Prescriptive Healthcare using LSTM

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You are a doctor and one of your patients has an immense stomache pain for several weeks. You look at the medical records, trajectory and the interventions already made. Next day you think of a way to combine all the long- and shortterm happenings in your medical record but you can not find a solution to your problem. As one can imagine, many medical students do not have the experience they can rely on just after finishing their studies, thus a helpful hand for prognosis and over all prescriptions of further therapy is very welcomed. Additionally the demographic change gets us more older patients that needs treatment or medical supervision, but enough trained staff is not provided. So, how can one help the medical area to obtain a better working system without the chance of medical staff to be overworked and maybe need medical treatment itself due to sever stress.

Solution

Predictive- and Prescriptive Healthcare

Prescriptive Healthcare

- IBM: Prescriptive analytics enables healthcare decision-makers optimize business outcomes by recommending the best course of action for patients or providers

Predictive Healthcare

- Philips: Predictive analytics aims to alert clinicians and caregivers of the likelihood of events and outcomes before they occur, helping them to prevent as much as cure health issues

Why predictive and prescriptive models in healthcare ?

- Exoneration for healthcare system and workers
- Less health insurance to pay
- Discharge for countries without proper healthcare system
- Efficient regarding time in critical course of disease

Infrastructure

- 01.01.2021 „elektronische Patientenakte“ provided by healthinsurance company
- Scandinavian Countries earlier (ex. Sweden 2012)

Natural Language Processing

Tokenization/Segmentation	Lemmatization	Stemming
POS tagging	Parsing	Sentence breaking

DeepCare

Experiments and Results

12 Years of data (2002-2013) from Australian Hospital

Diabetes

7,191 patients with 53,208 admissions

55.5% males, median age 73

vocabulary of 243 diagnosis, 773 procedure and 353 medication codes

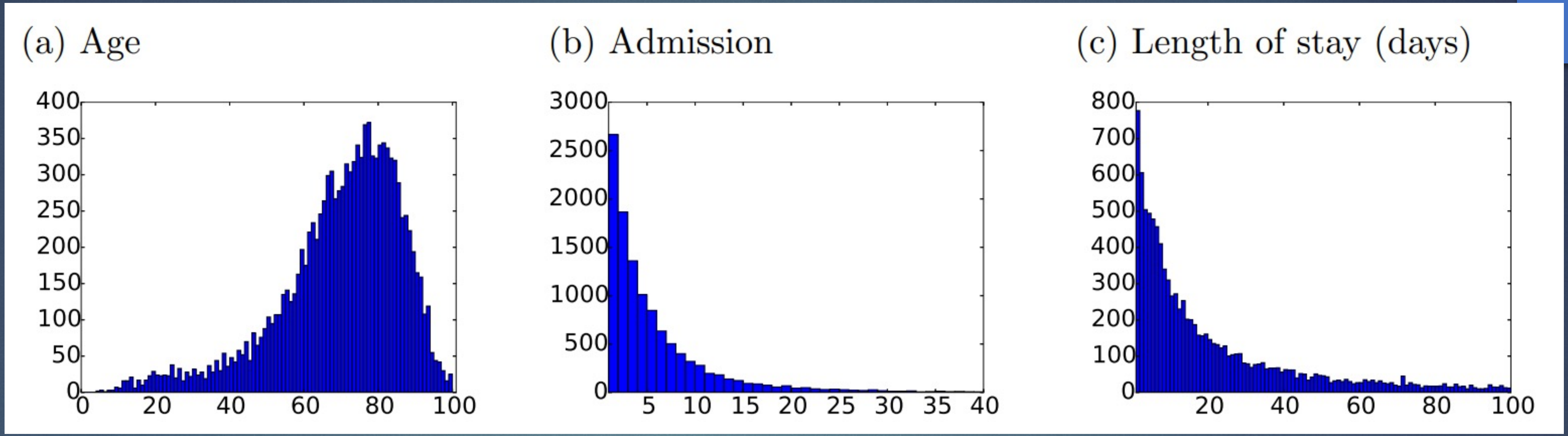
Mental

6,109 patients and 52,049 admissions

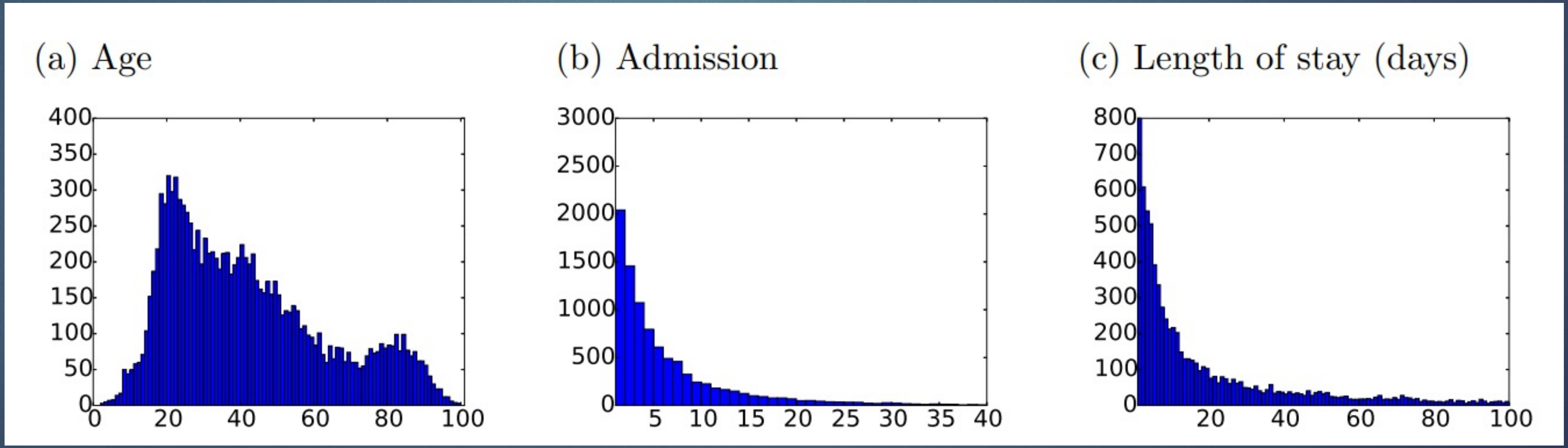
49.4% males, median age 37

vocabulary of 247 diagnosis, 752 procedure and 319 medication codes

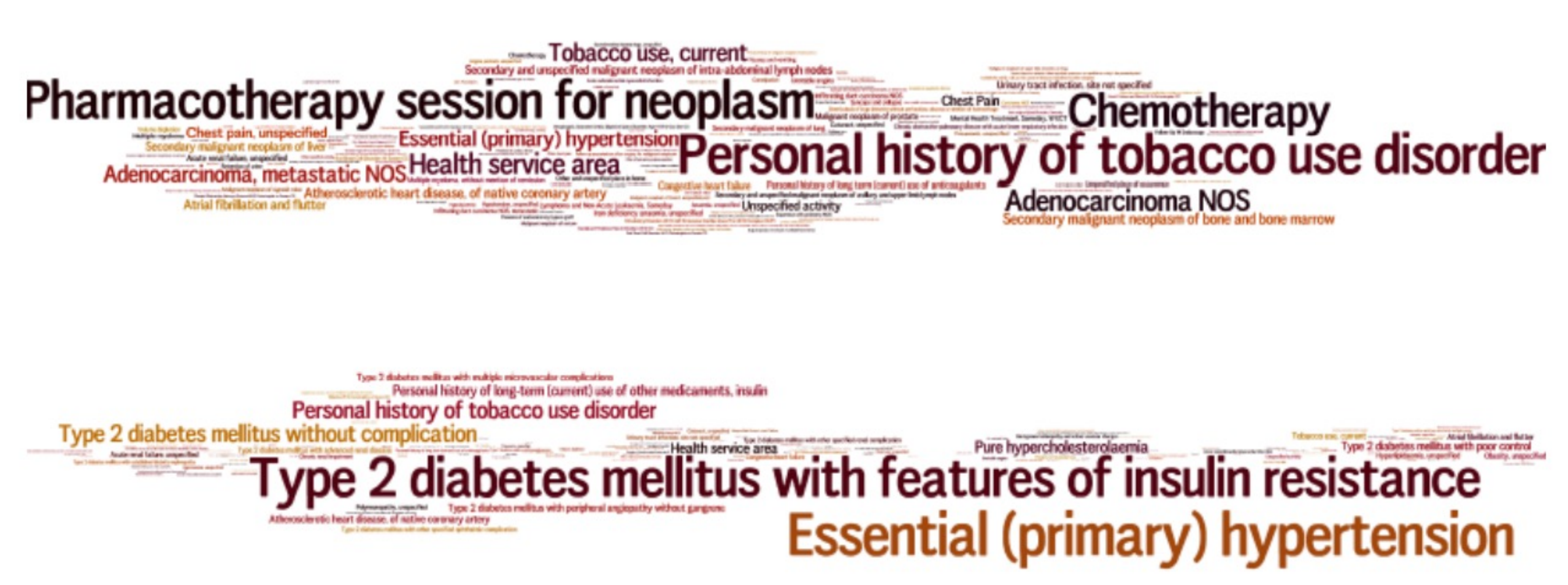
Diabetes



Mental



Diabetes Progression



Mental Progression

Model

- model predicts the next np diagnoses at each discharge

$$P\left(y_t = l \mid \boldsymbol{x}_{1:t}\right) = \operatorname{softmax}\left(\boldsymbol{v}_l^\top \boldsymbol{h}_t\right)$$

- Compared to HMM and RNN
- Evaluated by Performance Measurement

$$\text{Precision@}n_p = \frac{n_r}{n_p}$$

Results

Diagnosis prediction

	Diabetes			Mental		
	$n_p = 1$	$n_p = 2$	$n_p = 3$	$n_p = 1$	$n_p = 2$	$n_p = 3$
Markov	55.1	34.1	24.3	9.5	6.4	4.4
Plain RNN	63.9	58.0	52.0	50.7	45.7	39.5
DeepCare (mean adm.)	**66.2**	**59.6**	**53.7**	**52.7**	**46.9**	**40.2**
DeepCare (sum adm.)	65.5	59.3	53.5	51.7	46.2	39.8
DeepCare (max adm.)	66.1	59.2	53.2	51.5	46.7	**40.2**

Intervention Prediction

	Diabetes			Mental		
	$n_p = 1$	$n_p = 2$	$n_p = 3$	$n_p = 1$	$n_p = 2$	$n_p = 3$
Markov	35.0	17.6	11.7	20.7	12.2	8.1
Plain RNN	77.7	54.8	43.1	70.4	55.4	43.7
DeepCare (mean adm.)	77.8	54.9	43.3	70.3	55.7	44.1
DeepCare (sum adm.)	**78.7**	**55.5**	**43.5**	**71.0**	**55.8**	**44.7**
DeepCare (max adm.)	78.4	55.1	43.4	70.0	55.2	43.9

Risk prediction

unplanned readmission and high risk patients within X months

X = 12 for diabetes

X = 3 for mental health

F-Score

Model	Diabetes	Mental
1. SVM (*max-pooling*)	64.0	64.7
2. SVM (*sum-pooling*)	66.7	65.9
3. Random Forests (*max-pooling*)	68.3	63.7
4. Random Forests (*sum-pooling*)	71.4	67.9
5. Plain RNN (*logist. regress.*)	75.1	70.5
6. LSTM (*logit. regress.*)	75.9	71.7
7. DC (*nnets + mean adm.*)	76.5	72.8
8. DC ([*inv.+time decay*]*+recent.multi.pool.+nnets+mean adm.*)	77.1	74.5
9. DC ([*inv.+param. time*]*+recent.multi.pool.+nnets+mean adm.*)	**79.0**	**74.7**

Pretraining and Regularization

Approach	Mean adm.	Sum adm.	Max adm.
None	77.8	77.9	78.3
Pretrain	78.3	78.6	**78.9**
Regularization	**79.0**	78.7	78.6
Both	78.4	**78.9**	78.8

Performance Review

- DeepCare based on human memory system:

Semantic memory

Meaning of concepts & its relations

embedding

Episodic memory

Experiences triggered by events

store, update, forget and manipulate illness experiences over time-stamped episodes

Working memory

Temporarily loading & processing infos as part of complex cognitive tasks

Thanks for your attention

Discussion

1) Imagine the legal situation when a patient gets a treatment from the algorithm and is not recovering well or gets the wrong treatment

2) Will in particular older people have trust in the prognosis of an algorithm

literatur

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