Vers un système de dialogue oral pour la saisie de prescriptions médicales

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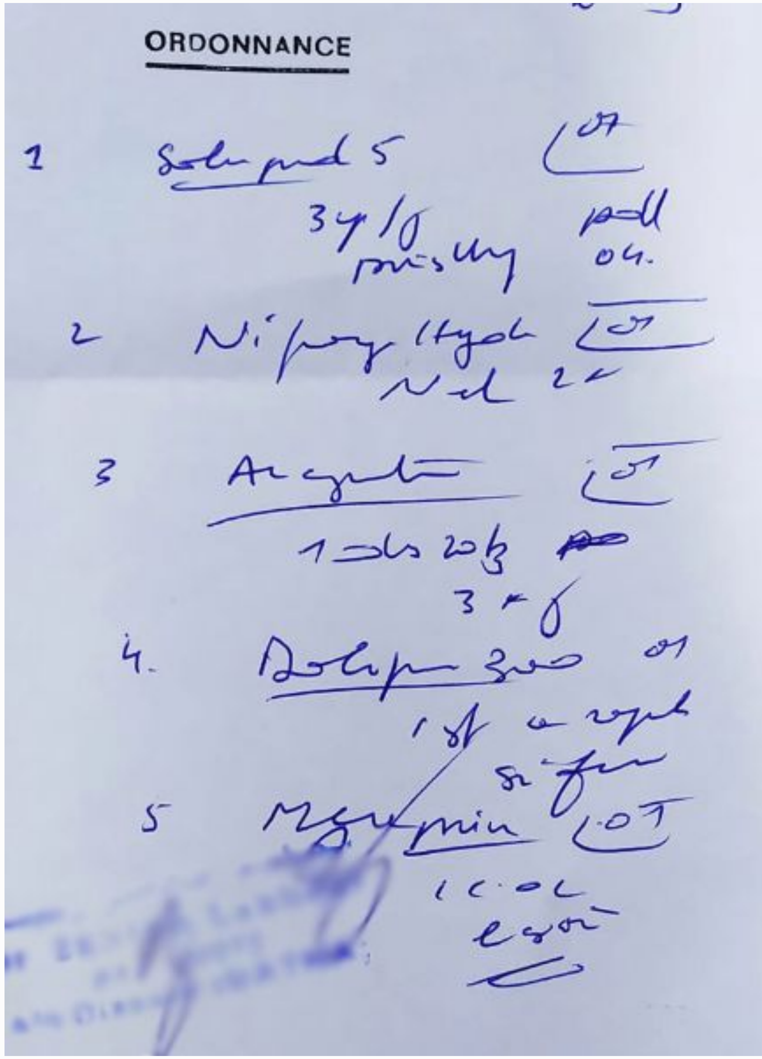
Introduction – Towards Computired Medical Prescriptions



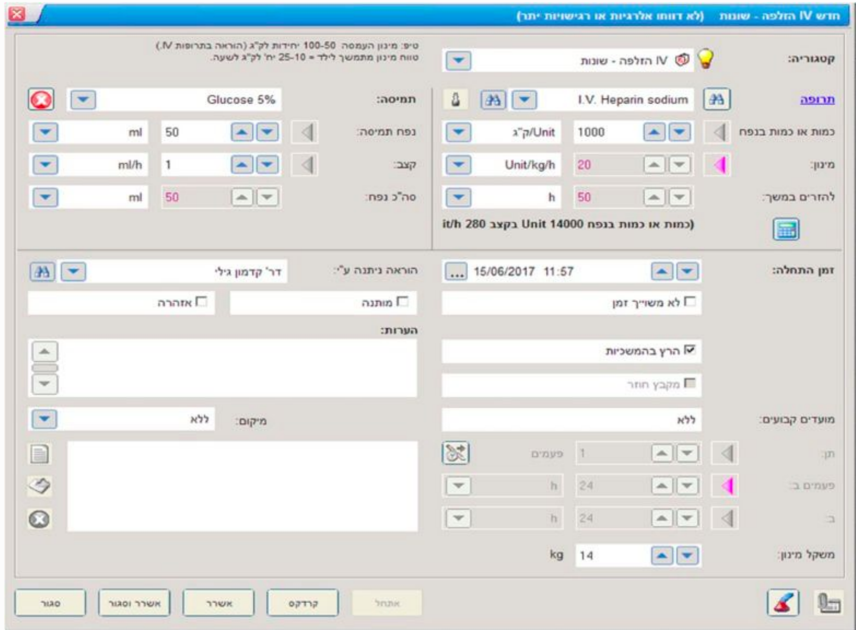
- ~2% errors in 5000 prescriptions in France (Augry et al., 2000)
    - 42% incomplete, 32% overdosage, 6% underdosage
- 0.3% prescribing errors per patient per day in a study of hospital medical units (Bates et al., 1995)
- ¾ prescribing and administration errors (Leape et al., 1995)

=> medical errors in general are the third <u>leading cause of death</u> in the USA

- Prescription management systems
    - As a part of health information technologies
    - routine in most GP and hospitals

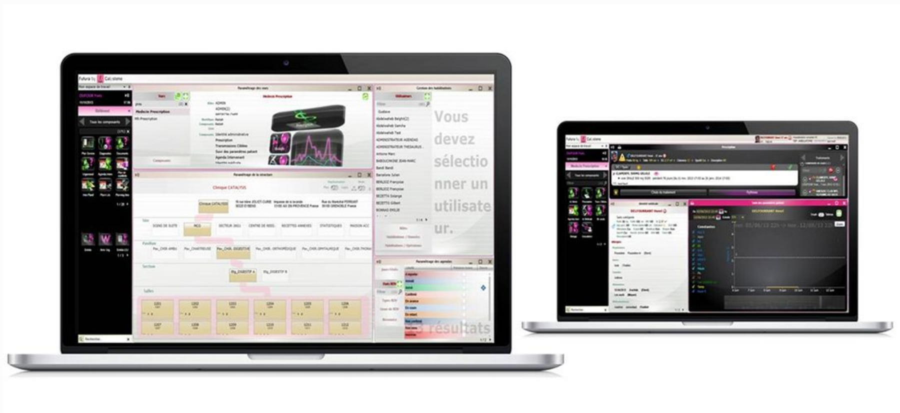
Introduction – Towards Medical Prescription Understanding

- Use of prescription management systems in health institutions
- Reduction of errors using information technology (kadmon, 2017)
- Ensuring security, adequacy and efficiency of prescriptions
- But time consuming, not available at the point of care.

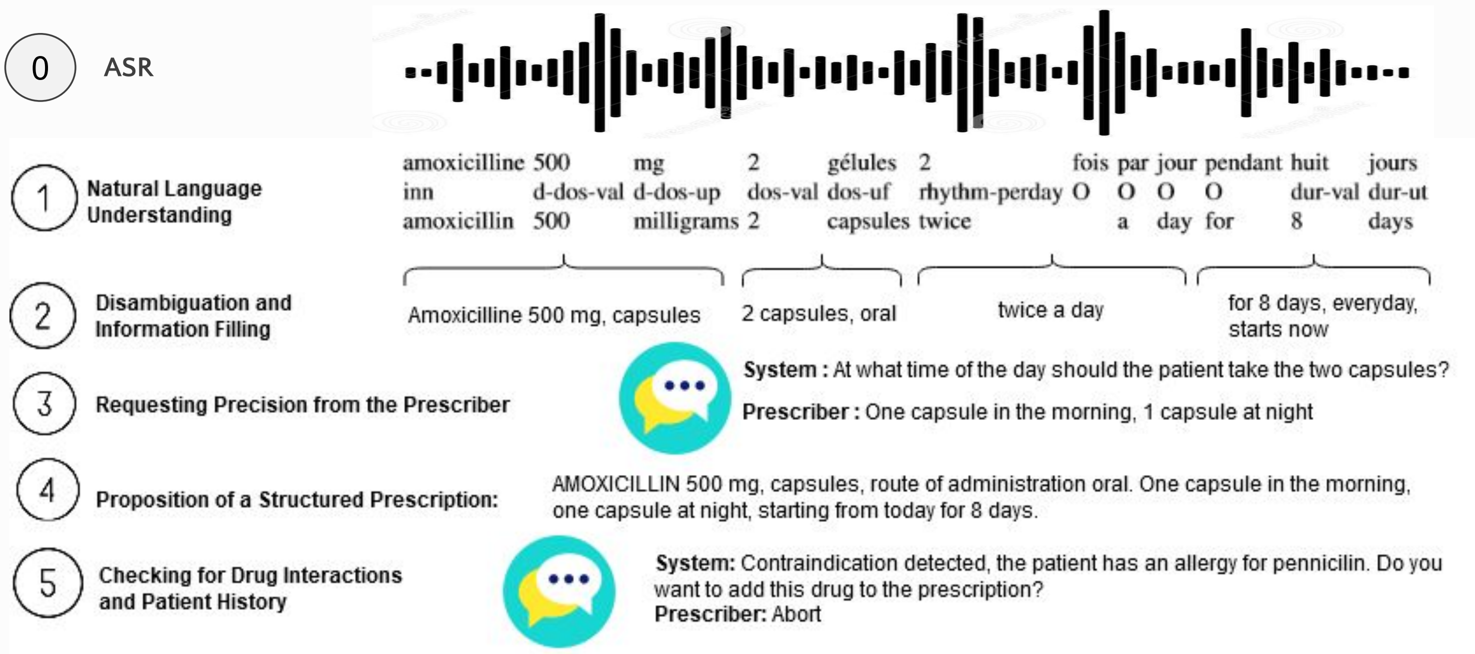


Introduction – Towards Medical Prescription Understanding

- Provide a natural language interface to prescription management systems
- Enable practitioners to record their prescriptions orally
- Prescription at the point of care
- Provide a form closer to their usual practice
- Integration of PMS into the dialogue policy
- Futura Smart Design®



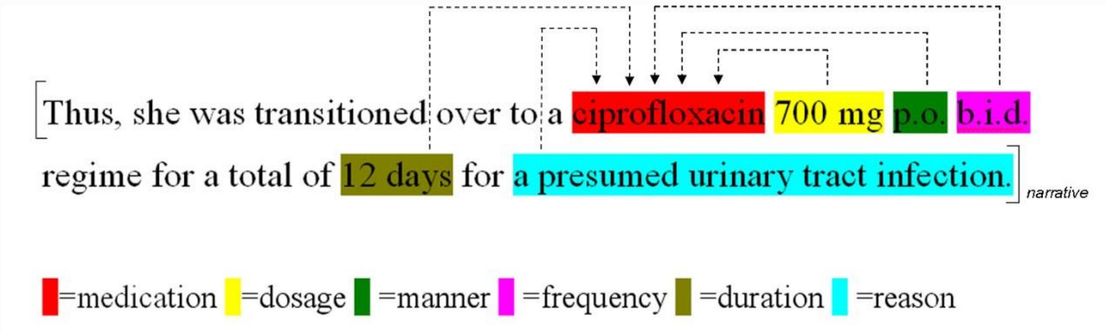
Introduction – Approach



- Spoken medical prescriptions as a dialogue task
- Utterance understood, disambiguated and completed through dialogue
- Expert automatic information checking to avoid mistakes
    - Using medical thesaurus and PMS

Related Work

- Large body of work on automatic biomedical information extraction
  - MedLee(Friedman, 2000)
  - Metamap(Arason et al., 2010)

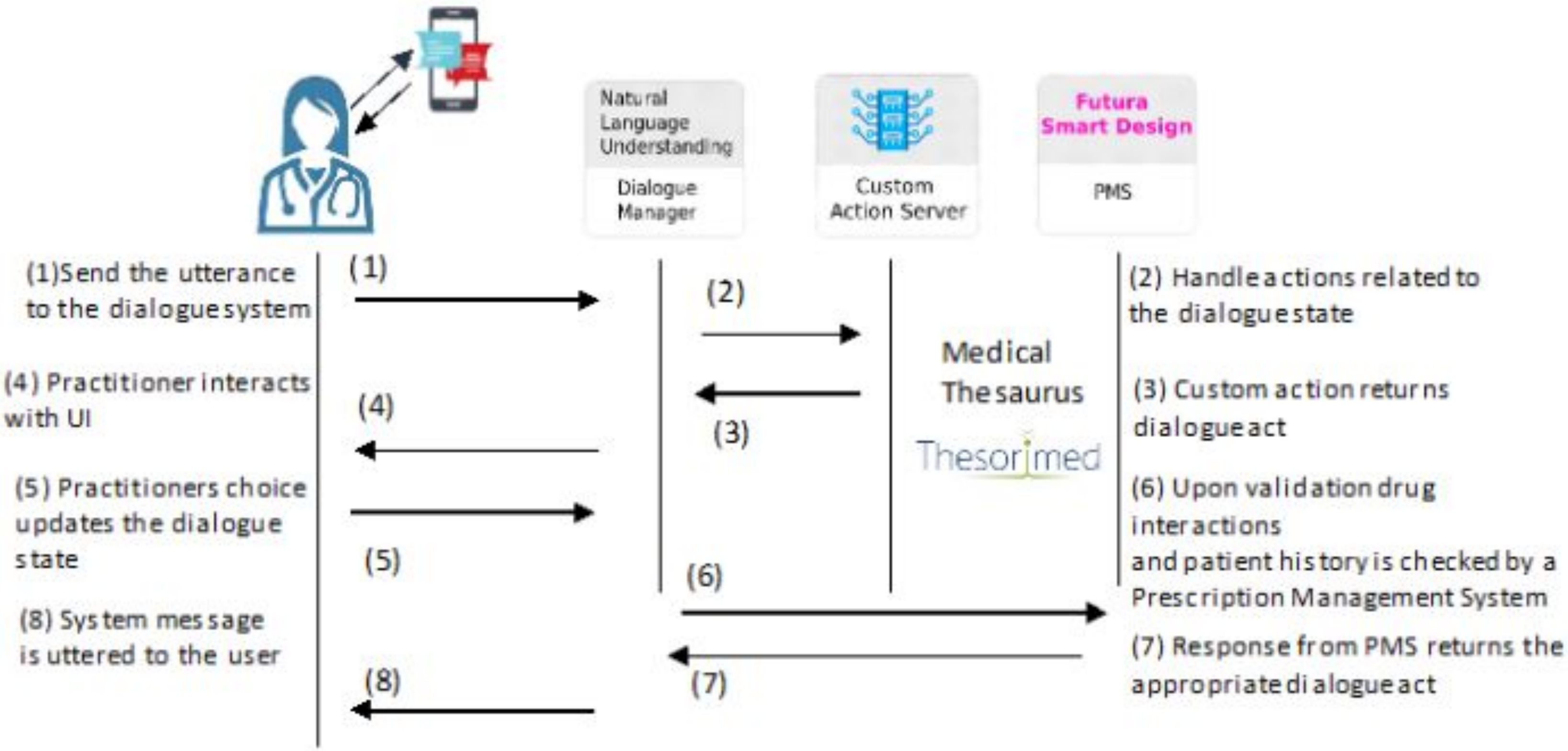


- I2B2 2009 Shared Task on Medication Information Extraction (Uzuner et al., 2010)

- Almost no work for French (Deléger,2010)

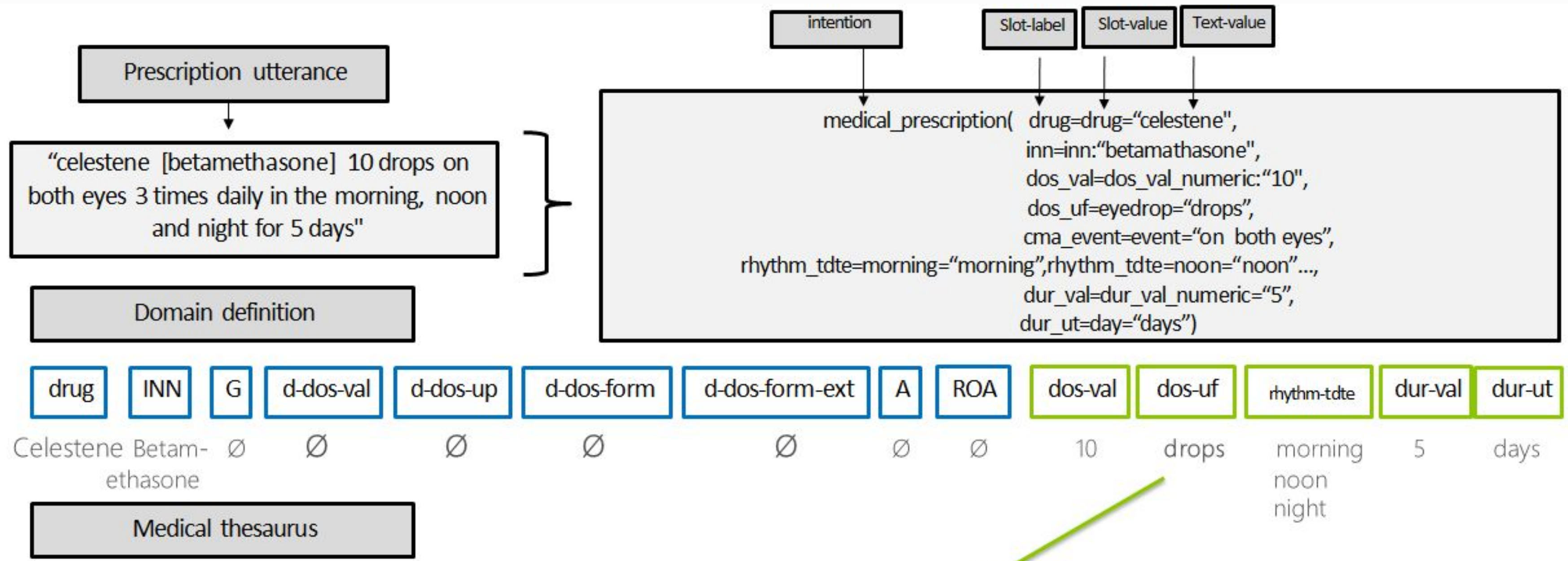
- Not aware of any spoken prescription systems

Overall System



Approach – NLU

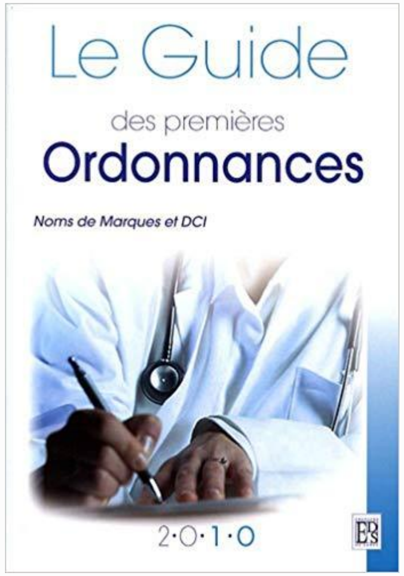
- Slot filling and disambiguation



CELESTENE 0,05 %, solution in drops	solution in drops
~~CELESTENE 0,5 mg, tablets~~	~~tablet~~
~~CELESTENE 2 mg, breakable dispersible tablet~~	~~breakable dispersible tablet~~
~~CELESTENE 20 mg/5 ml, injectable solution~~	~~injectable solution~~
~~CELESTENE 4 mg/1 ml, injectable solution~~	~~injectable solution~~
~~CELESTENE 8 mg/2 ml, injectable solution~~	~~injectable solution~~
~~CELESTENE CHRONODOSE 5,70 mg/ml, suspension for injection~~	~~suspension for injection~~

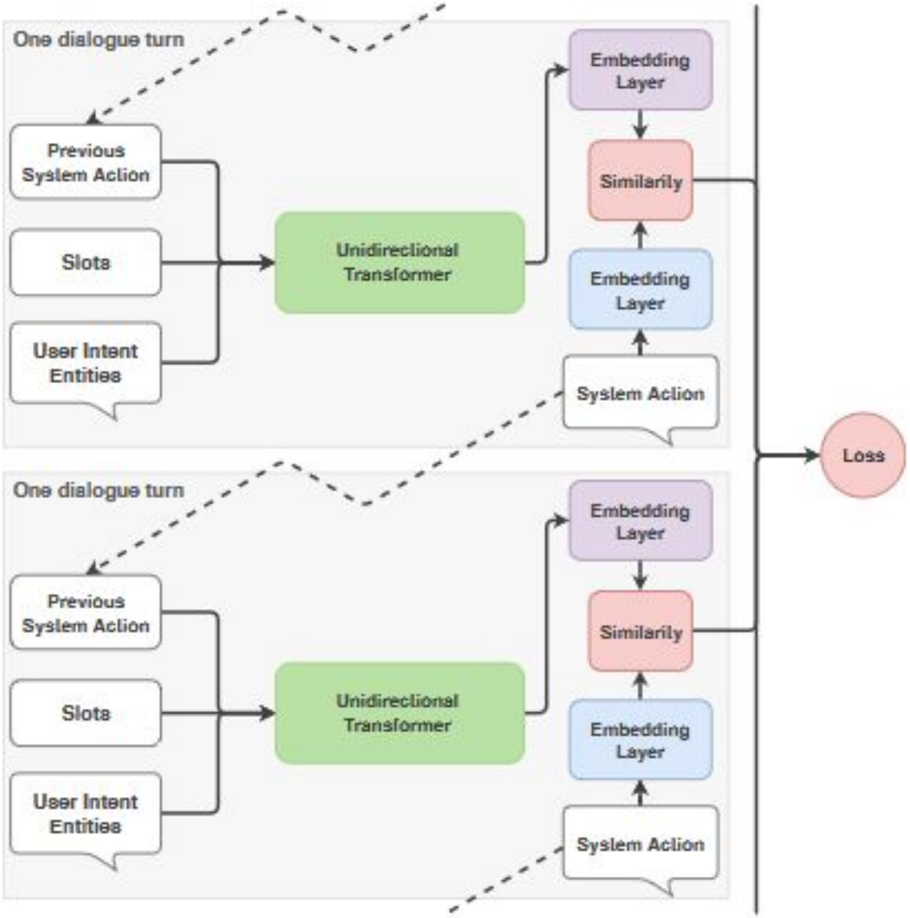
NLU handling and lack of data

- Merged textbook, generated data and coloquial data
- Added utterances from colloquial speech corpus ESLO
  - To recognize out-of-domain utterances
- Trained CRF, Tri-CRF, Attention-RNN and seq2seq models



Corpus	Train	Dev	Test
Textbook	417	99	316
Artificial	3034	0	0
ESLO	417	99	316
Total	3868	198	632

Dialogue handling



Dialogue Transformers (Vlasov et al., 2019)

- Based on the self-attention mechanism
- Attention over the past dialogue turns at each dialogue turn
- Enables to selectively ignore or attend to parts of dialogue history

Demo

https://videos.univ-grenoble-alpes.fr/video/14200-systeme-de-dialogue-oral-saisie-des-prescriptions-medicamenteuses/

Evaluation: initial results

NLU F-measure (2019)

Model	Intent	Slot-label
Baseline	-	0.61
RASA	0.97	0.67
Tri-CRF	0.97	**0.93**
Att-rnn	**0.99**	0.82
Seq2Seq	0.97	0.70

40 dialogs with 2 medical experts and 2 naive users (2020)

	Task Sucess Rate	Average Dialogue Turns	NLU (f-measure)	WER (ASR)	Drug Association Rate (on TP)	Average Time Elapsed (on success)
medical experts	45%	1.56	0.75	3.40%	0.62	30 seconds
naive users	16.6%	1.54	0.43	17.35%	0.65	35 seconds

Discussion and Future Work

- ➢ Extracting medical prescription information for a voice-based PMS
  - lack of medical data in French (where is the French MIMIC?)
  - lack of resource in French (where is the French BioBert?)
  - generation strategy leads to reasonable system
  - importance of external knowledge
  - company data difficult to leverage

- ➢ Data collection and experiments during the lockdown using smartphones
  - test of our system with physicians (CHU Grenoble) and naive users
  - current collection planned to be released as CC0.
  - adapt pre-trained model (Flaubert) (Le et al.,2019)
    - we improved I2B2-2009 using BlueBert (Peng et al.,2019)
  - develop semi-supervised approach to leverage unannotated French data

Thank you!

References :

Ali Can Kocabiyikoglu, François Portet, Jean-Marc Babouchkine, Hervé Blanchon, Spoken Medical Prescription Acquisition Through a Dialogue System on Smartphone: Perspective of a Healthcare Software Company. LREC 2020 Industry Track Language Resources and Evaluation Conference 11–16 May 2020, Nov 2020, Marseille, France

Ali Can Kocabiyikoglu, François Portet, Hervé Blanchon, Jean-Marc Babouchkine. Towards Spoken Medical Prescription Understanding. 10th Conference on Speech Technology and Human-Computer Dialogue, Oct 2019, Timişoara, Romania

References

[Aronson2010] A. R. Aronson and F.-M. Lang, “An overview of metamap: historical perspective and recent advances,” Journal of the American Medical Informatics Association, vol. 17, no. 3, pp. 229–236, 2010.

[Bates1995]Bates, D. W., Cullen, D. J., Laird, N., Petersen, L. A., Small, S. D., Servi, D., ... & Edmondson, A. (1995). Incidence of adverse drug events and potential adverse drug events: implications for prevention. *Jama*, *274*(1), 29-34.

[Deléger2010] Deléger L., Grouin C., Zweigenbaum P., « Extracting medication information from French clinical texts »,MEDINFO 2010, Amsterdam, p. 949-953, 2010

[Friedman2000] C. Friedman, “A broad-coverage natural language processing system.” in Proceedings of the AMIA Symposium. American Medical Informatics Association, 2000, p. 270.

[Kadmon2017] Gili Kadmon, Michal Pinchover, Avichai Weissbach, Shirley Kogan Hazan, Elhanan Nahum, Case Not Closed: Prescription Errors 12 Years after Computerized Physician Order Entry Implementation, The Journal of Pediatrics, 190, 2017, 236-240.

[Lau2010] F. Lau, C. Kuziemsky, M. Price, and J. Gardner, “A review on systematic reviews of health information system studies,” Journal of the American Medical Informatics Association, vol. 17, no. 6, pp. 637–645, 2010.

[Leapse1995]Leape, L. L., Bates, D. W., Cullen, D. J., Cooper, J., Demonaco, H. J., Gallivan, T., ... & Edmondson, A. (1995). Systems analysis of adverse drug events. *Jama*, *274*(1), 35-43.

[Le2019]Le, H., Vial, L., Frej, J., Segonne, V., Coavoux, M., Lecouteux, B., ... & Schwab, D. (2019). Flaubert: Unsupervised language model pre-training for french. *arXiv preprint arXiv:1912.05372*

[Makaray2016] Makary, M. A., & Daniel, M. (2016). Medical error—the third leading cause of death in the US. *Bmj*, *353*, i2139.

[Peng2019] Peng, Y., Yan, S., & Lu, Z. (2019, August). Transfer Learning in Biomedical Natural Language Processing: An Evaluation of BERT and ELMo on Ten Benchmarking Datasets. In Proceedings of the 18th BioNLP Workshop and Shared Task (pp. 58-65).

[Uzuner2010]Uzuner, Ö., Solti, I., & Cadag, E. (2010). Extracting medication information from clinical text. *Journal of the American Medical Informatics Association*, *17*(5), 514-518.

[Vlasov2019] Vlasov, V., Mosig, J. E., & Nichol, A. (2019). Dialogue transformers. arXiv preprint arXiv:1910.00486.

[Williams2007]Williams, J. D., & Young, S. (2007). Partially observable Markov decision processes for spoken dialog systems. *Computer Speech & Language*, *21*(2), 393-422.

[Williams2017] Williams, J. D., Asadi, K., & Zweig, G. (2017). Hybrid code networks: practical and efficient end-to-end dialog control with supervised and reinforcement learning. arXiv preprint arXiv:1702.03274.