

Nestor: A Tool for Natural Language Annotation of Short Texts

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1. Summary

Nestor is a software tool that annotates natural language CSV (comma-separated variable) files, with a UTF-8 (Unicode Transformation Format – 8-bit) encoding, using a process called tagging [1]. The objective of Nestor is to help analysts make their natural language data, which is often unstructured, filled with technical content, jargon, misspellings, and abbreviations, computable to improve analysis. An example of natural language data that could be input to Nestor and the subsequent output data and the corresponding output is shown in Table 1.

The annotated datasets generated by Nestor (as either a CSV or .h5 file) can be used for different analysis techniques, such as failure prediction, problem hot spot identification, and maintenance technician expertise assessment, as shown in [2–10]. Currently, the majority of use cases involve maintenance in the engineering domain (manufacturing, mining, heating ventilation and air conditioning (HVAC)), however, any natural language CSV file with UTF-8 encoding can be input to Nestor.

Table 1. An example of natural language input (**Raw Text** column in this example) and subsequent output (**Item(s)**, **Problem(s)**, **Solution(s)**, **Problem(s) & Item(s)**, **Solution(s) & Item(s)** columns in this example) for Nestor. These input files often also contain other non-text based data points that can be used for other analysis, but are not directly used by Nestor.

Raw Text	Item(s)	Problem(s)	Solution(s)	Problem(s) & Item(s)	Solution(s) & Item(s)
<i>Hyd leak at saw attachment. Replaced seal in saw attachment but still leaking - Reapirs pending with ML</i>	Hydraulic; Saw attachment; Seal	Leak	Replaced; Repaired	Hydraulic Leak	Replaced Seal
<i>HP Coolant pressure at 75 psi; Bad gauge/Low pressure lines cleaned ou</i>	High Pressure Coolant; Gauge; Low Pressure Line	Broken; Low Pressure	Cleaned	Broken Gauge	Cleaned Low Pressure Line
<i>Major hydraulic leak at SP#6 horseshoe. Repaired horseshoe seals.</i>	Hydraulic; SP#6; Horseshoe Seal	Leak	Repaired	Hydraulic Leak	Repaired Horseshoe Seal
<i>Clamping spool guard broken, replaced - operator could have done this!</i>	Clamping Spool Guard; Operator	Broken	Replaced	Clamping Spool Guard Broken	N/A

2. Software Specifications

NIST Operating Unit	Engineering Laboratory, Systems Integration Division, Informational Modeling and Testing Group
Category	Analysis Graphical User Interface (GUI).
Targeted Users	Manufacturers, Maintainers, Maintenance Technicians, Analysts
Operating Systems	Windows: Windows 10 or greater; Mac: OSX v10.1 or greater; Linux: Linux 5.0 x86_64 or greater
Programming Language	Executable: None; Source: Python v3.6 or greater See https://github.com/usnistgov/nestor/tree/master/requirements
Inputs/Outputs	Input: UTF-8 encoded .csv file. Output(s): Annotated .csv file, .h5 file dashboard.
Documentation	User's Guide - https://nestor.readthedocs.io/en/latest/index.html Source Code: https://github.com/usnistgov/nestor
Disclaimer	https://www.nist.gov/disclaimer

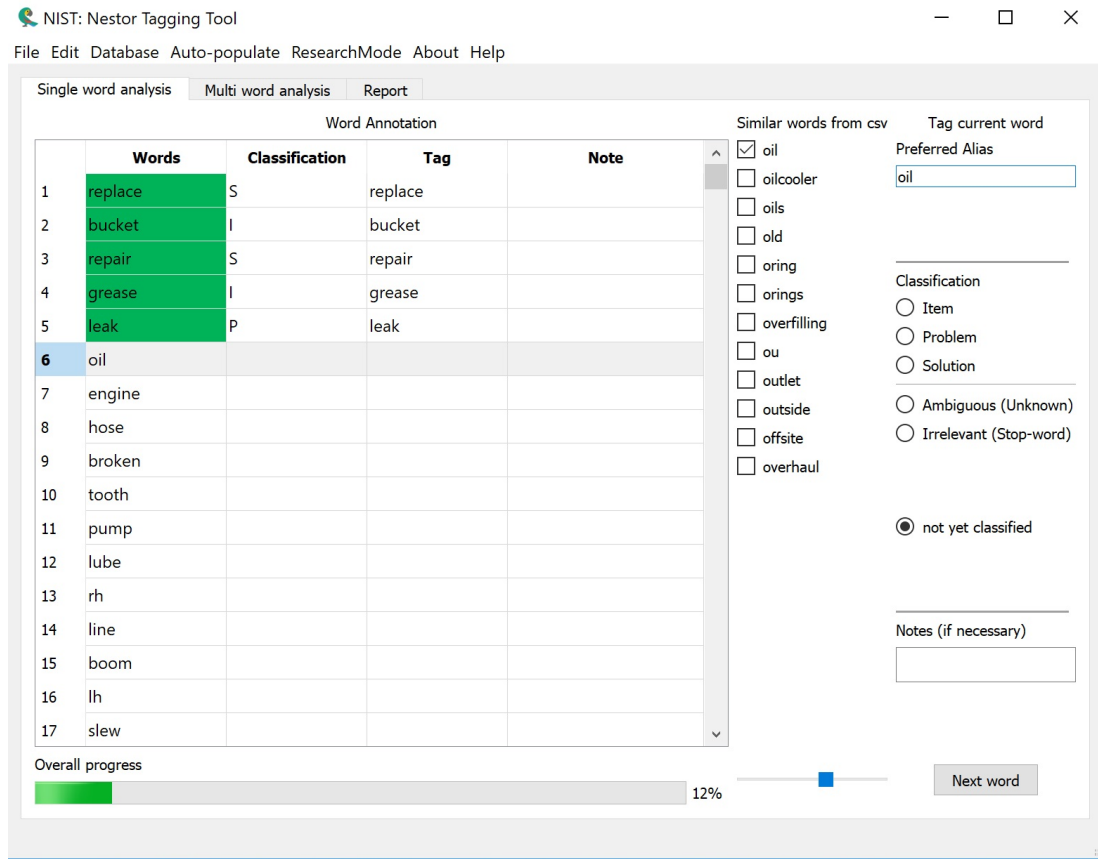


Fig. 1. A screenshot of the Nestor GUI.

3. Methods

This software provides a Graphical User Interface (GUI) (both as a standalone application¹ and the source code²) as seen in Fig. 1.

The software takes natural language inputs in the form of UTF-8 encoded CSV files and allows a user to select the columns containing natural language text. After columns in the CSV files are selected, the software will rank the concepts according to their frequency occurring in the data and allow the user to select similar concepts, create an alias, and provide a classification. Once the user completes this process, the software tool will automatically annotate the dataset and provide an annotated CSV and .h5 file as shown in Fig. 2. These files can then be used for various analysis techniques, such as problem identification, failure prediction, and technician skill assessment [2–7].

¹<https://www.nist.gov/services-resources/software/nestor>

²<https://github.com/usnistgov/nestor>

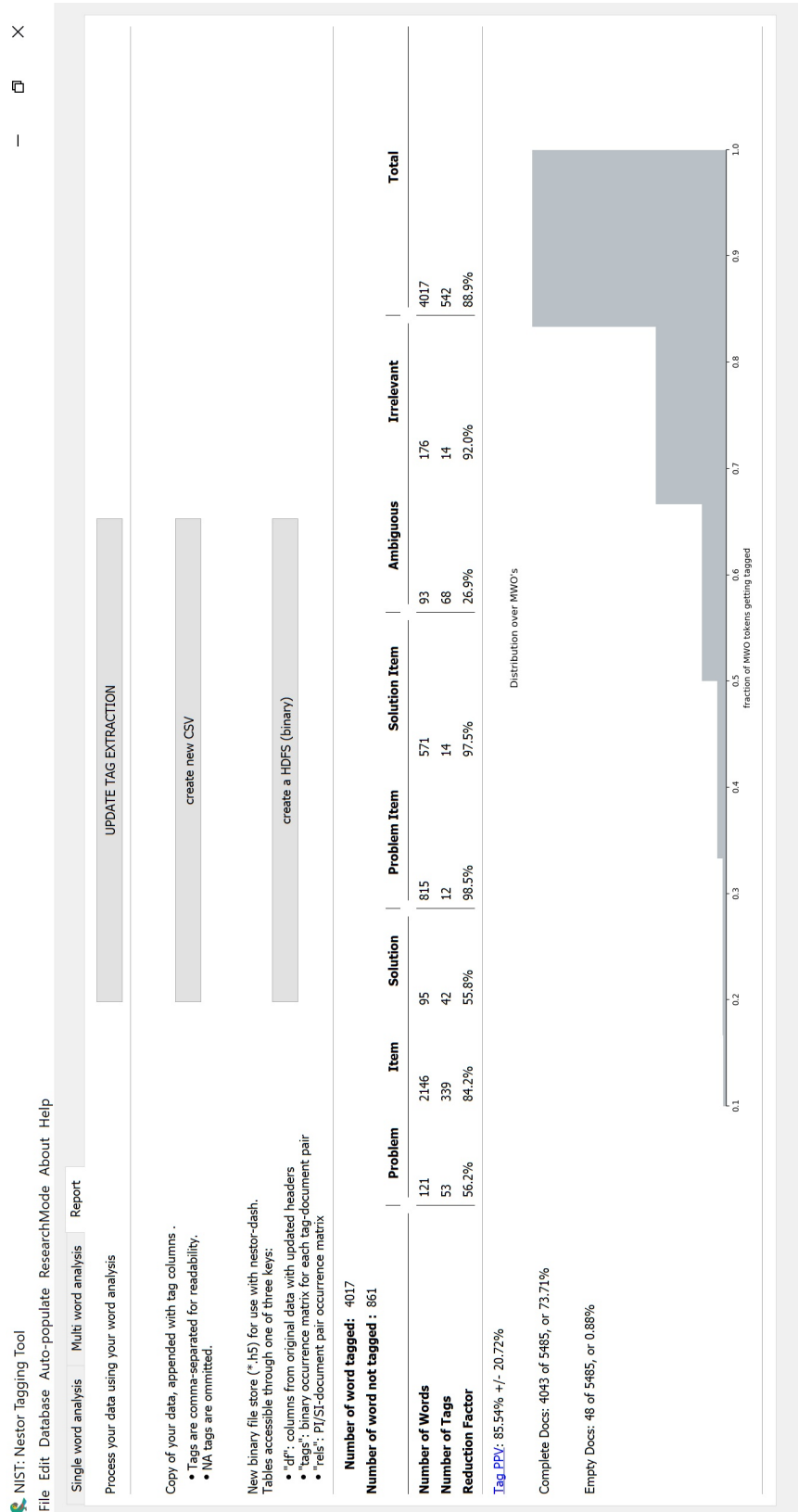


Fig. 2. A screenshot of the Nestor GUI report tab.

4. References

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