Centre for
Data Analytics

Insight

Background Knowledge Injection for Interpretable Sequence Classification

Severin Gsponer[1], Luca Costabello[2], Chan Le Van[2], Sumit Pai[2], Christophe Gueret[2], Georgiana Ifrim[1], Freddy Lecue[2]

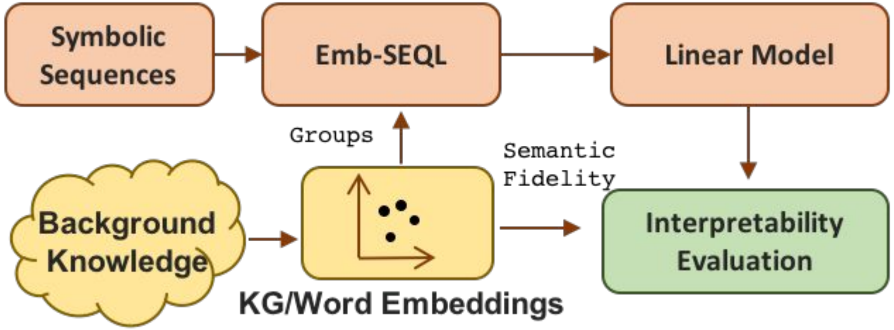
[1] Insight Centre for Data Analytics
University College Dublin

[2] Accenture Labs
Dublin

16.09.19

DCU NUI Galway OÉ Gaillimh UCC UCD Dublin SFI

Contributions



Groups:

Regex-like expansion of traditional *k*-mers

Emb-SEQL:

Injection of Background Knowledge into Sequence Learning Algorithm

Semantic Fidelity:

Metric to quantify interpretability

Symbolic Sequence Classification

Sequence	**Class**
ABBCBAABCBABCBABBBCBABBABBCB	+1
CCBBABACAABBABBAAABBBCCBBABA	-1
ACBBCACCCBAABCBABCCABCAABCCA	+1
BABACCBABCTABCBABBCAABCBBBCA	?

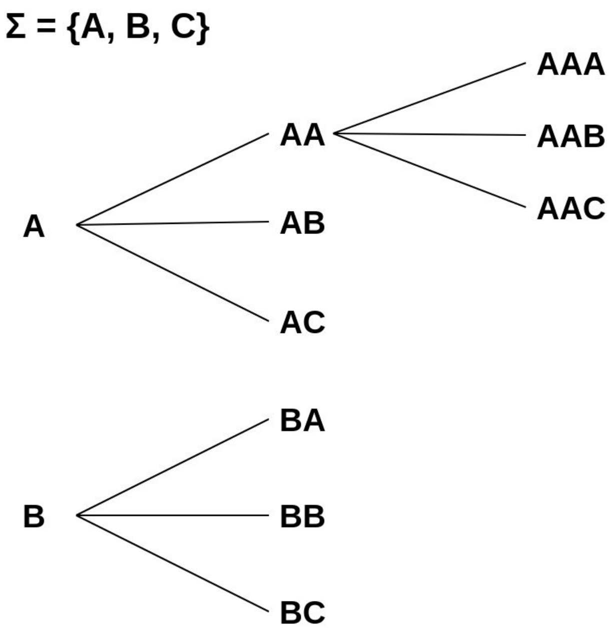
$\Sigma = \{A, B, C\}$

k-mers: Consecutive sequences *k* of symbols

2-mer: AB
5-mer: BCTCB

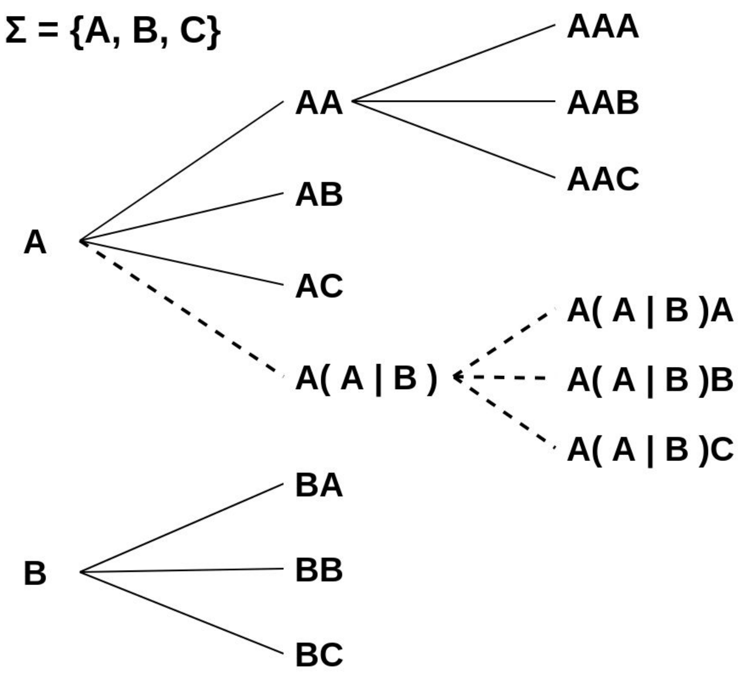
SEQL - Sequence Learner

- Integrated approach
- Learns sparse *k*-mer based linear models
- Feature space of all possible *k*-mers
- Gauss-Southwell coordinate descent
- Iteratively add best *k*-mer to model
- Exploits structure in feature space



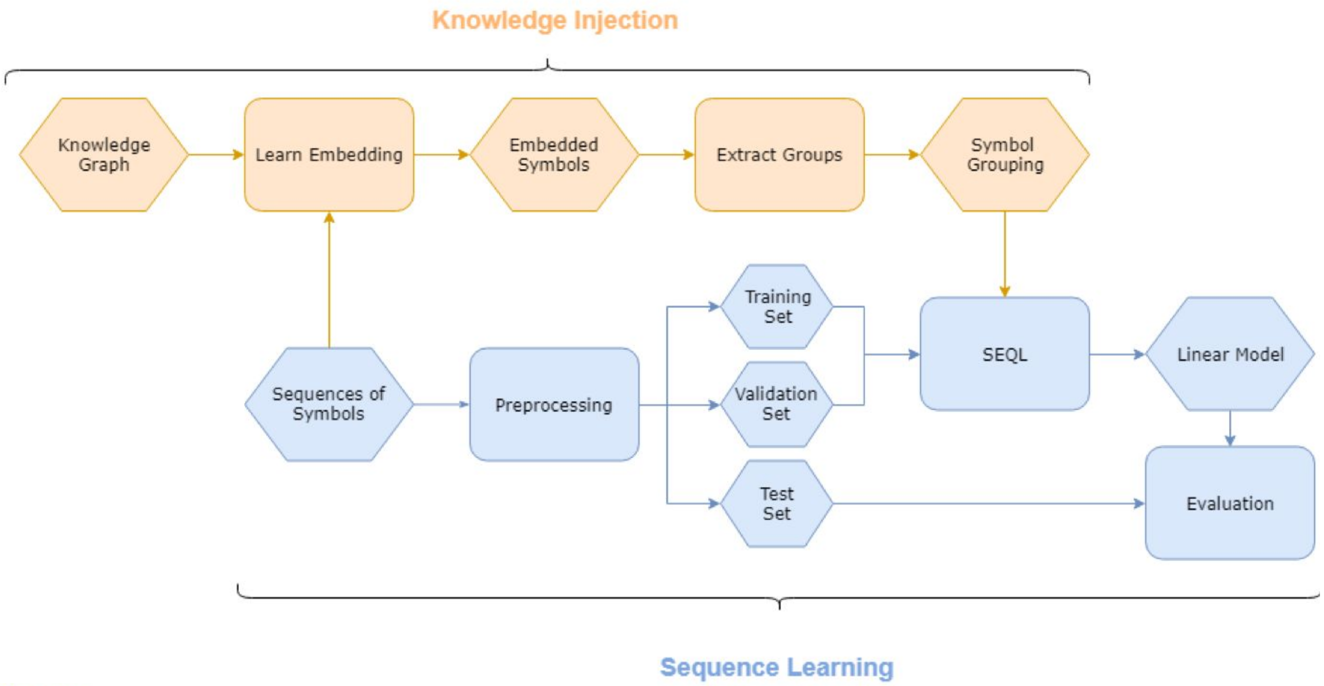
SEQL - Sequence Learner with *Groups*

- Exploit structure in symbol space
- Use *groups* to gain more flexibility
- *Groups* are built by combining basic symbols with OR
- Groups predefined by user or automatically generated



Automatic Group Generation

Emb-SEQL Pipeline



Interpretability

- Interpretability is crucial in some problems
- Accuracy-interpretability trade-off
- Measuring interpretability of models is an open question

Semantic Fidelity intuition:

- Positive features should be “close” to target class
- Negative features should be “close” to non-target class

Functional grounded protocol as proxy measurement

Semantic Fidelity

k-mer - Target Class Distance

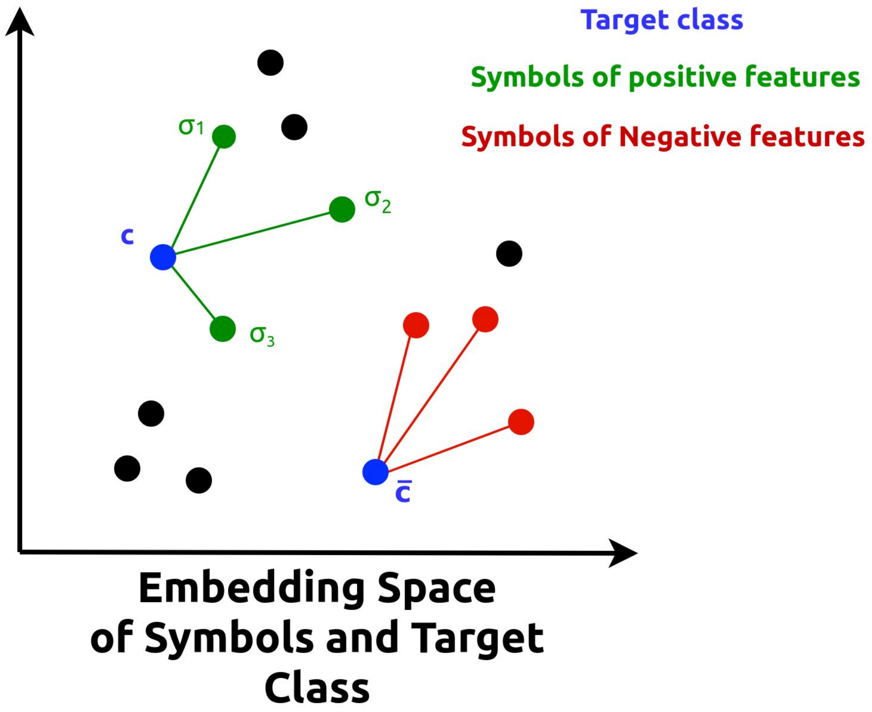
$$d_c(\phi, c) = \frac{1}{n_\phi} \sum_{\sigma_j \in \phi} \|\mathbf{E}_{\sigma_j} - \mathbf{e}_c\|$$

Weighted Target Class Distance

$$h(\phi) = |w| \begin{cases} d(\phi, c) & \text{if } w \geq 0 \\ d(\phi, \bar{c}) & \text{otherwise} \end{cases}$$

Semantic Fidelity

$$SF = 1 - \frac{1}{2n} \sum_{\phi_i \in \Phi} h(\phi_i)$$



Experiment

Opportunity - Human Composite Activity Recognition (HAR) [1]:

- Predict Composite Activity
- Multiclass classification problem
- Combinations of 5 low level features categories ($|\Sigma| > 1400$ symbols)

PhosphoELM - Protein Classification [2]:

- Binary classification problem
- Predict Kinase group
- Amino acid sequences ($|\Sigma| = 21$ symbols; 438 sequences)

Composite Activity Recognition

Predict composite activity based on sequence of low-level activity

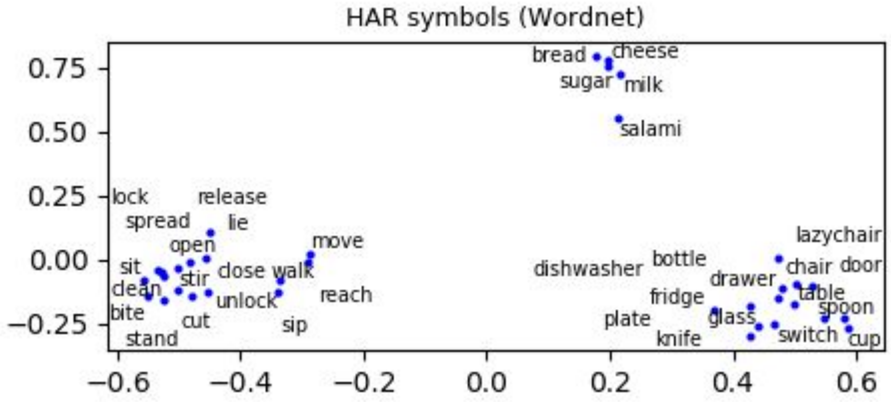
Sequence

```
<stand, open,   drawer, none, none>
<stand, none,   none,   grab, milk>
<stand, none,   none,   put,  milk>
<stand, close,  drawer, none, none>
                ...
<sit,   move,   plate,  move, cup>
```

?

Coffee time
Early morning
Cleanup
Sandwich time
Relaxing

Composite Activity Recognition



Atomic symbol embeddings

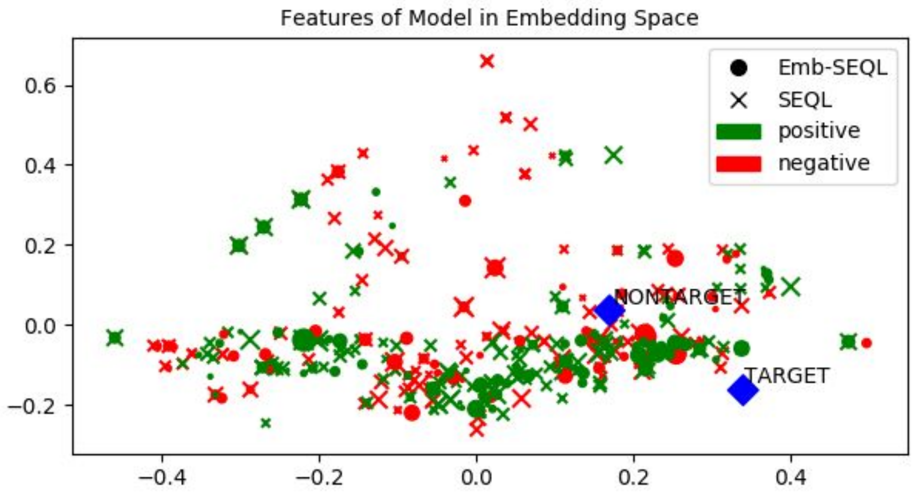
Weight	Feature
1.0	⟨ ([sit, release, cheese, move, knife cheese] OR [stand, move, plate, move, plate] OR [stand, move, plate, reach, drawer1] OR [stand, move, plate, open, drawer1] OR [stand, reach, bread, open, drawer3]) ⟩
	...
-0.867	⟨ ([stand, open, fridge, move, milk] OR [stand, none, none, release, milk] OR [walk, move, plate, none, none] OR [walk, move, plate, release, bread] OR [walk, none, none, move, plate] OR [stand, reach, sugar, reach, spoon]) , [stand, none, none, none, none] ⟩

Sandwich time model

Results - Semantic Fidelity

Dataset	Embeddings	Model	$\overline{SF}$	std	Class 1	Class 2	Class 3	Class 4	Class 5
HAR	GloVe	SEQL	0.902	0.028	0.930	0.871	0.925	0.865	0.921
		Emb-SEQL	**0.923**	0.025	0.958	0.888	0.931	0.901	0.938
	ConceptNet	SEQL	0.871	0.033	0.908	0.828	0.895	0.833	0.889
		Emb-SEQL	**0.875**	0.025	0.903	0.853	0.887	0.836	0.894
	YAGO-41	SEQL	**0.867**	0.029	0.899	0.847	0.893	0.823	0.872
		Emb-SEQL	0.835	0.043	0.897	0.824	0.861	0.767	0.827
	WordNet	SEQL	0.894	0.025	0.921	0.879	0.918	0.857	0.895
		Emb-SEQL	**0.936**	0.010	0.937	0.945	0.943	0.917	0.939
Protein	ChEBI-ChEMBL	SEQL	0.708	-					
		Emb-SEQL	**0.719**	-					

PCA Visualization



Target: Coffee time
Embedding: WordNet

Results - Classification Quality

Dataset	Model	Embeddings	F1	Accuracy
HAR	SVM		0.502	0.564
	LSTM		0.767	0.810
	SEQL		**0.973**	**0.961**
	Emb-SEQL	ConceptNet	0.965	0.951
		GloVe	0.961	0.945
		WordNet	0.968	0.955
		YAGO-41	0.957	0.941
Protein	SCIS_MA		-	**0.948**
	HMM		-	0.918
	LSTM		0.797	0.796
	SEQL		**0.902**	0.903
	Emb-SEQL	ChEBI-ChEMBL	0.898	0.901

SCIS_MA and HMM results from [2]

Achievements & Conclusion

- Introduction of ***Groups***, regex like k-mer symbols
- Generation of *Groups* from background knowledge sources
- **Emb-SEQL**, a method to learn sparse linear models
- **Semantic Fidelity** a way to measure interpretability

- Background knowledge injection improves interpretability measured by Semantic Fidelity without hurting accuracy of learned model

Limitations & Future Work

- High memory demand of Emb-SEQL for large *Groups*
- Clustering method and *Group* size is crucial
- Background knowledge source is needed

- Semantic Fidelity for non-linear models
- Human-based evaluation of Semantic Fidelity

Thank you!

Please email severin.gsponer@insight-centre.org if you have further questions

This work was funded by Science
Foundation Ireland (SFI) under Insight Centre for Data Analytics (grant 12/RC/2289)

References

[1] D. Roggen, A. Calatroni, M. Rossi, T. Holleczek, K. Förster, G. Tröster, P. Lukowicz, D. Bannach, G. Pirkl, A. Ferscha, J. Doppler, C. Holzmann, M. Kurz, G. Holl,R. Chavarriaga, H. Sagha, H. Bayati, M. Creatura, and J. d. R. Millàn. Collecting complex activity datasets in highly rich networked sensor environments. In 7th International Conference on Networked Sensing Systems (INSS)

[2] C. Zhou, B. Cule, and B. Goethals. Pattern based sequence classification. IEEE Transactions on Knowledge and Data Engineering, 28(5):1285–1298, 2016.