

Word-level interpretable scoring mechanism for novel text using Tsetlin Machine

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Novelty Detection Example

Trained topics: Baseball and Football events

Users Queries: Rugby events (New topic)

Example:

Intent – Who won the rugby match yesterday?

Answer- (can be anything)

Trained topics: Account and Card queries

Users Queries: Loan (New topic)

Example:

Intent – I have an account in this bank, How can I get a loan?

Answer- (can be anything)

Novelty Detection

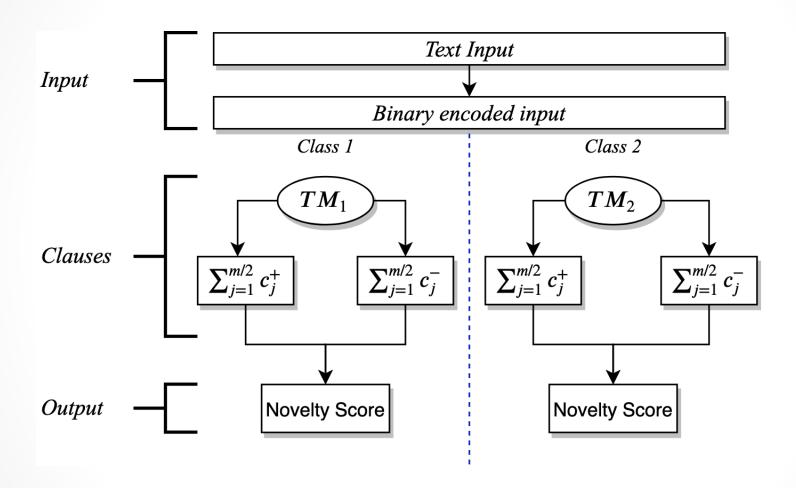
Example:

```
Intent – Who won the rugby match yesterday? 
TM Model- IF {(won) and (rugby) and (match) and (yesterday)} then New topic Novelty Score- Very low
```

Example:

```
Intent – I have an account in this bank, How can I get a loan? 
TM Model- IF {(account) and (bank) and (get) and (loan)} then New topic Novelty Score- Very low
```

TM Framework



Results

Algorithms	20 Newsgroup	Spooky action author	CMU movie	BBC sports	WOS
LOF	52.51 %	50.66 %	48.84 %	47.97 %	55.61 %
Feature Bagging	67.60 %	62.70 %	64.73 %	54.38 %	69.64 %
HBOS	55.03 %	48.55 %	48.57 %	49.53 %	55.09 %
Isolation Forest	52.01 %	48.66%	49.10 %	49.35%	54.70 %
Average KNN	76.35 %	57.76 %	56.21 %	55.54 %	79.22 %
K-Means clustering	81.00 %	61.30 %	49.20 %	47.70 %	41.31 %
One-class SVM	83.70 %	43.56 %	51.94 %	83.53 %	36.32 %
TM framework	82.50 %	63.15%	68.15 %	89.47 %	70.37 %

Table 3: Performance comparison of proposed TM framework with cluster and outlier based novelty detection algorithms.

New Problem Statement

Problems:

- Detecting Novel text is a challenging task, which we have addressed using Tsetlin Machines.
- Understanding what part of sentence is novel.

७ Goal:

Rank each word in a sentence for novelty.

Example: Novelty Description

Sentence: The apple that he ate yesterday was good.

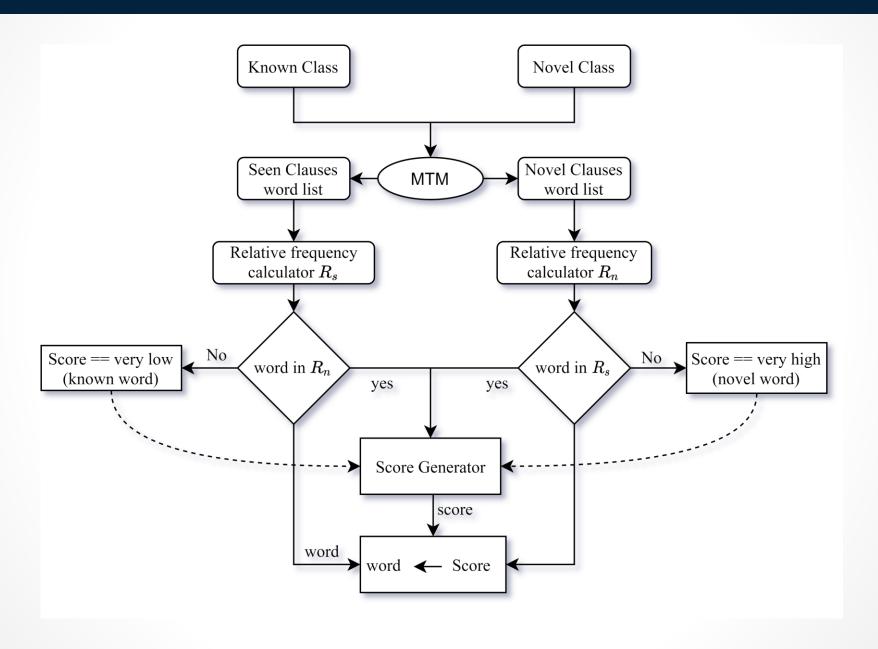
Category- Known

Sentence : The apple shares decreased over this week.

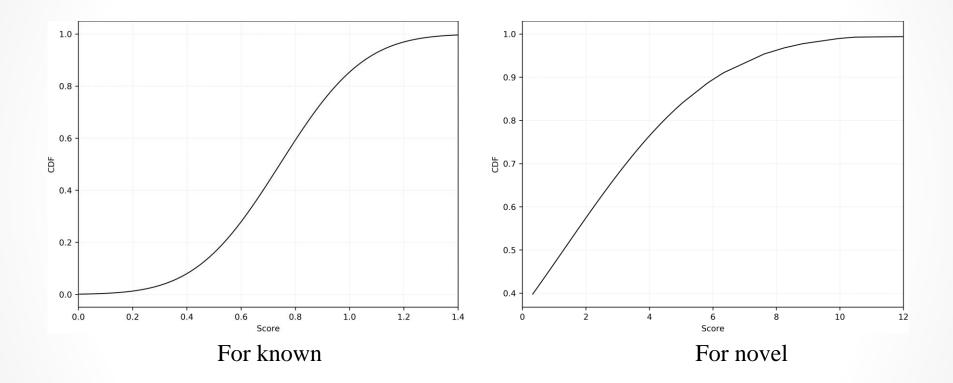
Category- Novel

■ Different scores for "apple": low for "apple" fruit, high for "apple" company/phone

Mechanism



Result



Context Correlations

Rugby Centre Scrumhalf Flanker Flyhalf

Rugby Centre Scrumhalf Flanker Flyhalf

	Rugby	Centre	oci ummai.	1 I I I I I I I I I I I I I I I I I I I	1 1 y 11 a 11
ſ	88.80	2.60	2.80	2.63	2.59
ſ	2.60	278.73	3.54	3.66	6.23
ſ	2.80	3.54	1718.11	4.05	2.96
ſ	2.63	3.66	4.05	1558.95	3.55
Ī	2.59	6.23	2.96	3.55	960.91

Confusion Matrix showing the correlation score

References

- [1] M. L. Tsetlin, "On behaviour of finite automata in random medium," *Avtomat. i Telemekh*, vol. 22, no. 10, pp. 1345, 1961.
- [2] O.-C. Granmo, "The Tsetlin Machine A Game Theoretic Bandit Driven Approach to Optimal Pattern Recognition with Propositional Logic," Apr. 2018.
- [3] O. C. Granmo and B. J. Oommen, "Solving stochastic nonlinear resource allocation problems using a hierarchy of twofold resource allocation automata," *IEEE Trans. Comput.*, vol. 59, no. 4, pp. 545–560, 2010.
- [4] K. D. Abeyrathna, O.-C. Granmo, L. Jiao, and M. Goodwin, "The Regression Tsetlin Machine: A Tsetlin Machine for Continuous Output Problems," May 2019.
- [5] G. T. Berge, O.-C. Granmo, T. O. Tveit, M. Goodwin, L. Jiao, and B. V. Matheussen, "Using the Tsetlin Machine to Learn Human-Interpretable Rules for High-Accuracy Text Categorization with Medical Applications," Sep. 2018.
- [6] Z. Yan *et al.*, "DocChat: An information retrieval approach for chatbot engines using unstructured documents," in *54th Annual Meeting of the Association for Computational Linguistics*, *ACL 2016 Long Papers*, 2016, vol. 1, pp. 516–525.
- [7] A. Ritter, C. Cherry, and W. B. Dolan, "Data-Driven Response Generation in Social Media."
- [8] A. Kannan et al., "Smart Reply: Automated Response Suggestion for Email."



Thank you!