IDENTIFICATION OF RADAR EMITTER TYPE WITH RECURRENT NEURAL NETWORKS

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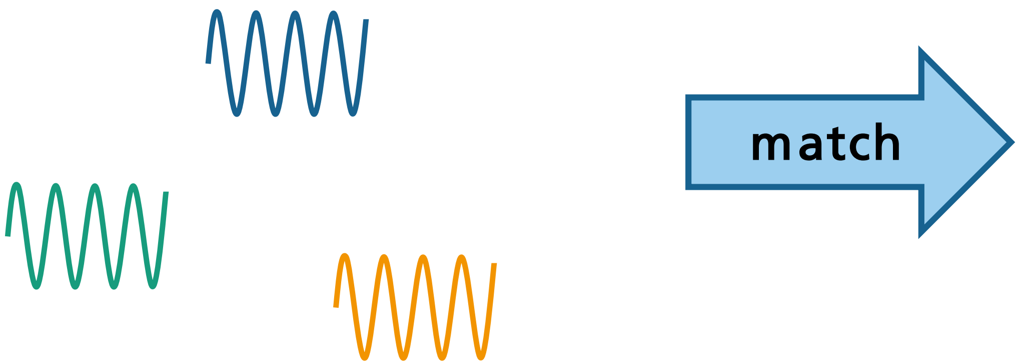
Introduction

Traditional emitter identification uses database

Intercepted signals

Database



Emitter	Mode	PRI [µs] min	PRI [µs] max	PRI [µs] mod	RF [GHz] min	RF [GHz] max	RF [GHz] mod	PW [µs] min	PW [µs] max	PW [µs] mod
Em01	M01	740	760	stable	10	11	stepped	7	8	stable
	M02	400	460	jittered	9.5	9.8	stable	4	5	jittered
Em02	M01	855	905	stable	4.5	5	stable	8	9	stable
	M02	200	700	stagger	4.5	5.5	stable	2	7	stagger
	M03	300	900	sine	4.5	5	stable	3	9	sine
Em03	M01	880	920	stable	4.7	5.3	stable	8	9	stable
	M02	900	1800	sawtooth	4	5	stable	9	18	sawtooth

Em03 M02 900 1800 sawtooth 4 5 stable 9 18 sawtooth
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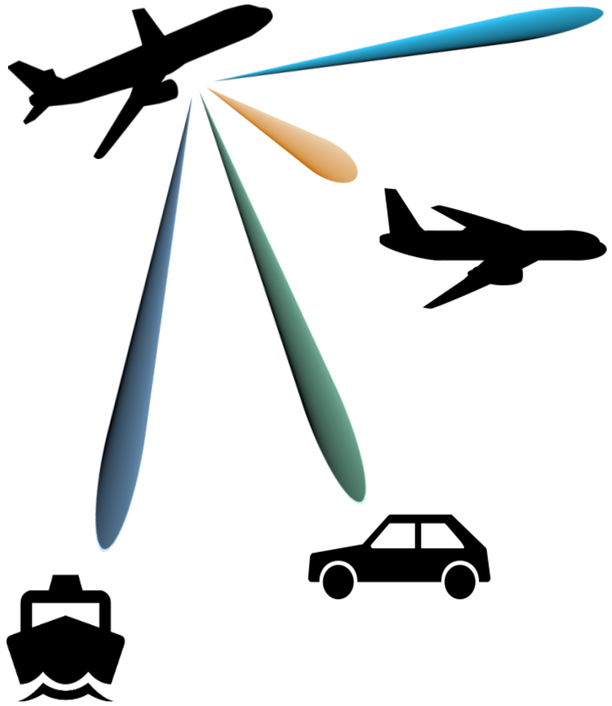
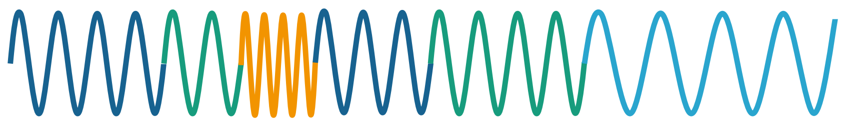
Introduction
Agile emitters require new methods

Multifunction Radars
- Perform several tasks in parallel
- Choose waveform parameters adaptively



Challenges
- No operational modes any more
- Fast switching between tasks
- Traditional database representation not suited

Needed
- New signal representation / modelling
- New methods for identification



Approach

REPRESENTATION & IDENTIFICATION

Approach

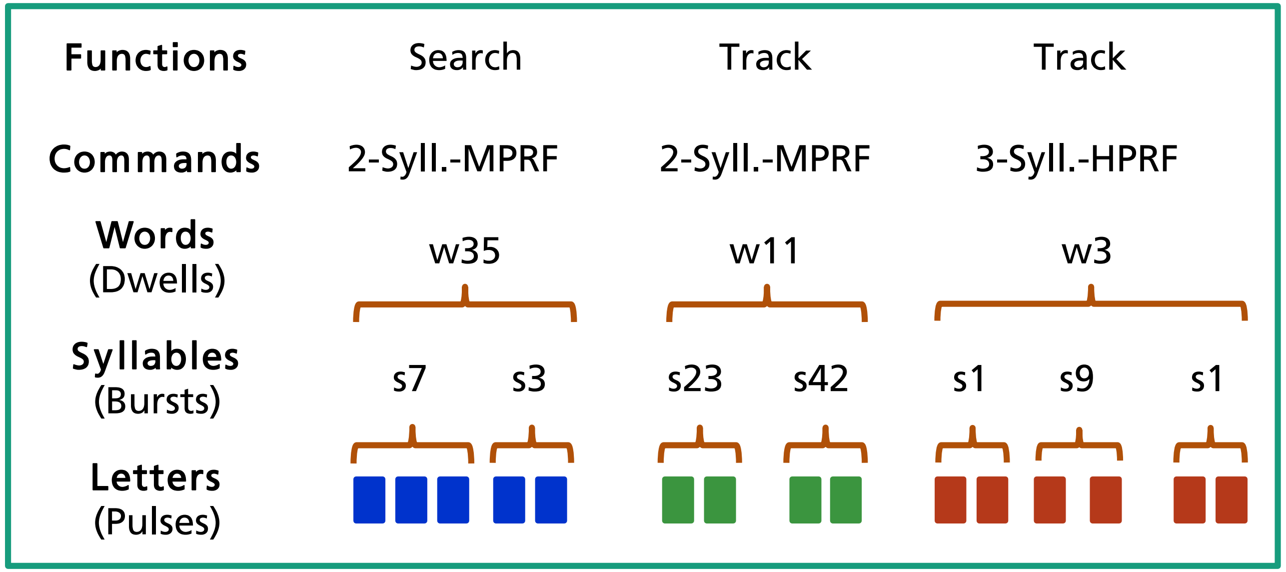
Radar as a system that speaks a language

MPRF = Medium Pulse Repetition Frequency

HPRF = High Pulse Repetition Frequency

Hierarchical Modelling

- Modelling of the radar as a system that speaks a language
- Grammar defines the structural rules of the emissions



N. A. Visnevski, V. Krishnamurthy, A. Wang, and S. Haykin, “Syntactic modeling and signal processing of multifunction radars: A stochastic context-free grammar approach,” Proceedings of the IEEE, 2007.

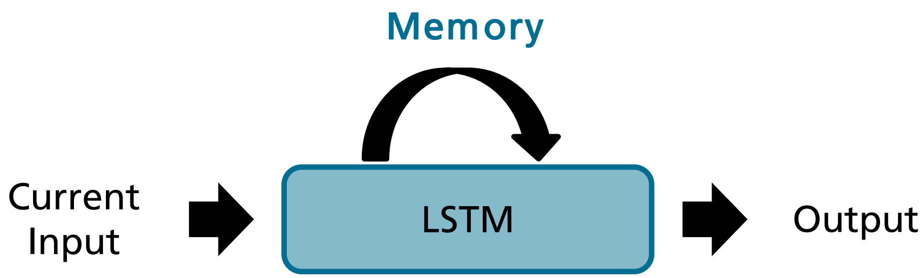
S. Apfeld, A. Charlish, and G. Ascheid, “Modelling, Learning and Prediction of Complex Radar Emitter Behaviour,” *IEEE International Conference on Machine Learning and Applications (ICMLA),* 2019.

Approach

Long Short-Term Memory

Long Short-Term Memory (LSTM)

- Variant of a recurrent neural network
- Keeps information about past input in its internal state (“memory”)
- Output depends on current and past inputs
- Allows for the analysis of long-term dependencies



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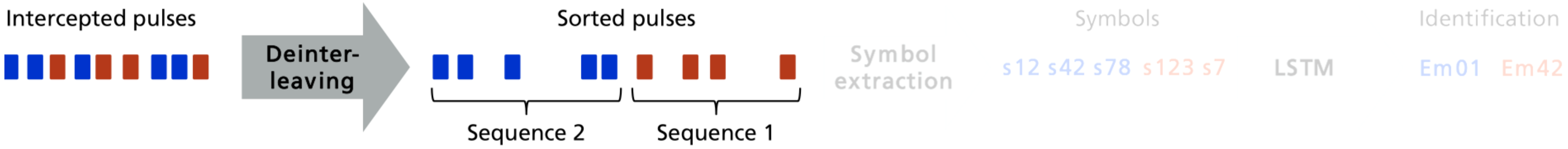
Identification of Emitter Type

Processing chain

Processing steps

1. Deinterleaving: Pulses are sorted by common properties (and hopefully by emitter)



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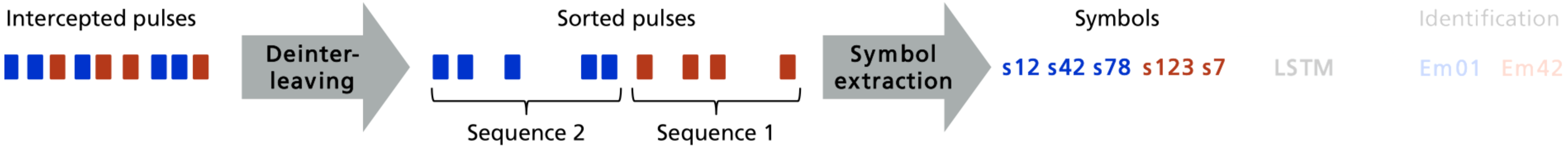
Identification of Emitter Type

Processing chain

Processing steps

1. Deinterleaving: Pulses are sorted by common properties (and hopefully by emitter)
2. Symbol extraction: Pulses are translated to symbols



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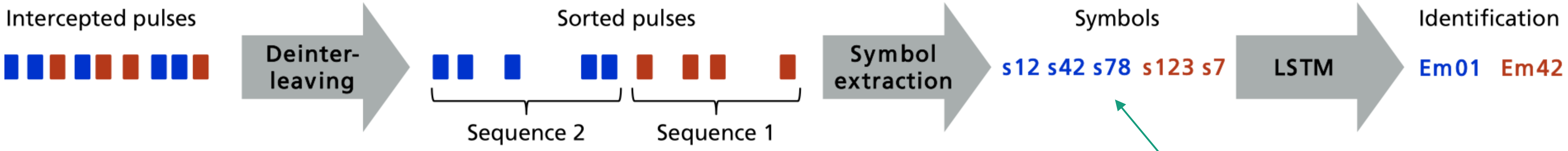
Identification of Emitter Type

Processing chain

Processing steps

1. Deinterleaving: Pulses are sorted by common properties (and hopefully by emitter)
2. Symbol extraction: Pulses are translated to symbols
3. **LSTM: Emitters are identified based on symbols**



Identification accuracy depends on number of consecutive symbols from the same emitter!

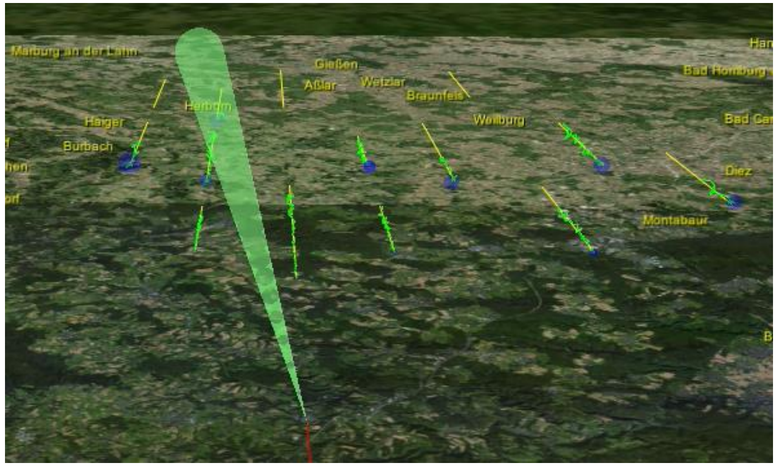
Identification of Emitter Type

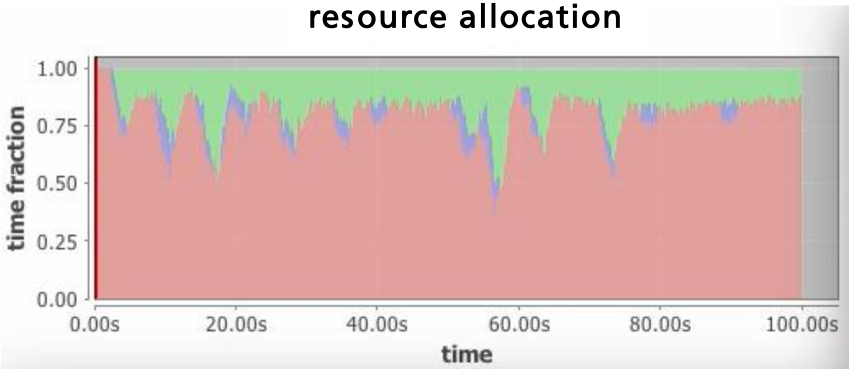
Example emitter with different resource management methods

Example Emitter

- Simulated airborne radar
- Three different resource management methods:
  - Quality of Service (QoS)
  - Simple Rules (Rules-v1)
  - Improved Rules (Rules-v2)
- Like three emitters with same language but different grammar
  - ➔ Especially hard to distinguish!

Example scenario with resource allocation





Functions: search confirm track

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Identification of Emitter Type

Example emitter with different resource management methods

Example Emitter

- Each emitter has a dictionary containing its symbols (i.e. letters, syllables, words, commands, and functions)
- Resource management methods differ in their complexity

Number of symbols used by each emitter

Method	Letter	Syllable	Word	Command	Function
QoS	18	25 380	26 653	10	3
Rules-v1	13	103	21	2	3
Rules-v2	18	27 786	34 440	10	3

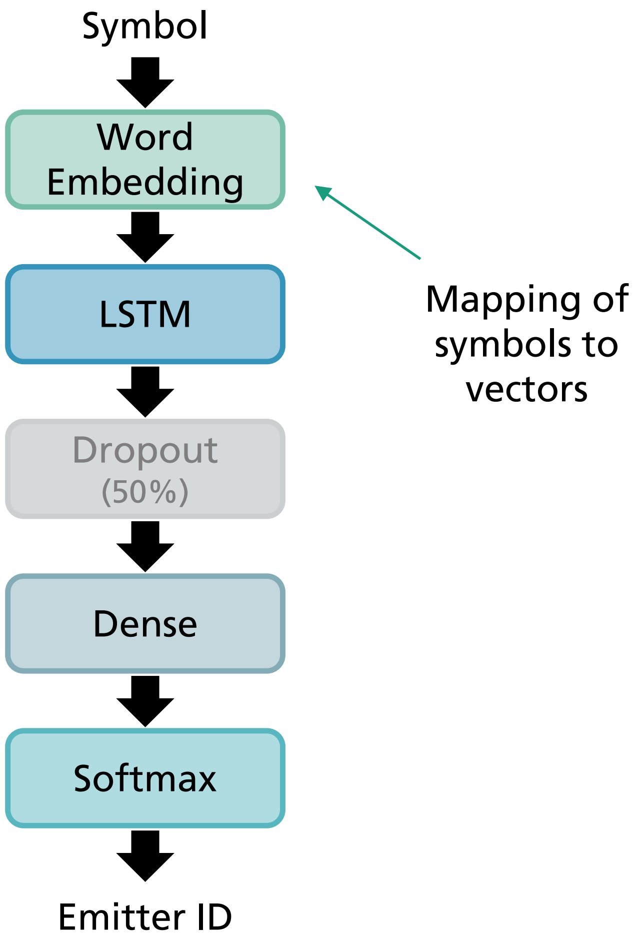
Identification of Emitter Type

LSTM training details

- LSTMs are trained with different sequence lengths (number of consecutive symbols from the same emitter)
  - LSTM_{10} Trained with a sequence length of 10 symbols
  - LSTM_{rand} Trained with random sequence lengths ∈ [1, 1400]
  - LSTM_{scen} Trained with complete scenarios

- Smallest network: one LSTM layer with 4 cells
- Largest network: one LSTM layer with 16 cells

- Batch: 120 simulation runs in parallel
- Internal state of LSTM cells kept between batches



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Identification of Emitter Type

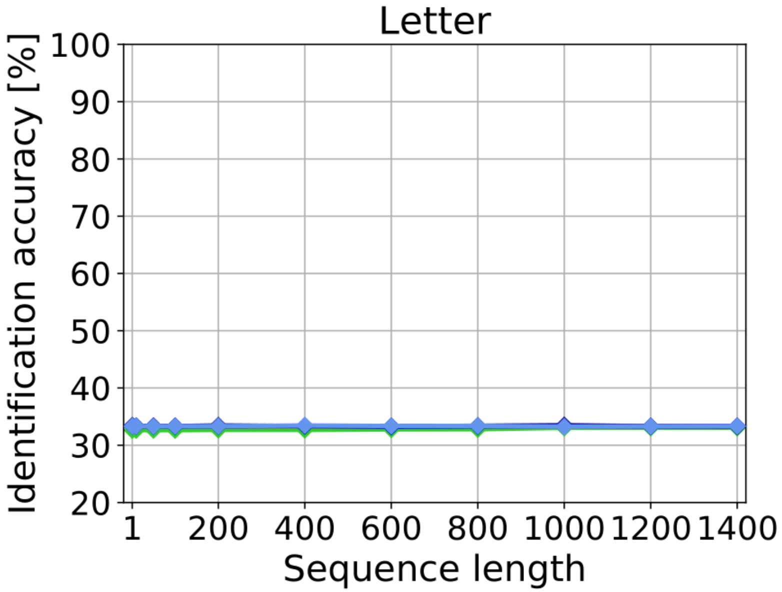
EXPERIMENTAL EVALUATION

Evaluation
Method

- Comparison of the LSTMs to
  - Random guessing
    - Uniform probability for each emitter, i.e. 33.33%
  - Dictionary lookup
    - Weight of an emitter is 1 if complete sequence is in its dictionary, 0 otherwise
    - Weights are normalised, random selection of emitter ID if equal weights
    - Resembles database lookup
- Sequence lengths: 1, 10, 50, 100, 200, 400, 600, 800, 1000, 1200, and 1400 symbols
- Scenarios:
  - Ideal data
  - Corrupted data with missing and additional symbols

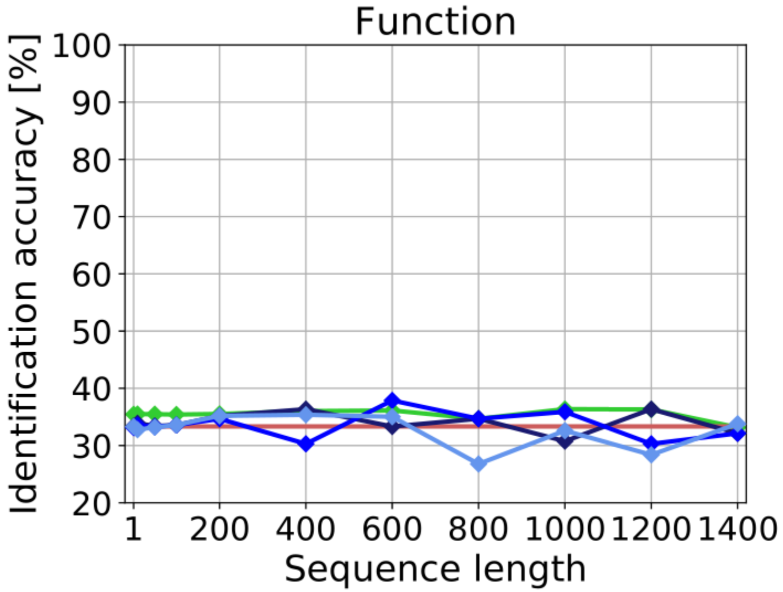
Evaluation

Results for letters & functions



Letters (Pulses) and Functions

- Emitters cannot be distinguished based on letters and functions
- LSTMs assign complete input to the same emitter



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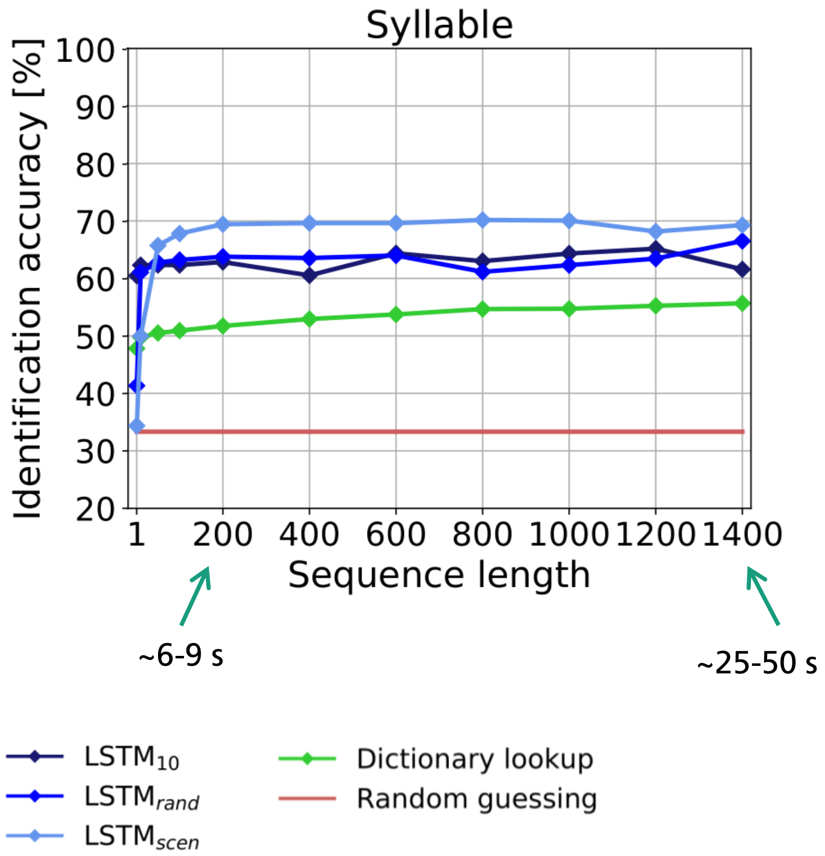
Evaluation

Results for syllables

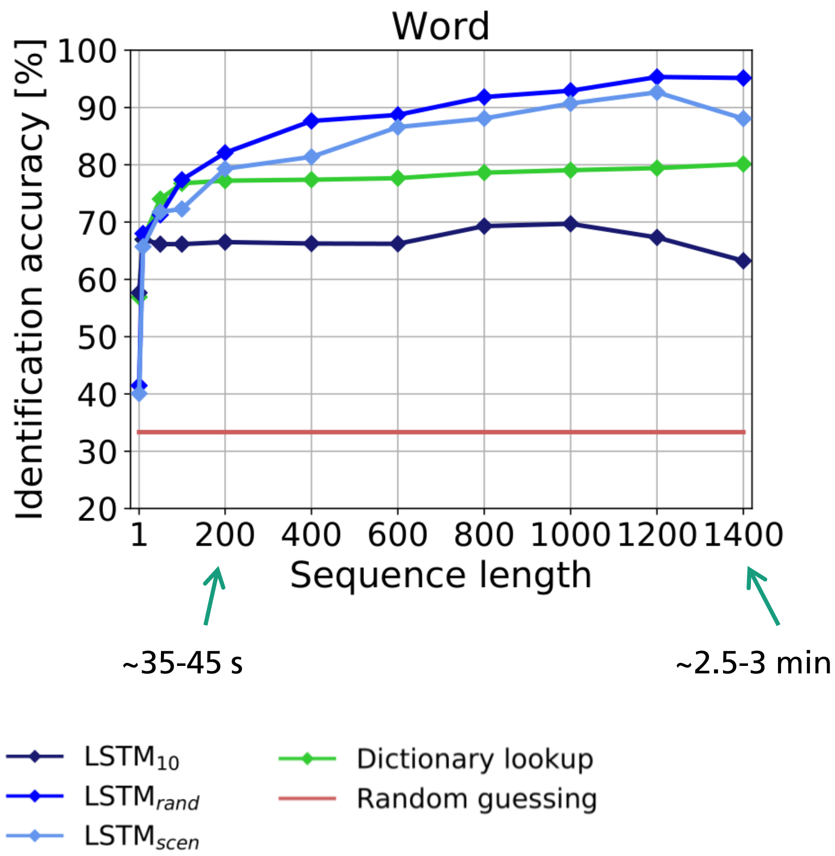


Syllables (Bursts)

- QoS radar is recognised based on its syllables
- Two rule based radars are confused
- $LSTM_{10}$ much better than the others for only one syllable

Evaluation

Results for words

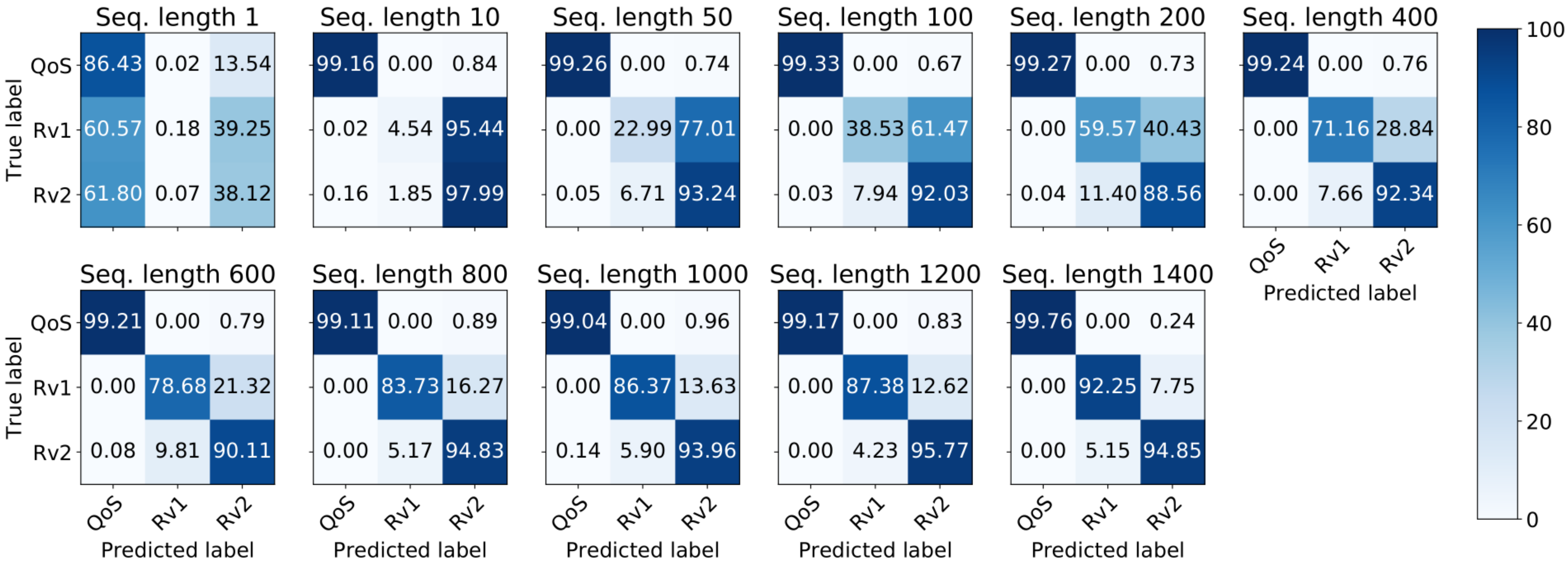


Words (Dwells)

- QoS radar is recognised based on its words
- Two rule based radars are distinguished with increasing sequence length
- LSTM_{10} much better than the others for only one word but does not improve with increasing sequence length

Evaluation

Results for words – LSTM$_{rand}$



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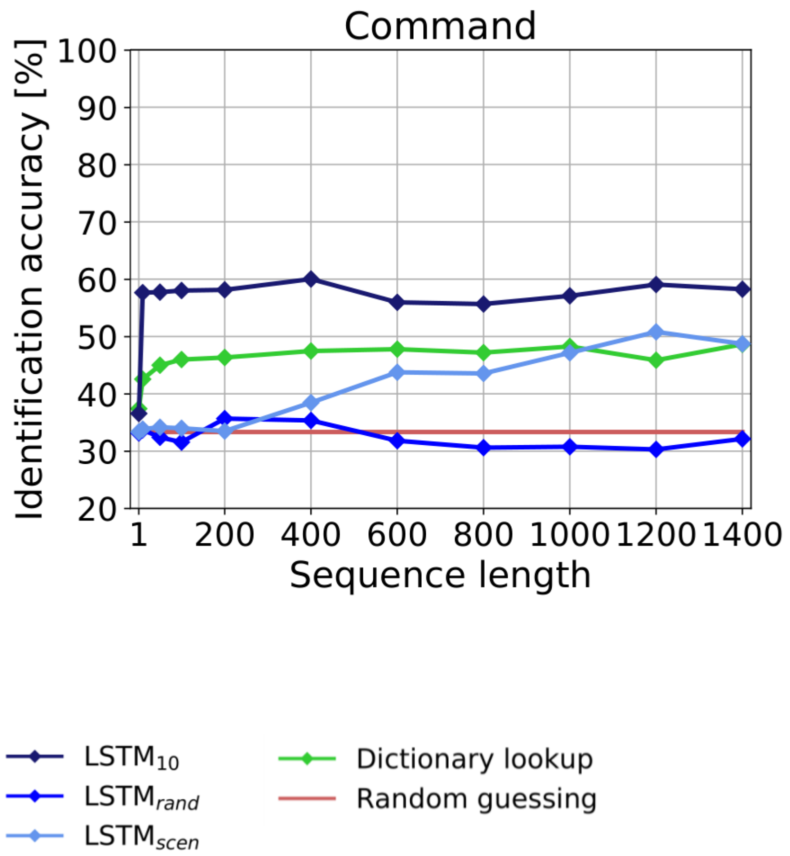
Evaluation

Results for commands



Commands

- Emitters are hard to distinguish based on the commands
- LSTM_{10} identifies the QoS radar with 77% accuracy
- LSTM_{scen} recognises the rules-v1 radar with 50% accuracy when sequences are longer, but almost never the QoS radar

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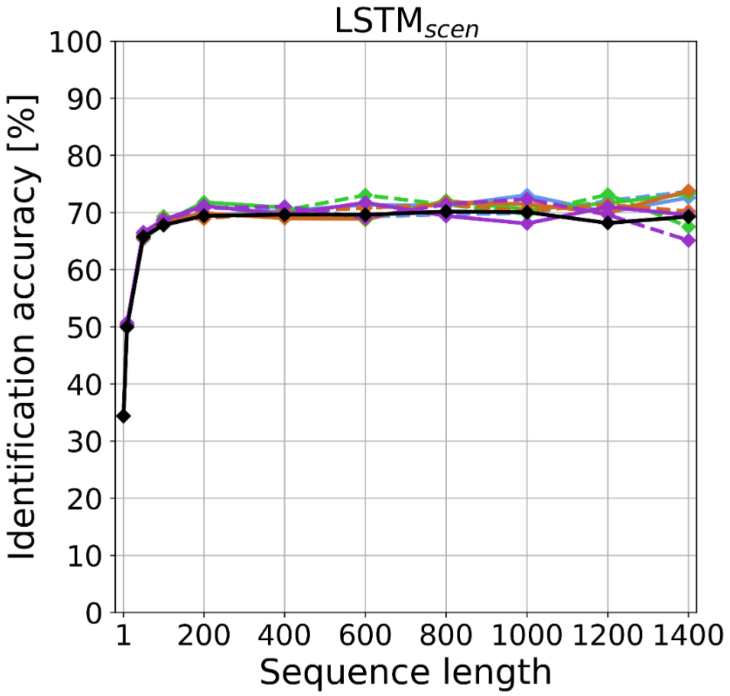
Evaluation

RESULTS WITH CORRUPTED DATA

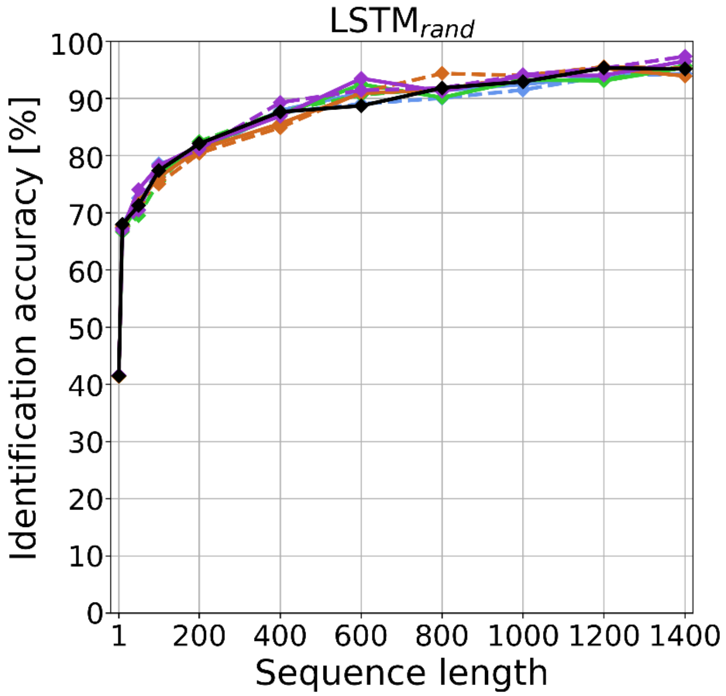
Evaluation
Missing symbols

LSTMs are very robust

Syllables



Words



Missing symbols [%]

- 0
- 1, single
- 1, blocks of five
- 5, single
- 5, blocks of five
- 10, single
- 10, blocks of five
- 20, single
- 20, blocks of five

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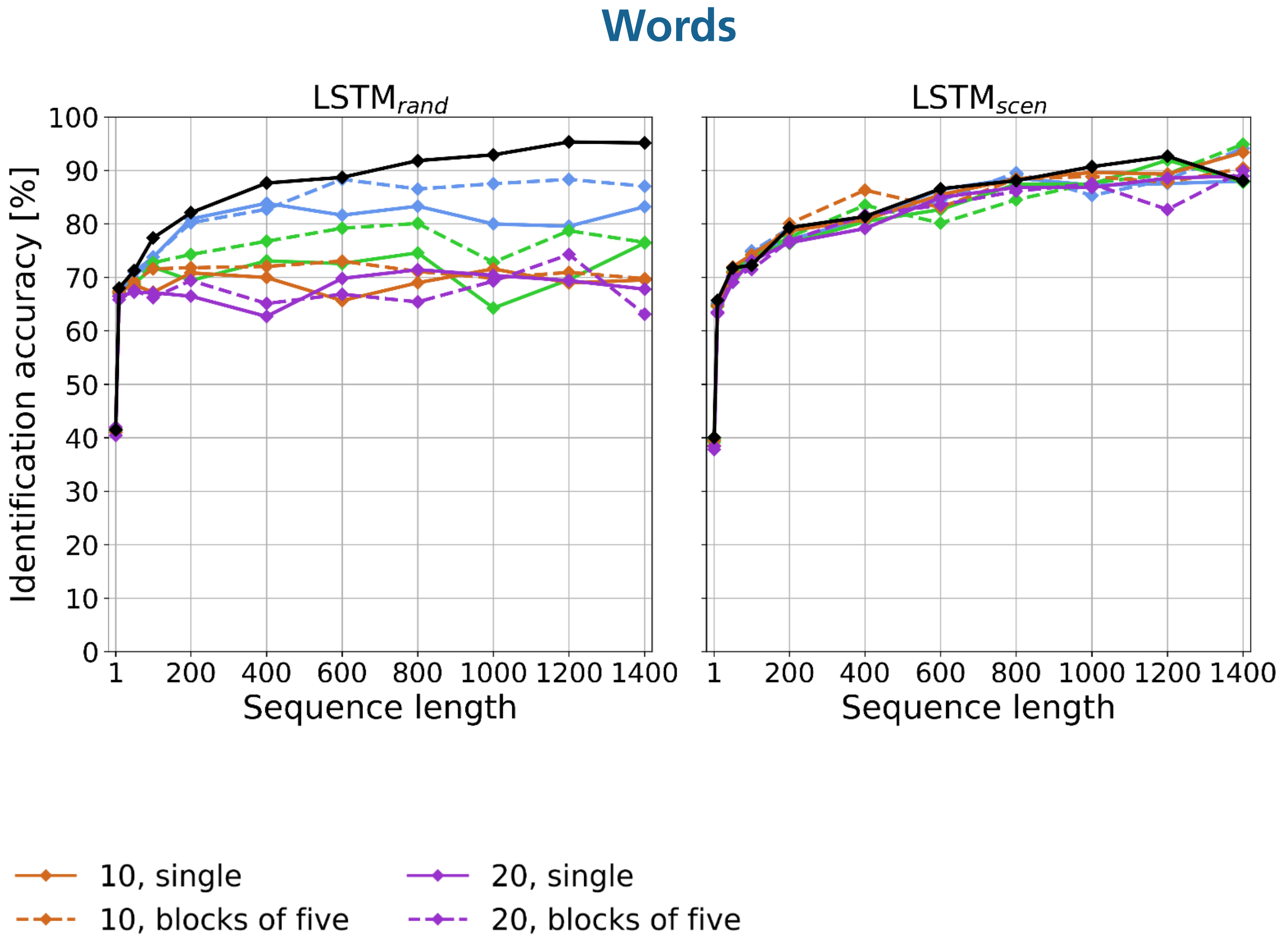
Evaluation
Additional symbols

- All LSTMs are very robust with respect to additional syllables
- $\text{LSTM}_{\text{rand}}$ does not perform as well as the others with additional words



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Summary & Conclusion

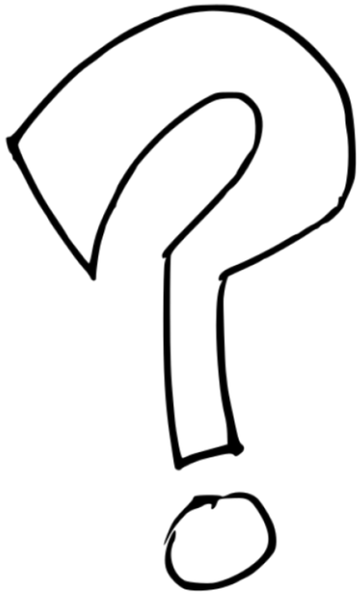
Emitter type identification with hierarchical modelling

- Example emitters mainly use the same symbols → especially hard to distinguish
- LSTMs are able to recognise the resource management method

- Identification accuracy depends on sequence length
  - More symbols needed to distinguish between very similar emitters

- Radar words (dwells) are the modelling level best suited for identification

- LSTMs are in general very robust with respect to missing and additional symbols



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