OP2.4 Machine learning and deep learning techniques to code injury data from French and/or German language narratives registered in hospital's Emergency Departments

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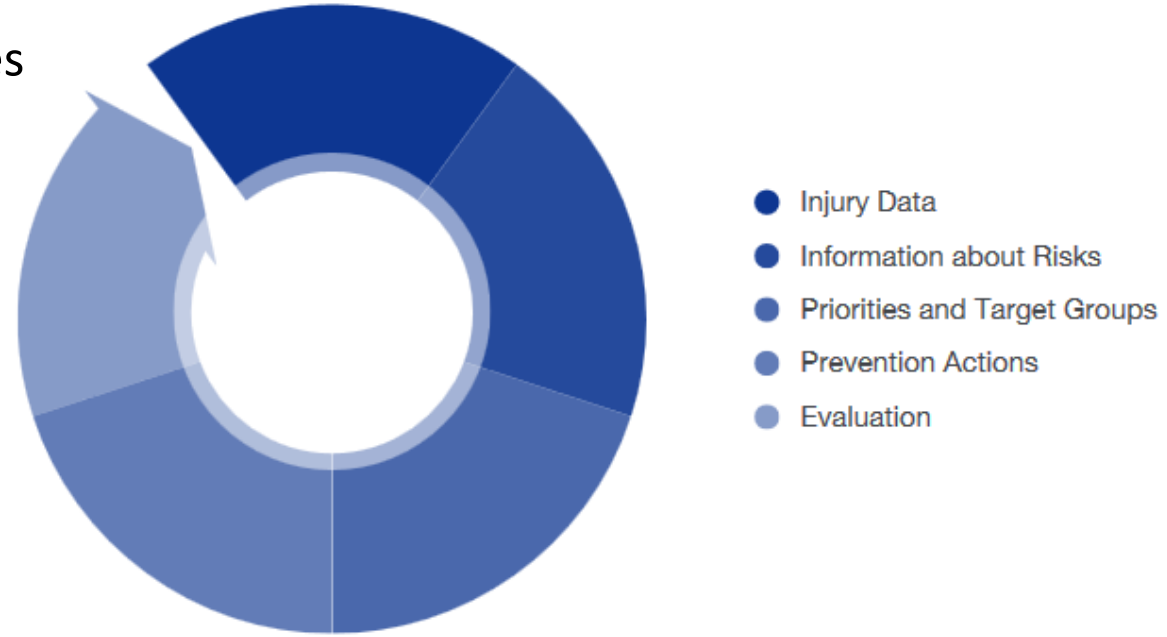
Introduction

- Information collected routinely at Hospital's Emergency Departments (HED) is important for injury prevention
  - 1 out of 10 inhabitants will visit emergency services



- **Coding/Analyzing** textual injury data of a large number of cases is a **burden** for **sustainable** injury **surveillance**

Goal

- Use Artificial Intelligence techniques to code textual injury data in German and/or French collected in HED

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Methods

MDS

Data set

- ~ 390 000 manually coded cases (2013-2017)
- Split 70% training / 30% testing

Algorithm

- Gradient boosted trees

FDS

Data set

- ~ 80 0000 manually coded cases (2013-2018)
- 2013-2017 learning / 2018 testing

Algorithm

- Recurrent neural network of type Long Short-Term Memory (LSTM)

Set up

- One model per variable (trained independently)

Evaluation

- f1-score

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F1-score

		Machine learning		Recall (Sensitivity)
		1	0	
Manual Data Coding (Golden standard)	1	True positive (TP)	False negative (FN)	$\frac{TP}{TP + FN}$
	0	False positive (FP)	True negative (TN)	
Precision (Positive predictive value)		$\frac{TP}{TP + FP}$		

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recal}$$

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Results

MDS

Variable	F1-score
Intent	78.66 %
Activity	69.81 %
Mechanism	74.29 %
Location	74.29 %
Body part injury 1	82.10 %
Nature of injury 1	79.86 %

FDS

Variable	F1-score	Variable	F1-score
Intent	96.96 %	Triggering object	49.69 %
Activity	60.02 %	Direct object	74.13 %
Mechanism	50.55 %	Intermediate objects	90.48 %
Location	54.67 %	Relation victim/per.	67.62 %
Body part injury 1	60.49 %	Age of perpetrator	51.85 %
Nature of injury 1	82.38 %	Proximal risk factor	46.59 %
Body part injury 2	78.72 %	Mode of transport	55.20 %
Transport injury event	97.94 %	Counterpart	53.56 %

The remaining FDS variables are not shown because there were too few cases for which these variables were applicable.

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Prediction vs Golden Standard (1)

Score F1 pour : Accident de circulat...

97.95%

Rappel des modalités

Code	Valeur
1	Oui
2	Non
9	Inconnu

Matrice réel (en ligne) vs prédit (en colonne)

Modalite_Reelle	1	2	Total
1	1186	164	**1350**
2	151	18837	**18988**
9	2	103	**105**
Total	**1339**	**19104**	**20443**

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Prediction vs Golden Standard (2)

Score F1 pour : Mécanisme

50.54%

Rappel des modalités

Code	Valeur
1.51	Chute provoquée par un trébuchement (au même niveau)
1.52	Chute provoquée par un glissement (au même niveau)
1.53	Chute, trébuchement, saut, poussée au même niveau : autre
1.54	Chute, trébuchement, saut, poussée d'une hauteur inférieure à 1 mètre
1.55	Chute, trébuchement, saut, poussée d'une hauteur égale ou supérieure à 1 mètre
1.56	Chute, trébuchement, saut, poussée d'une

Matrice réel (en ligne) vs prédit (en colonne)

Modalite_Reelle	1.32	1.38	1.39	1.41	1.42	1.52	1.53	1.54	1.55	1.56	1.57	1.58	1.59	1.68	1.99	2.11	2.1
1.41	1	2		353	31		8	5	1				2		11	2	
1.42				2											1		
1.48				26											2	1	
1.49				11	3										1		
1.51						15	101	12	2	1	3		3		1		
1.52			1			249	112	24	5	1	3		3	1	2		
1.53				2		52	1998	88	30		6	7	430	1	13		
1.54				1		20	312	370	172	1	2	2	33		1		
1.55						10	113	144	346	16	4	1	12				
1.56						7	244	76	51		4	1	61		4		
1.57					1	33	23	12	18	1	679	46			1		
1.58						10	125	39	23		3		26		2		
1.59		1				19	982	322	99	9	3	6	378	69	5	4	
1.68				1				1							1		
1.69																	
Total	**47**	**18**	**2**	**518**	**48**	**464**	**4518**	**1241**	**799**	**35**	**736**	**107**	**1106**	**84**	**1836**	**169**	**12**

Discussion

MDS

- Performance was worst for activity
  - Coding by deduction (Sport? No → Work? No → Other)
- No second lesion

FDS

- Module variables performed rather poorly
  - Fewer example to learn from

Overall

- No specific handling of language needed
- Not enough information in some report (missing data)
- Difference in data content and quality between hospitals
  - Different models for each hospital?

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Conclusion

- Automatic coding of injury narratives is promising
  - German and/or French injury narratives
  - Using only one classification model for both languages
- AI could be used to improve data quality
  - Double data entry (human and AI)

Future work

- Review features to improve performance
- Automatically coded typical and frequent ED injury cases (reducing manual data entry)
  - In 2018 and 2019, some cases were automatically encoded already (with a manual validation of a random sample)
  - For CHEM: about 15% of cases

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Thank you for your attention

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