Combining and Comparing Multiple Algorithms for Better Learning and Classification: A Case Study of MARF

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1. Introduction

This case study of MARF, an open-source Java-based Modular Audio Recognition Framework, is intended to show the general pattern recognition pipeline design methodology and, more specifically, the supporting interfaces, classes and data structures for machine learning in order to test and compare multiple algorithms and their combinations at the pipeline’s stages, including supervised and unsupervised, statistical, etc. learning and classification. This approach is used for a spectrum of recognition tasks, not only applicable to audio, but rather to general pattern recognition for various applications, such as in digital forensic analysis, writer identification, natural language processing (NLP), and others.

2. Chapter overview

First, we present the research problem at hand in Section 3. This is to serve as an example of what researchers can do and choose for their machine learning applications – the types of data structures and the best combinations of available algorithm implementations to suit their needs (or to highlight the need to implement better algorithms if the ones available are not adequate). In MARF, acting as a testbed, the researchers can also test the performance of their own, external algorithms against the ones available. Thus, the overview of the related software engineering aspects and practical considerations are discussed with respect to the machine learning using MARF as a case study with appropriate references to our own and others’ related work in Section 4 and Section 5. We discuss to some extent the design and implementation of the data structures and the corresponding interfaces to support learning and comparison of multiple algorithms and approaches in a single framework, and the corresponding implementing system in a consistent environment in Section 6. There we also provide the references to the actual practical implementation of the said data structures within the current framework. We then illustrate some of the concrete results of various MARF applications and discuss them in that perspective in Section 7. We conclude afterwards in Section 8 by outlining some of the advantages and disadvantages of the framework approach and some of the design decisions in Section 8.1 and lay out future research plans in Section 8.2.
3. Problem

The main problem we are addressing is to provide researchers with a tool to test a variety of pattern recognition and NLP algorithms and their combinations for whatever task at hand there is, and then select the best available combination(s) for that final task. The testing should be in a uniform environment to compare and contrast all kinds of algorithms, their parameters, at all stages, and gather metrics such as the precision, run-time, memory usage, recall, f-measure, and others. At the same time, the framework should allow for adding external plug-ins for algorithms written elsewhere as wrappers implementing the framework’s API for the same comparative studies.

The system built upon the framework has to have the data structures and interfaces that support such types of experiments in a common, uniform way for comprehensive comparative studies and should allow for scripting of the recognition tasks (for potential batch, distributed, and parallel processing).

These are very broad and general requirements we outlined, and further we describe our approach to them to a various degree using what we call the Modular Audio Recognition Framework (MARF). Over the course of years and efforts put into the project, the term Audio in the name became a lot less descriptive as the tool grew to be a lot more general and applicable to the other domains than just audio and signal processing, so we will refer to the framework as just MARF (while reserving the right to rename it later).

Our philosophy also includes the concept that the tool should be publicly available as an open-source project such that any valuable input and feedback from the community can help everyone involved and make it for the better experimentation platform widely available to all who needs it. Relative simplicity is another aspect that we require the tool to be to be usable by many.

To enable all this, we need to answer the question of “How do we represent what we learn and how do we store it for future use?” What follows is the summary of our take on answering it and the relevant background information.

4. Related work

There are a number of items in the related work; most of them were used as a source to gather the algorithms from to implement within MARF. This includes a variety of classical distance classifiers, such as Euclidean, Chebyshev (a.k.a city-block), Hamming, Mahalanobis, Minkowski, and others, as well as artificial neural networks (ANNs) and all the supporting general mathematics modules found in Abdi (2007); Hamming (1950); Mahalanobis (1936); Russell & Norvig (1995). This also includes the cosine similarity measure as one of the classifiers described in Garcia (2006); Khalifé (2004). Other related work is of course in digital signal processing, digital filters, study of acoustics, digital communication and speech, and the corresponding statistical processing; again for the purpose of gathering of the algorithms for the implementation in a uniform manner in the framework including the ideas presented in Bernsee (1999–2005); Haridas (2006); Haykin (1988); Ifeachor & Jervis (2002); Jurafsky & Martin (2000); O'Shaughnessy (2000); Press (1993); Zwicker & Fastl (1990). These primarily include the design and implementation of the Fast Fourier Transform (FFT) (used for both preprocessing as in low-pass, high-pass, band-pass, etc. filters as well as in feature extraction), Linear Predictive Coding (LPC), Continuous Fraction Expansion (CFE) filters and the corresponding testing applications.
implemented by Clement, Mokhov, Nicolacopoulos, Fan & the MARF Research & Development Group (2002–2010); Clement, Mokhov & the MARF Research & Development Group (2002–2010); Mokhov, Fan & the MARF Research & Development Group (2002–2010b; 2005–2010a); Sinclair et al. (2002–2010).

Combining algorithms, an specifically, classifiers is not new, e.g. see Cavalin et al. (2010); Khalifé (2004). We, however, get to combine and chain not only classifiers but algorithms at every stage of the pattern recognition pipeline.

Some of the spectral techniques and statistical techniques are also applicable to the natural language processing that we also implement in some form Jurafsky & Martin (2000); Vaillant et al. (2006); Zipf (1935) where the text is treated as a signal.

Finally, there are open-source speech recognition frameworks, such as CMU Sphinx (see The Sphinx Group at Carnegie Mellon (2007–2010)) that implement a number of algorithms for speech-to-text translation that MARF does not currently implement, but they are quite complex to work with. The advantages of Sphinx is that it is also implemented in Java and is under the same open-source license as MARF, so the latter can integrate the algorithms from Sphinx as external plug-ins. Its disadvantages for the kind of work we are doing are its size and complexity.

5. Our approach and accomplishments

MARF’s approach is to define a common set of integrated APIs for the pattern recognition pipeline to allow flexible comparative environment for diverse algorithm implementations for sample loading, preprocessing, feature extraction, and classification. On top of that, the algorithms within each stage can be composed and chained. The conceptual pipeline is shown in Figure 1 and the corresponding UML sequence diagram, shown in Figure 2, details the API invocation and message passing between the core modules, as per Mokhov (2008d); Mokhov et al. (2002–2003); The MARF Research and Development Group (2002–2010).

Fig. 1. Classical Pattern Recognition Pipeline of MARF
MARF has been published or is under review and publication with a variety of experimental pattern recognition and software engineering results in multiple venues. The core founding works for this chapter are found in Mokhov (2008a;d; 2010b); Mokhov & Debbabi (2008); Mokhov et al. (2002–2003); The MARF Research and Development Group (2002–2010).

At the beginning, the framework evolved for stand-alone, mostly sequential, applications with limited support for multithreading. Then, the next natural step in its evolution was to make it distributed. Having a distributed MARF (DMARF) still required a lot of manual management, and a proposal was put forward to make it into an autonomic system. A brief overview of the distributed autonomic MARF (DMARF and ADMARF) is given in terms of how the design and practical implementation are accomplished for local and distributed learning and self-management in Mokhov (2006); Mokhov, Huynh & Li (2007); Mokhov et al. (2008); Mokhov & Jayakumar (2008); Mokhov & Vassev (2009a); Vassev & Mokhov (2009; 2010) primarily relying on distributed technologies provided by Java as described in Jini Community (2007); Sun Microsystems, Inc. (2004; 2006); Wollrath & Waldo (1995–2005).

Some scripting aspects of MARF applications are also formally proposed in Mokhov (2008f). Additionally, another frontier of the MARF’s use in security is explored in Mokhov (2008e); Mokhov, Huynh, Li & Rassai (2007) as well as the digital forensics aspects that are discussed for various needs of forensic file type analysis, conversion of the MARF’s internal data structures as MARFL expressions into the Forensic Lucid language for follow up forensic analysis, self-forensic analysis of MARF, and writer identification of hand-written digitized documents described in Mokhov (2008b); Mokhov & Debbabi (2008); Mokhov et al. (2009); Mokhov & Vassev (2009c).

Furthermore, we have a use case and applicability of MARF’s algorithms for various multimedia tasks, e.g. as described in Mokhov (2007b) combined with PureData (see Puckette & PD Community (2007–2010)) as well as in simulation of a solution to the intelligent systems challenge problem Mokhov & Vassev (2009b) and simply various aspects of software engineering associated with the requirements, design, and implementation of the framework outlined in Mokhov (2007a); Mokhov, Miladinova, Ormandjieva, Fang & Amirghahari (2008–2010).

Some MARF example applications, such as text-independent speaker-identification, natural and programming language identification, natural language probabilistic parsing, etc. are released along with MARF as open-source and are discussed in several publications mentioned earlier, specifically in Mokhov (2008–2010c); Mokhov, Sinclair, Clement, Nicolacopoulos & the MARF Research & Development Group (2002–2010); Mokhov & the MARF Research & Development Group (2003–2010a;-); as well as voice-based authentication application of MARF as an utterance engine is in a proprietary VocalVeritas system. The most recent advancements in MARF’s applications include the results on identification of the decades and place of origin in the francophone press in the DEFT2010 challenge presented in Forest et al. (2010) with the results described in Mokhov (2010a;b).

6. Methods and tools

To keep the framework flexible and open for comparative uniform studies of algorithms and their external plug-ins we need to define a number of interfaces that the main modules would implement with the corresponding well-documented API as well as what kind of data structures they exchange and populate while using that API. We have to provide the data structures to encapsulate the incoming data for processing as well as the data
Fig. 2. UML Sequence Diagram of the Classical Pattern Recognition Pipeline of MARF structures to store the processed data for later retrieval and comparison. In the case of classification, it is necessary also to be able to store more than one classification result, a result set, ordered according to the classification criteria (e.g. sorted in ascending manner for minimal distance or in descending manner for higher probability or similarity). The external applications should be able to pass configuration settings from their own options to the MARF’s configuration state as well as collect back the results and aggregate statistics.
While algorithm modules are made fit into the same framework, they all may have arbitrary number of reconfigurable parameters for experiments (e.g. compare the behavior of the same algorithm under different settings) that take some defaults if not explicitly specified. There has to be a generic way of setting those parameters by the applications that are built upon the framework, whose Javadoc’s API is detailed here: http://marf.sourceforge.net/api-dev/.

In the rest of the section we describe what we used to achieve the above requirements.

1. We use the Java programming language and the associated set of tools from Sun Microsystems, Inc. (1994–2009) and others as our primary development and run-time environment. This is primarily because it is dynamic, supports reflection (see Green (2001–2005)), various design patterns and OO programming (Flanagan (1997); Merx & Norman (2007)), exception handling, multithreading, distributed technologies, collections, and other convenient built-in features. We employ Java interfaces for the most major modules to allow for plug-ins.

2. All objects involved in storage are Serializable, such that they can be safely stored on disk or transmitted over the network.

3. Many of the data structures are also Cloneable to aid copying of the data structure the Java standard way.

4. All major modules in the classical MARF pipeline implement the IStorageManager interface, such that they know how to save and reload their state. The default API of IStorageManager provides for modules to implement their serialization in a variety of binary and textual formats. Its latest open-source version is at: http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Storage/IStorageManager.java?view=markup

5. The Configuration object instance is designed to encapsulate the global state of a MARF instance. It can be set by the applications, saved and reloaded or propagated to the distributed nodes. Details: http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Configuration.java?view=markup

6. The module parameters class, represented as ModuleParams, allows more fine-grained settings for individual algorithms and modules – there can be arbitrary number of the settings in there. Combined with Configuration it’s the way for applications to pass the specific parameters to the internals of the implementation for diverse experiments. Details: http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Storage/ModuleParams.java?view=markup

7. The Sample class represents the values either just loaded from an external source (e.g. a file) for preprocessing, or a “massaged” version thereof that was preprocessed already (e.g. had its noise and silence removed, filtered otherwise, and normalized) and is ready for feature extraction. The Sample class has a buffer of Double values (an array) representing the amplitudes of the sample values being processed at various frequencies and other parameters. It is not important that the input data may be an audio signal, a text, an image, or any kind of binary data – they all can be treated similarly in the spectral approach, so only one way to represent them such that all the modules can understand them. The Sample instances are usually of arbitrary length. Details: http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Storage/Sample.java?view=markup

8. The ITrainingSample interface is very crucial to specify the core storage models for all training samples and training sets. The latter are updated during the training mode of the classifiers and used in read-only manner during the classification stage. The interface also defines what and how to store of the data and how to accumulate the feature vectors that come from the feature extraction modules. Details: http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Storage/ITrainingSample.java?view=markup
9. The TrainingSample class is the first implementation of the ITrainingSample interface. It maintains the ID of the subject that training sample data corresponds to, the training data vector itself (usually either a mean or median cluster or a single feature vector), and a list of files (or entries alike) the training was performed on (this list is optionally used by the classification modules to avoid double-training on the same sample). Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Storage/TrainingSample.java?view=markup

10. The Cluster is a TrainingSample with a mean cluster data embedded and counted how many feature vectors were particularly trained on. Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Storage/Cluster.java?view=markup

11. The TrainingSet class encapsulates a collection of object instances implementing the ITrainingSample interface and whether they are simply TrainingSamples, Clusters, or FeatureSets. It also carries the information about which preprocessing and feature extraction methods were used to disambiguate the sets. Most commonly, the serialized instances of this class are preserved during the training sessions and used during the classification sessions. Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Storage/TrainingSet.java?view=markup

12. The FeatureSet class instance is a Cluster that allows maintaining individual feature vectors instead of just a compressed (mean or median) clusters thereof. It allows for the most flexibility and retains the most training information available at the cost of extra storage and look up requirements. The flexibility allows to compute the mean and median vectors and cache them dynamically if the feature set was not altered increasing performance. Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Storage/FeatureSet.java?view=markup

13. An instance of the Result data structure encapsulates the classification ID (usually supplied during training), the outcome for that result, and a particular optional description if required (e.g. human-readable interpretation of the ID). The outcome may mean a number of things depending on the classifier used: it is a scalar Double value that can represent the distance from the subject, the similarity to the subject, or probability of this result. These meanings are employed by the particular classifiers when returning the “best” and “second best”, etc. results or sort them from the “best” to the “worst” whatever these qualifiers mean. Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Storage/Result.java?view=markup

14. The ResultSet class corresponds to the collection of Results, that can be sorted according to each classifier’s requirements. It provides the basic API to get minima, maxima (both first, and second), as well as average and random and the entire collection of the results. Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Storage/ResultSet.java?view=markup

15. The IDatabase interface is there to be used by applications to maintain their instances of database abstractions to maintain statistics they need, such as precision of recognition, etc. generally following the Builder design pattern (see Freeman et al. (2004); Gamma et al. (1995); Larman (2006)). Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Storage/IDatabase.java?view=markup

16. The Database class instance is the most generic implementation of the IDatabase interface in case applications decide to use it. The applications such as SpeakerIdentApp, WriterIdentApp, FileTypeIdentApp, DEFT2010App and others have their corresponding subclasses of this class. Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Storage/Database.java?view=markup
17. The **StatisticalObject** class is a generic record about frequency of occurrences and potentially a rank of any statistical value. In MARF, typically it is the basis for various NLP-related observations. Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Stats/StatisticalObject.java?view=markup

18. The **WordStats** class is a **StatisticalObject** that is more suitable for text analysis and extends it with the lexeme being observed. Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Stats/WordStats.java?view=markup

19. The **Observation** class is a refinement of **WordStats** to augment it with prior and posterior probabilities as well as the fact it has been “seen” or not yet. Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Stats/Observation.java?view=markup

20. The **Ngram** instance is an **Observation** of an occurrence of an \( n \)-ngram usually in the natural language text with \( n = 1, 2, 3, \ldots \) characters or lexeme elements that follow each other. Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Stats/Ngram.java?view=markup

21. The **ProbabilityTable** class instance builds matrices of \( n \)-grams and their computed or counted probabilities for training and classification (e.g. in LangIdentApp). Details:
http://marf.cvs.sf.net/viewvc/marf/marf/src/marf/Stats/ProbabilityTable.java?view=markup

7. Results

We applied the MARF approach to a variety experiments, that gave us equally a variety of results. The approaches tried refer to text independent-speaker identification using median and mean clusters, gender identification, age group, spoken accent, and biometrics alike. On the other hand, other experiments involved writer identification from scanned hand-written documents, forensic file type analysis of file systems, an intelligent systems challenge, natural language identification, identification of decades in French corpora as well as place of origin of publication (such as Quebec vs. France or the particular journal).

All these experiments yielded top, intermediate, and worst configurations for each task given the set of available algorithms implemented at the time. Here we recite some of the results with their configurations. This is a small fraction of the experiments conducted and results recorded as a normal session is about \( \approx 1500+ \) configurations.

1. Text-independent speaker (Mokhov (2008a;c); Mokhov et al. (2002–2003)), including gender, and spoken accent identification using mean vs. median clustering experimental (Mokhov (2008a;d)) results are illustrated in Table 1, Table 2, Table 3, Table 4, Table 5, and Table 6. These are primarily results with the top precision. The point these serve to illustrate is that the top configurations of algorithms are distinct depending on (a) the recognition task (“who” vs. “spoken accent” vs. “gender”) and (b) type of clustering performed. For instance, by using the mean clustering the configuration that removes silence gaps from the sample, uses the band-stop FFT filter, and uses the aggregation of the FFT and LPC features in one feature vector and the cosine similarity measure as the classifier yielded the top result in Table 1. However, an equivalent experiment in Table 2 with median clusters yielded band-stop FFT filter with FFT feature extractor and cosine similarity classifier as a top configuration; and the configuration that was the top for the mean was no longer that accurate. The individual modules used in the pipeline were all at their default settings (see Mokhov (2008d)). The meanings of the options are also described in Mokhov (2008d; 2010b); The MARF
Rank # | Configuration | GOOD1st | BAD1st | Precision1st, % | GOOD2nd | BAD2nd | Precision2nd, %
--- | --- | --- | --- | --- | --- | --- | ---
1 | -silence -bandstop -aggr -cos | 29 | 3 | 90.62 | 30 | 2 | 93.75
1 | -silence -bandstop -ft -cos | 29 | 3 | 90.62 | 30 | 2 | 93.75
1 | -bandstop -fft -cos | 28 | 4 | 87.50 | 29 | 3 | 90.62
2 | -silence -noise -bandstop -fft -cos | 28 | 4 | 87.50 | 30 | 2 | 93.75
2 | -silence -low -aggr -cos | 28 | 4 | 87.50 | 30 | 2 | 93.75
2 | -silence -noise -norm -aggr -cos | 28 | 4 | 87.50 | 30 | 2 | 93.75
2 | -silence -low -fft -cos | 28 | 4 | 87.50 | 30 | 2 | 93.75
2 | -silence -noise -norm -fft -cos | 28 | 4 | 87.50 | 30 | 2 | 93.75
2 | -silence -noise -low -aggr -cos | 28 | 4 | 87.50 | 30 | 2 | 93.75
2 | -silence -noise -low -fft -cos | 28 | 4 | 87.50 | 30 | 2 | 93.75
2 | -bandstop -aggr -cos | 28 | 4 | 87.50 | 30 | 2 | 93.75
2 | -noise -norm -cos | 28 | 4 | 87.50 | 30 | 2 | 93.75
2 | -silence -raw -aggr -cos | 28 | 4 | 87.50 | 30 | 2 | 93.75
2 | -silence -noise -raw -aggr -cos | 28 | 4 | 87.50 | 30 | 2 | 93.75
3 | -silence -noise -bandstop -aggr -cos | 28 | 4 | 87.50 | 30 | 2 | 93.75
3 | -silence -norm -fft -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75
3 | -silence -norm -aggr -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75
3 | -low -fft -cos | 27 | 5 | 84.38 | 28 | 4 | 87.50
3 | -noise -bandstop -aggr -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75
3 | -noise -raw -aggr -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75
3 | -silence -noise -raw -fft -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75
3 | -noise -norm -aggr -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75
3 | -noise -raw -aggr -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75
3 | -noise -raw -fft -cos | 27 | 5 | 84.38 | 28 | 4 | 87.50
3 | -raw -fft -cos | 26 | 6 | 81.25 | 28 | 4 | 87.50
3 | -noise -bandstop -fft -cos | 26 | 6 | 81.25 | 28 | 4 | 87.50
4 | -noise -norm -lp -cos | 26 | 6 | 81.25 | 28 | 4 | 87.50
4 | -noise -raw -lp -cos | 26 | 6 | 81.25 | 28 | 4 | 87.50
5 | -endp -lp -cheb | 25 | 7 | 78.12 | 26 | 6 | 81.25
6 | -silence -bandstop -ft -eucl | 24 | 8 | 75.00 | 26 | 6 | 81.25
6 | -bandstop -lp -eucl | 24 | 8 | 75.00 | 26 | 6 | 81.25
6 | -silence -norm -ft -eucl | 24 | 8 | 75.00 | 26 | 6 | 81.25
6 | -silence -bandstop -ft -diff | 24 | 8 | 75.00 | 26 | 6 | 81.25
6 | -silence -norm -aggr -eucl | 24 | 8 | 75.00 | 26 | 6 | 81.25
6 | -raw -fft -eucl | 24 | 8 | 75.00 | 26 | 6 | 81.25
6 | -noise -aggr -eucl | 24 | 8 | 75.00 | 26 | 6 | 81.25
6 | -silence -bandstop -aggr -eucl | 24 | 8 | 75.00 | 26 | 6 | 81.25
6 | -bandstop -aggr -eucl | 24 | 8 | 75.00 | 26 | 6 | 81.25
6 | -noise -raw -fft -eucl | 24 | 8 | 75.00 | 26 | 6 | 81.25
6 | -silence -raw -fft -eucl | 24 | 8 | 75.00 | 26 | 6 | 81.25
6 | -silence -noise -raw -aggr -eucl | 24 | 8 | 75.00 | 26 | 6 | 81.25
6 | -silence -noise -raw -aggr -eucl | 24 | 8 | 75.00 | 26 | 6 | 81.25

Table 1. Top Most Accurate Configurations for Speaker Identification, 1st and 2nd Guesses, Mean Clustering (Mokhov (2008d))

Research and Development Group (2002–2010). We also illustrate the “2nd guess” statistics – often what happens is that if we are mistaken in our first guess, the second one is usually the right one. It may not be obvious how to exploit it, but we provide the statistics to show if the hypothesis is true or not.

While the options listed of the MARF application (SpeakerIdentApp, see Mokhov, Sinclair, Clement, Nicolacopoulos & the MARF Research & Development Group (2002-2010)) are described at length in the cited works, here we briefly summarize their meaning for the unaware reader: -silence and -noise tell to remove the silence and noise components of a sample; -band, -bandstop, -high and -low correspond to the band-pass, band-stop, high-pass and low-pass FFT filters; -norm means normalization; -endp corresponds to endpointing; -raw does a pass-through (no-op) preprocessing.
In Mokhov & Debbabi (2008), an experiment was conducted to use a MARF-based FileTypeIdentApp for bulk forensic analysis of file types using signal processing techniques as opposed to the Unix file utility (see Darwin et al. (1973–2007–)). That experiment was a “cross product” of:

- \texttt{fft}, \texttt{lpc}, and \texttt{aggr} correspond to the FFT-based, LPC-based, or aggregation of the two feature extractors; \texttt{cos}, \texttt{eucl}, \texttt{cheb}, \texttt{hamming}, \texttt{mink}, and \texttt{diff} correspond to the classifiers, such as cosine similarity measure, Euclidean, Chebyshev, Hamming, Minkowski, and diff distances respectively.

2. In Mokhov & Debbabi (2008), an experiment was conducted to use a MARF-based FileTypeIdentApp for bulk forensic analysis of file types using signal processing techniques as opposed to the Unix file utility (see Darwin et al. (1973–2007–)). That experiment was a “cross product” of:

| Rank # | Configuration | GOOD\textsubscript{1st} | BAD\textsubscript{1st} | Precision$\textsubscript{1st}$,\% | GOOD\textsubscript{2nd} | BAD\textsubscript{2nd} | Precision$\textsubscript{2nd}$,\% |
|-------|--------------|----------------|----------------|-----------------|----------------|----------------|----------------|
| 1     | -bandstop -fft -cos | 29 | 3 | 90.62 | 30 | 2 | 93.75 |
| 2     | -bandstop -aggr -cos | 29 | 3 | 90.62 | 30 | 2 | 93.75 |
| 3     | -silence -bandstop -aggr -cos | 28 | 4 | 87.5 | 30 | 2 | 93.75 |
| 4     | -silence -bandstop -fft -cos | 28 | 4 | 87.5 | 30 | 2 | 93.75 |
| 5     | -low -fft -cos | 28 | 4 | 87.5 | 30 | 2 | 93.75 |
| 6     | -noise -bandstop -aggr -cos | 28 | 4 | 87.5 | 30 | 2 | 93.75 |
| 7     | -silence -raw -fft -cos | 28 | 4 | 87.5 | 30 | 2 | 93.75 |
| 8     | -noise -raw -fft -cos | 28 | 4 | 87.5 | 30 | 2 | 93.75 |
| 9     | -raw -fft -cos | 28 | 4 | 87.5 | 29 | 3 | 90.62 |
| 10    | -noise -bandstop -fft -cos | 28 | 4 | 87.5 | 30 | 2 | 93.75 |
| 11    | -norm -fft -cos | 28 | 4 | 87.5 | 30 | 2 | 93.75 |
| 12    | -noise -raw -fft -cos | 28 | 4 | 87.5 | 30 | 2 | 93.75 |
| 13    | -noise -norm -fft -cos | 28 | 4 | 87.5 | 30 | 2 | 93.75 |
| 14    | -noise -low -aggr -cos | 28 | 4 | 87.5 | 30 | 2 | 93.75 |
| 15    | -norm -aggr -cos | 28 | 4 | 87.5 | 30 | 2 | 93.75 |
| 16    | -silence -norm -fft -cos | 27 | 5 | 84.38 | 29 | 3 | 90.62 |
| 17    | -silence -low -aggr -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75 |
| 18    | -silence -norm -aggr -cos | 27 | 5 | 84.38 | 29 | 3 | 90.62 |
| 19    | -noise -norm -aggr -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75 |
| 20    | -silence -low -fft -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75 |
| 21    | -silence -noise -norm -fft -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75 |
| 22    | -silence -noise -low -aggr -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75 |
| 23    | -noise -low -fft -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75 |
| 24    | -noise -low -aggr -cos | 27 | 5 | 84.38 | 29 | 3 | 90.62 |
| 25    | -noise -raw -aggr -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75 |
| 26    | -silence -noise -raw -aggr -cos | 27 | 5 | 84.38 | 30 | 2 | 93.75 |
| 27    | -noise -norm -aggr -cos | 27 | 5 | 84.38 | 29 | 3 | 90.62 |
| 28    | -silence -noise -bandstop -fft -cos | 26 | 6 | 81.25 | 30 | 2 | 93.75 |
| 29    | -bandstop -lpc -diff | 26 | 6 | 81.25 | 31 | 1 | 96.88 |
| 30    | -bandstop -lpc -cheb | 26 | 6 | 81.25 | 31 | 1 | 96.88 |
| 31    | -noise -silence -bandstop -aggr -cos | 26 | 6 | 81.25 | 30 | 2 | 93.75 |
| 32    | -bandstop -lpc -eucl | 25 | 7 | 78.12 | 31 | 1 | 96.88 |
| 33    | -noise -raw -lpc -cos | 25 | 7 | 78.12 | 26 | 6 | 91.25 |
| 34    | -bandstop -lpc -cos | 25 | 7 | 78.12 | 29 | 3 | 90.62 |
| 35    | -noise -raw -lpc -cos | 25 | 7 | 78.12 | 26 | 6 | 81.25 |
| 36    | -raw -lpc -cos | 25 | 7 | 78.12 | 26 | 6 | 81.25 |
| 37    | -norm -lpc -cos | 25 | 7 | 78.12 | 26 | 6 | 81.25 |
| 38    | -silence -norm -lpc -eucl | 24 | 8 | 75 | 26 | 6 | 81.25 |
| 39    | -bandstop -fft -cheb | 24 | 8 | 75 | 26 | 6 | 81.25 |
| 40    | -silence -norm -aggr -eucl | 24 | 8 | 75 | 26 | 6 | 81.25 |
| 41    | -endp -lpc -cheb | 24 | 8 | 75 | 26 | 6 | 81.25 |
| 42    | -bandstop -aggr -cheb | 24 | 8 | 75 | 26 | 6 | 81.25 |
| 43    | -bandstop -fft -diff | 24 | 8 | 75 | 26 | 6 | 81.25 |
| 44    | -bandstop -aggr -diff | 24 | 8 | 75 | 26 | 6 | 81.25 |
| 45    | -bandstop -lpc -mink | 24 | 8 | 75 | 30 | 2 | 93.75 |
| 46    | -silence -bandstop -fft -eucl | 23 | 9 | 71.88 | 26 | 6 | 81.25 |
| 47    | -silence -bandstop -aggr -cheb | 23 | 9 | 71.88 | 26 | 6 | 81.25 |
| 48    | -bandstop -fft -eucl | 23 | 9 | 71.88 | 26 | 6 | 81.25 |
| 49    | -silence -bandstop -aggr -eucl | 23 | 9 | 71.88 | 26 | 6 | 81.25 |
| 50    | -silence -endp -lpc -cheb | 23 | 9 | 71.88 | 25 | 7 | 78.12 |
| 51    | -endp -lpc -eucl | 23 | 9 | 71.88 | 26 | 6 | 81.25 |

Table 2. Top Most Accurate Configurations for Speaker Identification, 1\textsuperscript{st} and 2\textsuperscript{nd} Guesses, Median Clustering (Mokhov (2008d))
| Rank # | Configuration                                      | GOOD \(_{1\text{st}}\) | BAD \(_{1\text{st}}\) | Precision\(_{1\text{st}}\),% | GOOD \(_{2\text{nd}}\) | BAD \(_{2\text{nd}}\) | Precision\(_{2\text{nd}}\),% |
|--------|---------------------------------------------------|-------------------------|----------------------|---------------------------|-------------------------|----------------------|---------------------------|
| 1      | silence-endp-lpc-cheb                              | 24                      | 8                    | 75                        | 26                      | 6                    | 81.25                     |
| 2      | bandstop-lpc-cos                                  | 23                      | 9                    | 71.88                     | 22                      | 5                    | 84.38                     |
| 3      | -noise-norm-aggr-cos                              | 23                      | 9                    | 71.88                     | 22                      | 5                    | 84.38                     |
| 4      | noise-bandstop-lpc-cos                            | 22                      | 10                   | 68.75                     | 26                      | 6                    | 81.25                     |
| 5      | -noise-bandstop-lpc-cos                           | 22                      | 10                   | 68.75                     | 27                      | 5                    | 84.38                     |
| 6      | -noise-bandstop-lpc-cos                           | 22                      | 10                   | 68.75                     | 27                      | 5                    | 84.38                     |
| 7      | -noise-bandstop-lpc-cos                           | 22                      | 10                   | 68.75                     | 27                      | 5                    | 84.38                     |
| 8      | -noise-bandstop-lpc-cos                           | 22                      | 10                   | 68.75                     | 27                      | 5                    | 84.38                     |
| 9      | -noise-bandstop-lpc-cos                           | 22                      | 10                   | 68.75                     | 27                      | 5                    | 84.38                     |
| 10     | -noise-bandstop-lpc-cos                           | 22                      | 10                   | 68.75                     | 27                      | 5                    | 84.38                     |

Table 3. Top Most Accurate Configurations for Spoken Accent Identification, 1\(^{\text{st}}\) and 2\(^{\text{nd}}\) Guesses, Mean Clustering (Mokhov (2008d))

- 3 loaders
- strings and n-grams (4)
- noise and silence removal (4)
- 13 preprocessing modules
- 5 feature extractors
- 9 classifiers
Table 4. Top Most Accurate Configurations for Spoken Accent Identification, 1st and 2nd Guesses, Median Clustering (Mokhov (2008d))
## Table 5. Top Most Accurate Configurations for Gender Identification, 1st and 2nd Guesses, Mean Clustering (Mokhov (2008d))

| Rank # | Configuration | GOOD1st | BAD1st | PrecisionGOOD1st | BAD2nd | PrecisionBAD2nd |
|--------|---------------|---------|--------|------------------|--------|-----------------|
| 1      | -noise -high -aggr -mink | 26 | 6 | 81.25 | 32 | 0 | 100 |
| 1      | -noise -noise -band -aggr -cheb | 26 | 6 | 81.25 | 32 | 0 | 100 |
| 1      | -noise -noise -band -lpc -cos | 26 | 6 | 81.25 | 32 | 0 | 100 |
| 1      | -noise -noise -bandstop -fft -diff | 26 | 6 | 81.25 | 32 | 0 | 100 |
| 1      | -noise -bandstop -fft -cheb | 26 | 6 | 81.25 | 32 | 0 | 100 |
| 1      | -noise -bandstop -fft -diff | 26 | 7 | 78.12 | 31 | 1 | 96.88 |

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### Table 6. Top Most Accurate Configurations for Gender Identification, 1st and 2nd Guesses, Median Clustering (Mokhov (2008d))

| Run # | Configuration                      | GOOD 1st | BAD 1st | Precision 1st, % | GOOD 2nd | BAD 2nd | Precision 2nd, % |
|-------|------------------------------------|----------|---------|------------------|----------|---------|------------------|
| 1     | -silence -noise -band -lpc -cos    | 26       | 6       | 81.25            | 30       | 2       | 93.75            |
| 1     | -silence -noise -endp -lpc -eucl  | 26       | 6       | 81.25            | 31       | 1       | 96.88            |
| 2     | -silence -band -lpc -cos          | 25       | 7       | 78.12            | 31       | 1       | 96.88            |
| 2     | -silence -noise -band -aggr -cheb | 25       | 7       | 78.12            | 32       | 0       | 100              |
| 2     | -silence -band -lpc -mark         | 25       | 7       | 78.12            | 32       | 0       | 100              |
| 2     | -endp -lpc -cheb                  | 25       | 7       | 78.12            | 31       | 1       | 96.88            |
| 2     | -silence -noise -band -filt -cheb | 25       | 7       | 78.12            | 32       | 0       | 100              |
| 2     | -noise -endp -lpc -eucl           | 25       | 7       | 78.12            | 31       | 1       | 96.88            |
| 2     | -silence -noise -endp -lpc -cheb  | 25       | 7       | 78.12            | 32       | 0       | 100              |
| 2     | -silence -noise -band -aggr -diff | 25       | 7       | 78.12            | 32       | 0       | 100              |
| 2     | -silence -noise -bandstop -aggr -cheb | 25       | 7       | 78.12            | 32       | 0       | 100              |
| 2     | -silence -noise -bandstop -filt -cheb | 25       | 7       | 78.12            | 32       | 0       | 100              |
| 2     | -silence -noise -band -filt -diff | 25       | 7       | 78.12            | 32       | 0       | 100              |
| 2     | -silence -noise -bandstop -aggr -diff | 25       | 7       | 78.12            | 32       | 0       | 100              |
| 3     | -noise -high -aggr -mink           | 24       | 8       | 75               | 31       | 1       | 96.88            |
| 3     | -low -lpc -cheb                    | 24       | 8       | 75               | 31       | 1       | 96.88            |
| 3     | -silence -noise -bandstop -filt -diff | 24       | 8       | 75               | 32       | 0       | 100              |
| 3     | -noise -high -aggr -eucl           | 24       | 8       | 75               | 30       | 2       | 93.75            |
| 3     | -noise -high -lpc -cos             | 24       | 8       | 75               | 30       | 2       | 93.75            |
| 3     | -noise -norm -lpc -cheb            | 24       | 8       | 75               | 31       | 1       | 96.88            |
| 3     | -noise -low -lpc -cheb             | 24       | 8       | 75               | 32       | 0       | 100              |
| 3     | -noise -norm -lpc -eucl            | 24       | 8       | 75               | 30       | 2       | 93.75            |
| 3     | -noise -low -lpc -eucl             | 24       | 8       | 75               | 31       | 1       | 96.88            |
| 3     | -noise -norm -lpc -mark             | 24       | 8       | 75               | 30       | 2       | 93.75            |
| 3     | -noise -norm -lpc -hamming        | 24       | 8       | 75               | 29       | 3       | 90.62            |
| 3     | -noise -bandstop -filt -diff       | 24       | 8       | 75               | 32       | 0       | 100              |
| 3     | -noise -endp -lpc -diff            | 24       | 8       | 75               | 32       | 0       | 100              |
| 3     | -endp -lpc -eucl                   | 24       | 8       | 75               | 30       | 2       | 93.75            |
| 3     | -bandstop -aggr -cos               | 24       | 8       | 75               | 31       | 1       | 96.88            |
| 3     | -low -lpc -diff                    | 24       | 8       | 75               | 31       | 1       | 96.88            |
| 3     | -silence -noise -low -aggr -eucl   | 24       | 8       | 75               | 32       | 0       | 100              |
| 3     | -noise -norm -lpc -diff            | 24       | 8       | 75               | 31       | 1       | 96.88            |
| 3     | -noise -low -lpc -diff             | 24       | 8       | 75               | 32       | 0       | 100              |
| 3     | -endp -lpc -diff                   | 24       | 8       | 75               | 30       | 2       | 93.75            |
| 3     | -endp -lpc -cos                    | 24       | 8       | 75               | 29       | 3       | 90.62            |
| 3     | -silence -noise -band -lpc -cheb   | 24       | 8       | 75               | 32       | 0       | 100              |
| 3     | -noise -endp -lpc -cos             | 24       | 8       | 75               | 31       | 1       | 96.88            |
| 3     | -noise -endp -lpc -hamming         | 24       | 8       | 75               | 31       | 1       | 96.88            |
| 3     | -noise -bandstop -aggr -cheb       | 24       | 8       | 75               | 32       | 0       | 100              |
| 3     | -noise -bandstop -filt -cheb       | 24       | 8       | 75               | 32       | 0       | 100              |
| 4     | -noise -endp -lpc -cheb            | 23       | 9       | 71.88            | 30       | 2       | 93.75            |
| 4     | -noise -noise -band -lpc -eucl     | 23       | 9       | 71.88            | 32       | 0       | 100              |
| 4     | -silence -noise -norm -lpc -cos    | 23       | 9       | 71.88            | 29       | 3       | 90.62            |
| 4     | -silence -band -lpc -eucl          | 23       | 9       | 71.88            | 32       | 0       | 100              |
| 4     | -silence -low -filt -cos           | 23       | 9       | 71.88            | 32       | 0       | 100              |
| 4     | -noise -norm -lpc -hammering       | 23       | 9       | 71.88            | 31       | 1       | 96.88            |
| 4     | -high -aggr -mink                  | 23       | 9       | 71.88            | 32       | 0       | 100              |
| 4     | -noise -low -aggr -diff            | 23       | 9       | 71.88            | 32       | 0       | 100              |
| 4     | -low -filt -cos                    | 23       | 9       | 71.88            | 29       | 3       | 90.62            |
| 4     | -noise -noise -low -filt -cos      | 23       | 9       | 71.88            | 29       | 3       | 90.62            |
| 4     | -silence -band -lpc -diff          | 23       | 9       | 71.88            | 32       | 0       | 100              |
| 4     | -noise -band -aggr -cos            | 23       | 9       | 71.88            | 32       | 0       | 100              |
| 4     | -silence -noise -low -filt -diff   | 23       | 9       | 71.88            | 32       | 0       | 100              |
| 4     | -bandstop -filt -eucl              | 23       | 9       | 71.88            | 32       | 0       | 100              |

Robot Learning
Table 7. File types identification top results, bigrams (Mokhov & Debbabi (2008))

Certain results were quite encouraging for the first and second best statistics extracts in Table 7 and Table 8, as well as statistics per file type in Table 9. We also collected the worst statistics, where the use of a “raw” loader impacted negatively drastically the accuracy of the results as shown in Table 10 and Table 11; yet, some file types were robustly recognized, as shown in Table 12. This gives a clue to the researchers and investigators in which direction to follow to increase the precision and which ones not to use.

| Guess | Rank | Configuration | GOOD | BAD | Precision, % |
|-------|------|---------------|------|-----|--------------|
| 1     | 1    | -wav -raw -lpc -cheb | 140 | 75 | 75.13 |
| 1     | 1    | -wav -silence -noise -raw -lpc -cheb | 147 | 75 | 75.13 |
| 1     | 1    | -wav -noise -raw -lpc -cheb | 147 | 75 | 75.13 |
| 2     | 1    | -wav -silence -norm -fft -cheb | 129 | 72 | 64.18 |
| 3     | 1    | -wav -bandstop -fft -cheb | 125 | 76 | 62.19 |
| 3     | 1    | -wav -silence -noise -norm -fft -cheb | 125 | 76 | 62.19 |
| 3     | 1    | -wav -silence -low -fft -cheb | 125 | 76 | 62.19 |
| 4     | 1    | -wav -silence -norm -lpc -cheb | 124 | 77 | 61.69 |
| 5     | 1    | -wav -silence -noise -low -fft -cheb | 122 | 79 | 60.70 |
| 5     | 1    | -wav -silence -noise -raw -lpc -cos | 83 | 31 | 82.76 |
| 6     | 1    | -wav -noise -raw -lpc -cos | 120 | 81 | 59.70 |
| 6     | 1    | -wav -raw -lpc -cos | 120 | 81 | 59.70 |
| 6     | 1    | -wav -noise -norm -lpc -cos | 120 | 81 | 59.70 |
| 7     | 1    | -wav -noise -bandstop -fft -cheb | 119 | 82 | 59.20 |
| 7     | 1    | -wav -silence -noise -bandstop -lpc -cos | 119 | 82 | 59.20 |
| 7     | 1    | -wav -silence -noise -bandstop -lpc -cheb | 118 | 83 | 58.71 |
| 8     | 1    | -wav -silence -norm -fft -cos | 118 | 83 | 58.71 |
| 8     | 1    | -wav -silence -Bandstop -fft -cheb | 118 | 83 | 58.71 |
| 9     | 1    | -wav -Bandstop -fft -cos | 118 | 83 | 58.71 |
| 10    | 1    | -wav -silence -noise -bandstop -fft -cheb | 112 | 89 | 55.72 |
| 11    | 1    | -wav -noise -raw -fft -cheb | 111 | 90 | 55.22 |
| 11    | 1    | -wav -silence -noise -raw -fft -cheb | 111 | 90 | 55.22 |
| 11    | 1    | -wav -silence -raw -fft -cheb | 111 | 90 | 55.22 |
| 11    | 1    | -wav -silence -raw -fft -cos | 110 | 91 | 54.73 |
| 12    | 1    | -wav -silence -noise -raw -fft -cos | 110 | 91 | 54.73 |
| 12    | 1    | -wav -raw -fft -cos | 110 | 91 | 54.73 |
| 12    | 1    | -wav -silence -raw -fft -cos | 110 | 91 | 54.73 |
| 13    | 1    | -wav -noise -bandstop -lpc -cos | 109 | 92 | 54.23 |
| 13    | 1    | -wav -norm -fft -cos | 109 | 92 | 54.23 |
| 13    | 1    | -wav -norm -fft -cheb | 109 | 92 | 54.23 |
| 14    | 1    | -wav -silence -low -lpc -cheb | 105 | 96 | 52.24 |
| 15    | 1    | -wav -silence -noise -norm -lpc -cheb | 105 | 96 | 52.24 |
| 15    | 1    | -wav -silence -norm -lpc -cos | 101 | 100 | 50.25 |
| 16    | 1    | -wav -silence -bandstop -fft -cos | 99 | 102 | 49.25 |
| 17    | 1    | -wav -noise -norm -lpc -cos | 96 | 105 | 47.56 |
| 17    | 1    | -wav -low -lpc -cos | 96 | 105 | 47.56 |
| 18    | 1    | -wav -silence -noise -low -fft -cos | 92 | 109 | 45.77 |
| 19    | 1    | -wav -noise -low -lpc -cos | 91 | 110 | 45.27 |
| 20    | 1    | -wav -silence -norm -fft -cos | 87 | 114 | 43.28 |
| 20    | 1    | -wav -silence -norm -norm -fft -cos | 87 | 114 | 43.28 |
| 21    | 1    | -wav -noise -low -lpc -cheb | 86 | 120 | 40.30 |
| 22    | 1    | -wav -silence -low -lpc -cos | 85 | 116 | 42.29 |
| 22    | 1    | -wav -silence -noise -norm -lpc -cos | 85 | 116 | 42.29 |
| 23    | 1    | -wav -noise -low -fft -cos | 84 | 117 | 41.79 |
| 24    | 1    | -wav -low -lpc -cheb | 84 | 117 | 41.79 |
| 24    | 1    | -wav -noise -norm -lpc -cheb | 84 | 117 | 41.79 |
| 25    | 1    | -wav -noise -low -lpc -cheb | 82 | 119 | 40.80 |
| 25    | 1    | -wav -noise -norm -fft -cos | 81 | 120 | 40.30 |
| 25    | 1    | -wav -low -fft -cos | 81 | 120 | 40.30 |
| 26    | 1    | -wav -low -fft -cheb | 80 | 121 | 39.80 |
| 26    | 1    | -wav -noise -norm -lpc -cheb | 80 | 121 | 39.80 |
| 26    | 1    | -wav -noise -bandstop -lpc -cheb | 80 | 121 | 39.80 |
| 27    | 1    | -wav -noise -bandstop -fft -cheb | 78 | 122 | 38.81 |
| 28    | 1    | -wav -silence -noise -bandstop -fft -lpc | 76 | 123 | 37.81 |
| 29    | 1    | -wav -noise -bandstop -lpc -cheb | 76 | 122 | 37.31 |
| 30    | 1    | -wav -bandstop -lpc -cheb | 74 | 127 | 36.82 |
| 31    | 1    | -wav -silence -bandstop -lpc -cheb | 65 | 136 | 32.34 |
| 32    | 1    | -wav -bandstop -lpc -cos | 63 | 138 | 32.14 |
| 33    | 1    | -wav -bandstop -lpc -cos | 54 | 149 | 26.87 |

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| Rank | Configuration                                    | GOOD | BAD | Precision, % |
|------|-------------------------------------------------|------|-----|--------------|
| 1    | -wav -raw -lpc -cheb                            | 166  | 35  | 82.59        |
| 1    | -wav -silence -noise -raw -lpc -cheb            | 166  | 35  | 82.59        |
| 1    | -wav -noise -raw -lpc -cheb                     | 166  | 35  | 82.59        |
| 1    | -wav -norm -lpc -cheb                           | 166  | 35  | 82.59        |
| 2    | -wav -silence -raw -lpc -cheb                    | 166  | 35  | 82.59        |
| 2    | -wav -silence -norm -fft -cheb                  | 137  | 64  | 68.18        |
| 3    | -wav -bandstop -fft -cheb                        | 130  | 71  | 64.68        |
| 3    | -wav -silence -noise -norm -fft -cheb            | 140  | 61  | 69.65        |
| 3    | -wav -silence -low -fft -cheb                    | 140  | 61  | 69.65        |
| 3    | -wav -silence -norm -lpc -cheb                   | 116  | 25  | 74.56        |
| 3    | -wav -silence -noise -low -fft -cheb             | 142  | 59  | 70.65        |
| 3    | -wav -silence -noise -raw -lpc -cos              | 142  | 59  | 70.65        |
| 3    | -wav -noise -raw -lpc -cos                       | 142  | 59  | 70.65        |
| 3    | -wav -silence -raw -lpc -cos                     | 142  | 59  | 70.65        |
| 3    | -wav -norm -lpc -cos                             | 142  | 59  | 70.65        |
| 4    | -wav -noise -bandstop -fft -cheb                 | 138  | 63  | 68.66        |
| 5    | -wav -silence -noise -bandstop -lpc -cos         | 151  | 50  | 75.12        |
| 5    | -wav -silence -noise -bandstop -lpc -cheb        | 156  | 45  | 77.81        |
| 6    | -wav -silence -norm -fft -cos                    | 147  | 24  | 73.13        |
| 6    | -wav -silence -bandstop -fft -cheb               | 129  | 63  | 64.18        |
| 6    | -wav -silence -bandstop -lpc -cos                | 127  | 74  | 63.18        |
| 6    | -wav -silence -bandstop -fft -cheb               | 135  | 66  | 67.16        |
| 6    | -wav -noise -raw -fft -cheb                      | 122  | 79  | 60.20        |
| 6    | -wav -silence -noise -raw -fft -cheb             | 122  | 79  | 60.20        |
| 6    | -wav -silence -raw -fft -cheb                    | 122  | 79  | 60.20        |
| 6    | -wav -raw -fft -cos                              | 122  | 79  | 60.20        |
| 6    | -wav -silence -noise -raw -fft -cos              | 130  | 71  | 64.88        |
| 6    | -wav -noise -raw -fft -cos                       | 130  | 71  | 64.88        |
| 6    | -wav -raw -fft -cos                              | 130  | 71  | 64.88        |
| 6    | -wav -silence -raw -fft -cos                     | 130  | 71  | 64.88        |
| 6    | -wav -noise -bandstop -lpc -cos                  | 148  | 53  | 73.63        |
| 6    | -wav -norm -fft -cos                             | 130  | 71  | 64.88        |
| 6    | -wav -norm -fft -cheb                            | 121  | 80  | 60.20        |
| 6    | -wav -silence -low -lpc -cheb                    | 127  | 74  | 63.18        |
| 6    | -wav -silence -noise -norm -lpc -cheb            | 127  | 74  | 63.18        |
| 6    | -wav -silence -norm -lpc -cos                    | 151  | 50  | 75.12        |
| 6    | -wav -silence -bandstop -lpc -cos                | 135  | 66  | 67.16        |
| 6    | -wav -noise -norm -lpc -cos                      | 118  | 83  | 58.71        |
| 6    | -wav -low -lpc -cos                              | 118  | 83  | 58.71        |
| 6    | -wav -silence -noise -low -fft -cos              | 146  | 55  | 72.64        |
| 6    | -wav -noise -low -lpc -cos                       | 115  | 86  | 57.21        |
| 7    | -wav -silence -noise -low -lpc -cheb             | 120  | 81  | 59.70        |
| 7    | -wav -silence -low -fft -cos                     | 143  | 59  | 71.14        |
| 7    | -wav -noise -norm -fft -cos                      | 143  | 59  | 71.14        |
| 7    | -wav -noise -low -fft -cheb                      | 130  | 71  | 64.88        |
| 7    | -wav -silence -low -lpc -cos                     | 111  | 90  | 55.22        |
| 7    | -wav -silence -noise -norm -lpc -cos             | 111  | 90  | 55.22        |
| 7    | -wav -noise -low -fft -cos                       | 130  | 71  | 64.88        |
| 7    | -wav -low -lpc -cheb                             | 130  | 71  | 64.88        |
| 7    | -wav -noise -norm -lpc -cheb                     | 130  | 71  | 64.88        |
| 7    | -wav -noise -low -lpc -cheb                      | 129  | 72  | 64.18        |
| 7    | -wav -noise -norm -fft -cos                      | 129  | 72  | 64.18        |
| 7    | -wav -low -fft -cos                              | 129  | 72  | 64.18        |
| 7    | -wav -low -fft -cheb                             | 115  | 86  | 57.21        |
| 7    | -wav -noise -norm -fft -cheb                     | 115  | 86  | 57.21        |
| 7    | -wav -noise -bandstop -lpc -cheb                 | 127  | 74  | 63.18        |
| 7    | -wav -silence -noise -bandstop -fft -cos         | 125  | 76  | 64.19        |
| 7    | -wav -silence -noise -low -lpc -cos              | 118  | 83  | 58.71        |
| 7    | -wav -noise -bandstop -fft -cos                  | 123  | 78  | 61.19        |
| 7    | -wav -noise -bandstop -lpc -cheb                 | 111  | 90  | 55.22        |
| 7    | -wav -silence -bandstop -lpc -cheb               | 133  | 68  | 66.17        |
| 7    | -wav -silence -bandstop -lpc -cos                | 123  | 78  | 61.19        |
| 7    | -wav -silence -bandstop -lpc -cos                | 126  | 75  | 62.69        |

Table 8. File types identification top results, 2nd best, bigrams (Mokhov & Debbabi (2008))

In addition to the previously described options, here we also have: `-wav` that corresponds to a custom loader that translates any files into a WAV-like format. The detail that is not present in the resulting tables are the internal configuration of the loader’s n-grams loading or raw state.
3. The results in Table 13 represent the classification of the French publications using the same spectral techniques to determine whether a particular article in the French press was published in France or Quebec. The complete description of the related experiments and results can be found in Mokhov (2010a,b).

In addition to the previously mentioned options, we have: -title-only to indicate to work with article titles only instead of main body texts; -ref tells the system to validate against reference data supplied by the organizers rather than the training data.

| Guess | Rank | File type | GOOD | BAD | Precision, % |
|-------|------|-----------|------|-----|--------------|
| 1st   | 1    | Mach-O filetype=10 i386 | 64   | 0   | 100.00       |
| 1st   | 2    | HTML document text       | 64   | 0   | 100.00       |
| 1st   | 3    | TIFF image data; big-endian | 64   | 0   | 100.00       |
| 1st   | 4    | data                      | 64   | 0   | 100.00       |
| 1st   | 5    | ASCII c program text; with very long lines | 64   | 0   | 100.00       |
| 1st   | 6    | Rich Text Format data; version 1; Apple Macintosh | 128  | 0   | 100.00       |
| 1st   | 7    | ASCII English text        | 64   | 0   | 100.00       |
| 1st   | 8    | a / sw/bin/scanimrun script test executable | 516  | 60  | 89.58        |
| 1st   | 9    | perl script text executable | 832  | 192 | 81.25        |
| 1st   | 10   | NeXT/Apple typedstream data; big endian; version 4; system 1000 | 255  | 65  | 79.69        |
| 1st   | 11   | Macintosh Application (data) | 38   | 16  | 76.00        |
| 1st   | 12   | XML 1.0 document text     | 420  | 128 | 71.43        |
| 1st   | 13   | ASCII text                | 242  | 142 | 63.02        |
| 1st   | 14   | Mach-O executable i386    | 3651 | 3325 | 52.54       |
| 1st   | 15   | Bourne shell script text executable | 262  | 2558 | 10.43      |
| 2nd   | 1    | Mach-O filetype=10 i386   | 64   | 0   | 100.00       |
| 2nd   | 2    | HTML document text        | 64   | 0   | 100.00       |
| 2nd   | 3    | TIFF image data; big-endian | 64   | 0   | 100.00       |
| 2nd   | 4    | data                      | 64   | 0   | 100.00       |
| 2nd   | 5    | ASCII c program text; with very long lines | 64   | 0   | 100.00       |
| 2nd   | 6    | Rich Text Format data; version 1; Apple Macintosh | 128  | 0   | 100.00       |
| 2nd   | 7    | ASCII English text        | 64   | 0   | 100.00       |
| 2nd   | 8    | a / sw/bin/scanimrun script test executable | 529  | 47  | 91.84        |
| 2nd   | 9    | perl script text executable | 968  | 64  | 93.75        |
| 2nd   | 10   | NeXT/Apple typedstream data; big endian; version 4; system 1000 | 281  | 39  | 87.81        |
| 2nd   | 11   | Macintosh Application (data) | 64   | 0   | 100.00       |
| 2nd   | 12   | XML 1.0 document text     | 366  | 82  | 81.70        |
| 2nd   | 13   | ASCII text                | 250  | 134 | 65.10        |
| 2nd   | 14   | Mach-O executable i386    | 5091 | 1985 | 72.98       |
| 2nd   | 15   | Bourne shell script text executable | 207  | 2032 | 20.62       |

Table 9. File types identification top results, bigrams, per file type (Mokhov & Debbabi (2008))

8. Conclusion

We presented an overview of MARF, a modular and extensible pattern recognition framework for a reasonably diverse spectrum of the learning and recognition tasks. We outlined the pipeline and the data structures used in this open-source project in a practical manner. We provided some typical results one can obtain by running MARF’s implementations for various learning and classification problems.

8.1 Advantages and disadvantages of the approach

The framework approach is both an advantage and a disadvantage. The advantage is obvious – a consistent and uniform environment and implementing platform for comparative studies with a plug-in architecture. However, as the number of algorithms grows it is more difficult to adjust the framework’s API itself without breaking all the modules that depend on it.

The coverage of algorithms is as good as the number of them implemented in / contributed to the project. In the results mentioned in Section 7 we could have attained better precision in some cases if better algorithm implementations were available (or any bugs in exiting ones fixed).
| Guess | Rank | Configuration               | GOOD | BAD | Precision, % |
|-------|------|-----------------------------|------|-----|--------------|
| 1st   | 1    | -wav -noise -raw -fft -cheb | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -raw -lpc -cheb       | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -bandstop -fft -cheb  | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -noise -low -fft -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -noise -norm -fft -cos| 9    | 192 | 4.48         |
| 1st   | 1    | -wav -noise -low -fft -cheb| 9    | 192 | 4.48         |
| 1st   | 1    | -wav -low -fft -cos        | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -silence -noise -raw -lpc -cheb | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -noise -low -fft -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -silence -noise -raw -lpc -cheb | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -noise -bandstop -lpc -cos | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -noise -norm -lpc -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -silence -low -fft -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -silence -noise -norm -lpc -cheb | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -silence -noise -norm -lpc -cos | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -noise -bandstop -lpc -cheb | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -silence -noise -bandstop -lpc -cheb | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -silence -noise -norm -lpc -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -noise -norm -fft -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -silence -noise -norm -fft -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -silence -noise -norm -fft -cheb | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -norm -fft -cos       | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -noise -norm -fft -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -noise -lpc -cheb     | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -low -lpc -cheb       | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -silence -noise -lpc -cheb | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -noise -norm -lpc -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -silence -low -lpc -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -norm -lpc -cheb      | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -low -lpc -cheb       | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -norm -fft -cos       | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -noise -norm -fft -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -noise -norm -fft -cheb | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -norm -lpc -cos       | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -noise -bandstop -fft -cheb | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -low -fft -cos        | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -silence -bandstop -fft -cheb | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -norm -ftp -cheb      | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -noise -bandstop -fft -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -silence -noise -norm -lpc -cheb | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -noise -norm -ftp -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -noise -norm -ftp -cheb | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -noise -bandstop -ftp -cheb | 9 | 192 | 4.48 |
| 1st   | 1    | -wav -noise -bandstop -ftp -cos | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -bandstop -lpc -cheb  | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -bandstop -lpc -cos   | 9    | 192 | 4.48         |
| 1st   | 1    | -wav -bandstop -lpc -cheb  | 9    | 192 | 4.48         |

Table 10. File types identification worst results, raw loader (Mokhov & Debbabi (2008))

8.2 Future work
The general goals of the future and ongoing research include:

- There are a lot more algorithms to implement and test for the existing tasks.
- Apply to more case studies.
- Enhance statistics reporting and details thereof (memory usage, run-time, recall, f-measure, etc.).
MARF: Comparative Algorithm Studies for Better Machine Learning  

• Scalability studies with the General Intensional Programming System (GIPSY) project (see Mokhov & Paquet (2010); Paquet (2009); Paquet & Wu (2005); The GIPSY Research and Development Group (2002–2010); Vassev & Paquet (2008)).

| Guess | Rank | Configuration | GOOD | BAD | Precision, % |
|-------|------|---------------|------|-----|--------------|
| 2nd   | 1    | -wav -noise -raw -fft -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -raw -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -bandstop -fft -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -low -fft -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -norm -fft -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -low -fft -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -noise -raw -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -low -fft -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -noise -raw -fft -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -low -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -noise -low -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -bandstop -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -norm -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -noise -low -fft -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -low -fft -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -noise -raw -fft -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -low -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -norm -fft -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -norm -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -norm -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -low -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -raw -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -norm -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -norm -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -raw -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -low -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -raw -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -bandstop -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -bandstop -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -noise -bandstop -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -norm -fft -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -norm -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -norm -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -norm -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -norm -fft -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -norm -fft -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -norm -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -noise -norm -fft -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -noise -norm -fft -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -silence -bandstop -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -bandstop -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -noise -bandstop -lpc -cos | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -noise -bandstop -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -bandstop -lpc -cheb | 10   | 191 | 4.98         |
| 2nd   | 1    | -wav -noise -bandstop -lpc -cos | 10   | 191 | 4.98         |

Table 11. File types identification worst results, 2nd guess, raw loader (Mokhov & Debbabi (2008))
| Guess | Rank | File type | GOOD | BAD | Precision, % |
|-------|------|-----------|------|-----|--------------|
| 1st   | 1    | a /sw/bin/ocamlrun script text executable | 576  | 0   | 100.00      |
| 1st   | 2    | Bourne shell script text executable    |     |     | 0.00         |
| 1st   | 3    | Mach-O filetype=10 i386                  | 0    | 64  | 0.00         |
| 1st   | 4    | HTML document text                      | 0    | 64  | 0.00         |
| 1st   | 5    | NeXT/Apple typedstream data; big endian; version 4; system 1000 | 0 | 520 | 0.00 |
| 1st   | 6    | Mach-O executable i386                   |     |     | 0.00         |
| 1st   | 7    | ASCII text                              | 0    | 384 | 0.00         |
| 1st   | 8    | TIFF image data; big endian              | 0    | 64  | 0.00         |
| 1st   | 9    | Macintosh Application (data)             | 0    | 64  | 0.00         |
| 1st   | 10   | data                                    | 0    | 64  | 0.00         |
| 1st   | 11   | ASCII c program text; with very long lines | 0 | 64  | 0.00 |
| 1st   | 12   | perl script text executable              | 0    | 1024| 0.00        |
| 1st   | 13   | Rich text Format data; version 1; Apple Macintosh | 0 | 128 | 0.00 |
| 1st   | 14   | XML 1.0 document text                    | 0    | 448 | 0.00         |
| 1st   | 15   | ASCII English text                       | 0    | 64  | 0.00         |
| 2nd   | 1    | a /sw/bin/ocamlrun script text executable | 96   | 9   | 100.00      |
| 2nd   | 2    | Bourne shell script text executable      |     |     | 0.00         |
| 2nd   | 3    | Mach-O filetype=10 i386                  | 0    | 64  | 0.00         |
| 2nd   | 4    | HTML document text                       | 0    | 64  | 0.00         |
| 2nd   | 5    | NeXT/Apple typedstream data; big endian; version 4; system 1000 | 0 | 320 | 0.00 |
| 2nd   | 6    | Mach-O executable i386                   |     |     | 0.00         |
| 2nd   | 7    | ASCII text                              | 0    | 384 | 0.00         |
| 2nd   | 8    | TIFF image data; big endian              | 0    | 64  | 0.00         |
| 2nd   | 9    | Macintosh Application (data)             | 64   | 0   | 100.00      |
| 2nd   | 10   | data                                    | 0    | 64  | 0.00         |
| 2nd   | 11   | ASCII c program text; with very long lines | 0 | 64  | 0.00 |
| 2nd   | 12   | perl script text executable              | 0    | 1024| 0.00        |
| 2nd   | 13   | Rich text Format data; version 1; Apple Macintosh | 0 | 128 | 0.00 |
| 2nd   | 14   | XML 1.0 document text                    | 0    | 448 | 0.00         |
| 2nd   | 15   | ASCII English text                       | 0    | 64  | 0.00         |

Table 12. File types identification worst results, per file, raw loader (Mokhov & Debbabi (2008))

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Table 13. Geographic location identification using article titles only on reference data (Mokhov (2010b))

| Rank # | Guess | Configuration               | GOOD | BAD | Precision, % |
|--------|-------|-----------------------------|------|-----|--------------|
| 1      | 1st   | title-only-ref-silence-noise-norm -aggr-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -fft-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-low-aggr-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-noise-norm -aggr-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-low -aggr-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-noise-norm -fft-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-low -fft-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-low-fft-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-noise-endp -aggr-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-endp -aggr-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-bandstop -aggr-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-bandstop -fft-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -aggr-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -fft-euc | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -aggr-cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -fft-cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-noise-norm -aggr-cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-noise-norm -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-bandstop -fft -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -aggr -cos | 17/14 | 7/68 | 69.06        |
| 1      | 1st   | title-only-ref-silence-noise-norm -fft -cos | 17/14 | 7/68 | 69.06        |

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