

INTRODUCTION

Outline

Interfaces

Case Studies

Summary

CLASSICAL MACHINE LEARNING

- Don't the cool kids use neural nets these days?

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CLASSICAL MACHINE LEARNING

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- ▶ *PCA, SVM, ElasticNet, kernel methods, ...*
- ▶ But still easier to interpret and faster if domain suits

WHY LINFA?

Why do classical ML in Rust? Doesn't scikit-learn solve everything?

WHY LINFA?

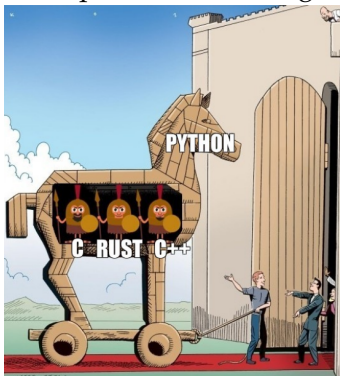
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 - Low memory environments (IoT)

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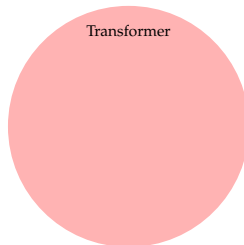
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 - ... now hosted by the Rust ML WG ...
 - ... and developed by a number growing number of contributors.

CLASSES OF ALGORITHMS

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- Examples
 - Kernel methods
 - *PCA*, Diffusion maps
 - t-SNE

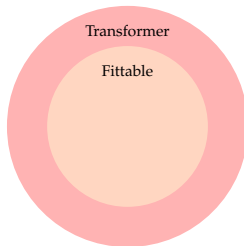


```
pub trait Transformer<R: Records, T> {  
    fn transform(&self, x: R) -> T;  
}
```

CLASSES OF ALGORITHMS

► Examples

- Decision trees
- Hierarchical clustering
- DBSCAN, Optics

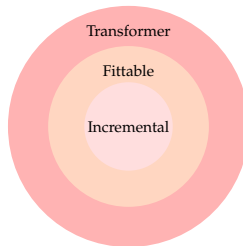


```
pub trait Fit<R: Records, T: Targets> {  
    type Object;  
  
    fn fit(&self, dataset: &Dataset<R, T>) -> Self::Object;  
}
```

CLASSES OF ALGORITHMS

► Examples

- ElasticNet
- Gaussian mixture model
- Fast ICA




```
pub trait IncrementalFit<R: Records, T: Targets> {  
  type Object;  
  
  fn fit_with<I>(&self, model: I, dataset: &Dataset<R, T>) -> Self::Object  
    where I: Into<Option<Self::Object>>;  
}
```

DATASET

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- ▶ Associated types for late binding in *Records*, *Targets* traits



```
pub struct Dataset<R, T>
where
  R: Records,
  T: Targets,
{
  records: R,
  targets: T,

  weights: Vec<f32>,
}
```

DATASET

- ▶ Offer unified interface for data and targets
- ▶ Associated types for late binding in *Records*, *Targets* traits
- ▶ Differentiate between probabilities, floating values and discrete labels

```
// Probability type
pub struct Pr(f32);

// Floating value, implemented for f32/f64
pub trait Float: NdFloat + Default + .. {}

// Discrete Label, implemented for int/str/bool
pub trait Label: Eq + Hash + Clone {}
```

METRIC - CLASSIFICATION

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- Use confusion matrix as entry point to various classification metrics



```
let cm = pred.confusion_matrix(&ground_truth);  
println!("accuracy {:.2}, precision {:.2}, MCC {:.2}",  
        cm.accuracy(), cm.precision, cm.mcc());
```

METRIC - CLASSIFICATION


- ▶ Use confusion matrix as entry point to various classification metrics
- ▶ ROC curves for binary classifications



```
// prediction is probability, ground_truth binary label  
let roc = pred.roc(&ground_truth);  
let curve = roc.get_curve();  
let auc = roc.area_under_curve();
```

DATASET - EXAMPLES

► K-Folding



```
Dataset::new(data, targets)
  .fold(12)
  .into_iter()
  .map(|(train, valid)| {
    let model = params.fit(&train);
    let predi = model.predict(&valid);
    predi.confusion_matrix(&valid)
  })
  .map(|cm| cm.accuracy())
  .sum() / 12.0;
```

DATASET - EXAMPLES

- ▶ K-Folding
- ▶ One-vs-All



```
dataset.one_vs_all()  
  .map(|(x, label)| (params.fit(&x), label))  
  .collect::<Vec<_>>()  
  .into_multi_model();
```

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- ▶ First available algorithm, implemented at RustFest 2019
- ▶ Simple Expectation-Maximization optimization with hard assignment
- ▶ Done in two days, performance already improved when compared to *Scikit-learn*

Library	Training time
Linfa	476.2 ms
Scikit-learn	604.7 ms

Table: Mean training time for model of 1 mio data points

DIFFUSION MAPS

- Connectivity as transition probability matrix \mathbf{M}

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$$v_i \rightarrow \mathbf{e}_i^T \mathbf{M}^t = (M_{i1}^{(t)}, \dots, M_{in}^{(t)}) \quad (2)$$

- Perform spectral decomposition of \mathbf{M} and project onto axis along it diffuses

DIFFUSION MAPS - EXAMPLE

```
// generate sparse RBF kernel with eps=2.0
let kernel = Kernel::params()
    .kind(KernelType::Sparse(15))
    .method(KernelMethod::Gaussian(2.0))
    .transform(&dataset);

// embed similarity matrix with diffusion maps
let embedding = DiffusionMap::<f64>::params(2)
    .steps(1)
    .build()
    .transform(&kernel);

// get embedding
let embedding = embedding.embedding();
```

Figure: Kernel method and diffusion maps invocation in Linfa

DIFFUSION MAPS - EXAMPLE

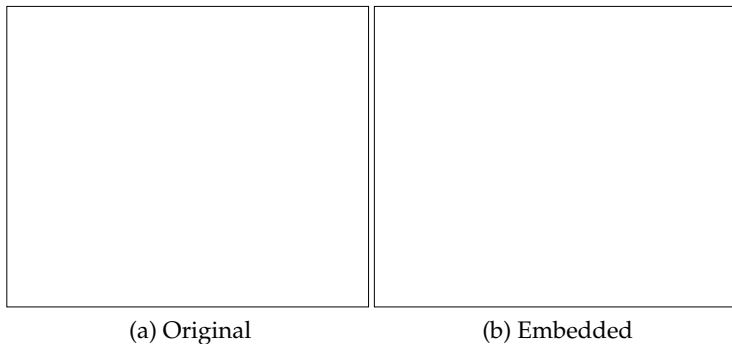


Figure: Nested rings and its transformation with diffusion maps.

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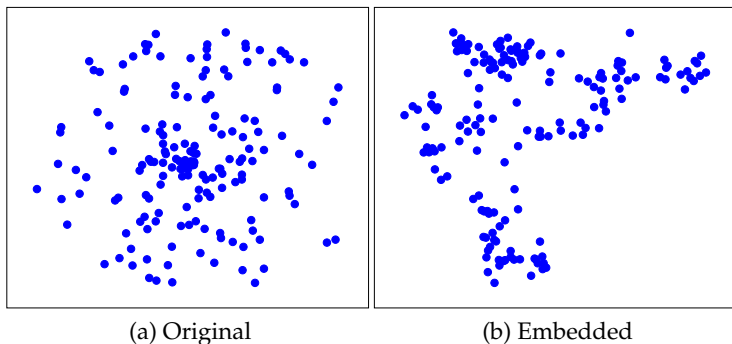


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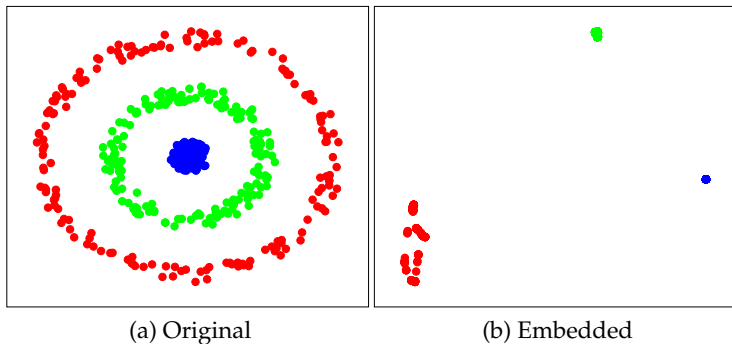



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DIFFUSION MAPS - LOBPCG

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► Locally Optimal Block Preconditioned Conjugate

Conversation 11 Commits 30 Checks 7 Files changed 14

 **bytesnake** commented on Mar 12 • edited ▾ Contributor

This PR ports the LOBPCG algorithm from [scipy](#) to Rust. The algorithm is useful for the symmetric eigenproblem for just a couple of eigenvalues (for example for multidimensional scaling of gaussian kernels). Solves the issue [#160](#)

I did not implement the generalized eigenproblem for matrix `B` different to identity, as its a uncommon use-case (at least in machine-learning), but if required the modification should be minor.

It also adds access to the functions `ssygv`, `dsygv`, `zhegv`, `chegv` for the generalized eigenvalue problem

$$\mathbf{A}\phi_i = \lambda_i \mathbf{B}\phi_i, \quad (i = 1, \dots, n)$$

with additional mass matrix `B`. The traits are implemented for tuples of `A` and `B`, so you can use it like this

```
let (eigvals, (eigvecs, B_cholesky)) = (A, B).eigh(UPLD::Upper);
```

Remaining issues:

- ☒ Implement the orthogonalization to the constraint matrix `Y`
- ☒ Improve documentation of the `lobpcg.rs` file and add examples
- ☒ Implement truncated eigenvalue decomposition
- ☒ Implement truncated SVD based on [this](#)
- ☒ Benchmark the implementation
- ☒ Add restart routine if cholesky fails

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lobpcg commented on Mar 21



pls let me know if you need any advice on LOBPCG implementation tricks

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- ▶ Ordinary least squares, generalize linear models, *elastic net*
- ▶ Fast Independent Component Analysis
- ▶ *Gaussian Naive Bayes*
- ▶ *Ensemble algorithms, Random Forest*

NEXT STEPS

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► Good progress in Roadmap Roadmap #7



LukeMathWalker opened this issue on Dec 2, 2019 · 44 comments



LukeMathWalker commented on Dec 2, 2019 · edited by bytesnake

Member



In terms of functionality, the mid-term end goal is to achieve an offering of ML algorithms and pre-processing routines comparable to what is currently available in Python's [scikit-learn](#).

These algorithms can either be:

- re-implemented in Rust;
- re-exported from an existing Rust crate, if available on [crates.io](#) with a compatible interface.

In no particular order, focusing on the main gaps:

- Clustering:
 - ☒ DBSCAN
 - ☒ Spectral clustering;
 - ☒ Hierarchical clustering;
 - ☐ OPTICS.
- Preprocessing:
 - ☒ PCA
 - ☒ ICA
- ≡ ☐ Normalisation (@InCogNiTo124 is working on it)
- ☐ CountVectoriser (@bplevin36 is working on it)
- ☐ TFIDF (@bplevin36 is working on it)
- Supervised Learning:
 - ☒ Linear regression;
 - ☐ Ridge regression; (@paulkoerbitz)
 - ☐ LASSO; (@paulkoerbitz)
 - ☐ ElasticNet; (@paulkoerbitz)
 - ☒ Support vector machines;
 - ☐ Nearest Neighbours; (@mstallmo is working on it)
 - ☐ Gaussian processes; (integrating [friedrich](#) - tracking issue [nestordemeure/friedrich#1](#))
 - ☒ Decision trees;
 - ☐ Random Forest (@foadaleta)



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- ▶ But: Most algorithms only implement “the basics”
- ▶ Good testing is hard and still needs improvement
- ▶ Interfaces are currently being unified and polished
- ▶ We also need better documentation
- ▶ And most important of all: do some real-world experiments

Thank you For Your Attention

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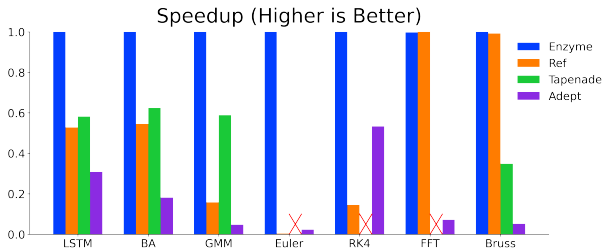
And To All Contributors



WHAT IS ABOUT AD AND GPU?

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- Enzyme: Automatically generate differentiated functions in LLVM



WHAT IS ABOUT AD AND GPU?

- ▶ Enzyme: Automatically generate differentiated functions in LLVM
- ▶ Highly parallel execution on GPUs