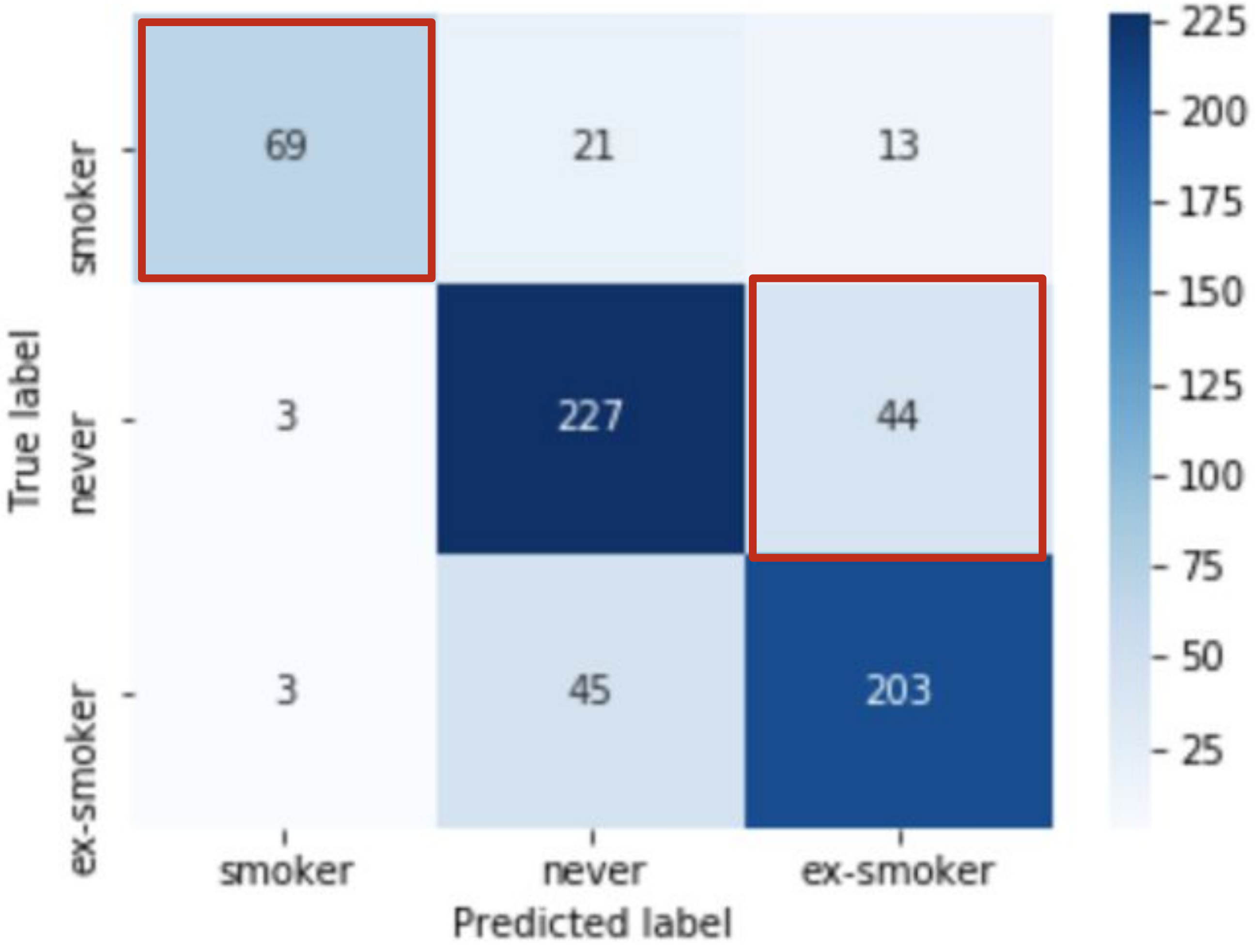
	BERTje *4.978 training examples*			SNORKEL+BERTje *5.490 training examples*		
	precision	recall	F1	precision	recall	F1
SMOKING	0.82	0.64	0.72	**0.86**	0.64	**0.73**
NON-SMOKING	0.74	0.76	0.75	**0.79**	**0.84**	**0.81**
EX-SMOKING	**0.82**	**0.83**	**0.82**	0.78	0.80	0.79

Confusion Matrices (on the Test set)

BERTje



BERTje + SNORKEL:



CONCLUSION

Things we learned

- real-world data is more complicated than shared task data

"How can we best automatically detect and classify the smoking status of primary care patients' EMR on the basis of the free text in GP doctor's notes, and overcome the sparsely labelled data problem?"

- Weakly supervised method works for some classes (SMOKING, NON-SMOKING), where there is in-class improvement, but no overall improvement over supervised learning;
- Rule-based method → does not seem to generalize well;
- A model trained on general language understanding (BERTje) is performing relatively well in smoking status classification of EMRs.

References

Uzuner, Ö., Goldstein, I., Luo, Y., & Kohane, I. (2008). Identifying patient smoking status from medical discharge records. Journal of the American Medical Informatics Association, 15(1), 14-24.

Wang, Y., Sohn, S., Liu, S., Shen, F., Wang, L., Atkinson, E. J., ... & Liu, H. (2019). A clinical text classification paradigm using weak supervision and deep representation. BMC medical informatics and decision making, 19(1), 1.

CBS. 2018. Helft van laagopgeleide 25- tot 45-jarige mannen rookt. https://www.cbs.nl/nl-nl/nieuws/2018/22/helft-van-laagopgeleide-25-tot-45-jarige-mannen-rookt

Ford, E., Carroll, J. A., Smith, H. E., Scott, D., & Cassell, J. A. (2016). Extracting information from the text of electronic medical records to improve case detection: a systematic review. Journal of the American Medical Informatics Association, 23(5), 1007-1015.

Kreimeyer, K., Foster, M., Pandey, A., Arya, N., Halford, G., Jones, S. F., ... & Botsis, T. (2017). Natural language processing systems for capturing and standardizing unstructured clinical information: a systematic review. Journal of biomedical informatics, 73, 14-29.

Palmer, E. L., Hassanpour, S., Higgins, J., Doherty, J. A., & Onega, T. (2019). Building a tobacco user registry by extracting multiple smoking behaviors from clinical notes. BMC medical informatics and decision making, 19(1), 141.

de Vries, W., van Cranenburgh, A., Bisazza, A., Caselli, T., van Noord, G., & Nissim, M. (2019). Bertje: A dutch bert model. arXiv preprint arXiv:1912.09582.

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Ratner, A., Bach, S. H., Ehrenberg, H., Fries, J., Wu, S., & Ré, C. (2017, November). Snorkel: Rapid training data creation with weak supervision. In Proceedings of the VLDB Endowment. International Conference on Very Large Data Bases (Vol. 11, No. 3, p. 269). NIH Public Access.

Questions?

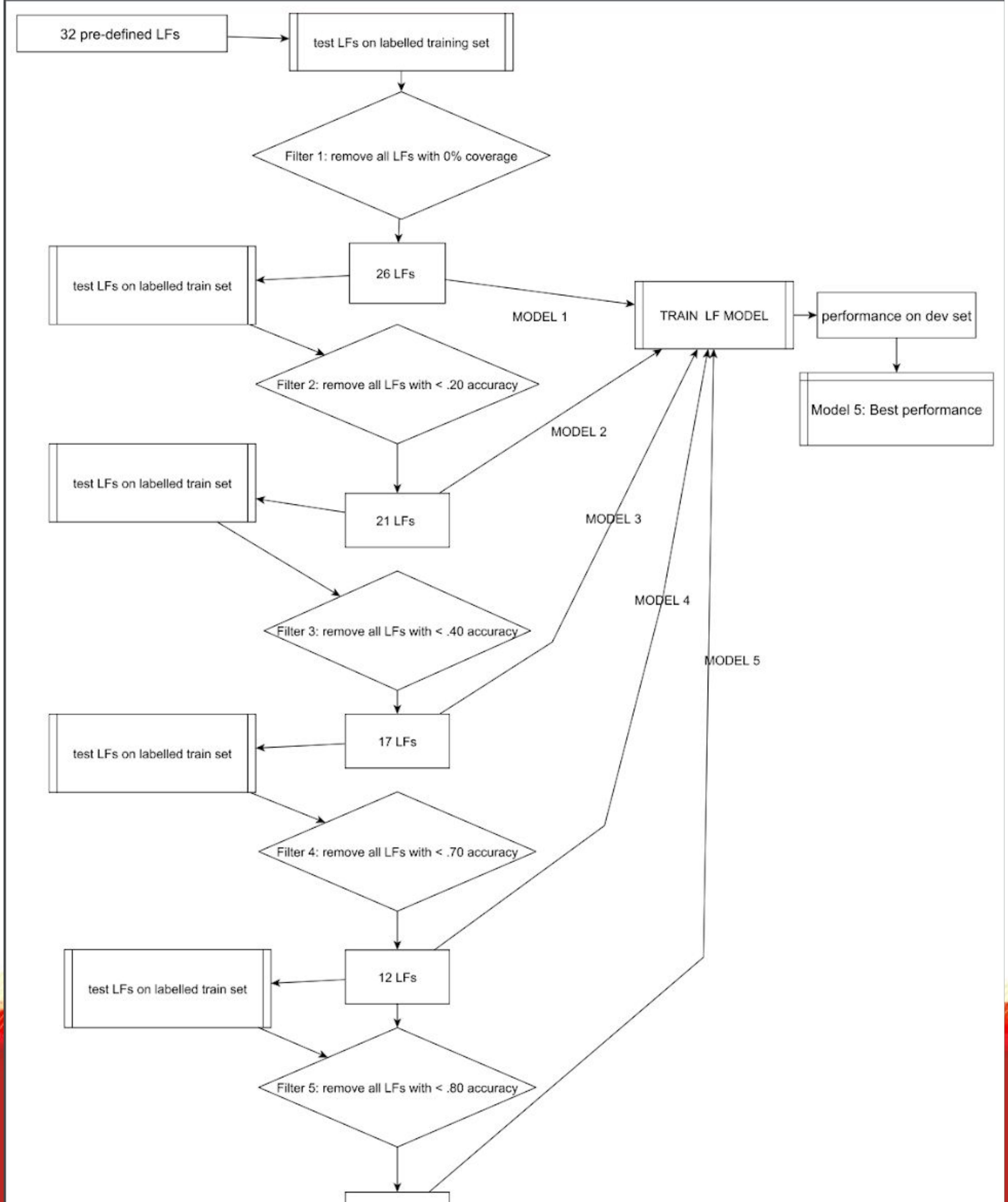
Problem in Earlier Smoking Status Classification Work

- Small training sets e.g. Uzuner (2006) → 502 EMRs, Weng et. al. (2019) --> 475 EMRs → especially not enough training examples for neural models

- Sparsely labelled → roughly 2% of the Electronic Medical Records (EMRs)'s consultations has a recorded smoking status in our dataset

- Mainly tested on 'clean' benchmarking datasets in the literature (ib2b 2006 shared task, Mayo Clinic dataset in Wang et. al. (2019):
  - **pro:** open data
  - **con:** not realistic in real clinical settings, sparsely labelled data

Our goal: overcome this sparsely labelled data problem and improve over simple, rule-based models, on 'real' clinical data.



SNORKEL: training a LabelModel

Interesting results LFs:

- of all ‘quit smoking’ medicines mentioned in the health directive, only “champix” had any coverage;

- “roken” gave opposite result: the word was more often mentioned with people who never smoked (.45 accuracy) than with smokers, which was expected (.19 accuracy).

snorkel