

## Lib15x: A Template Approach towards Building Generic Machine Learning Library



# Outline

- 1 Introduction
- 2 Inheritance or Template
- 3 Minimizing Data Copy
- 4 Back to Design

# About Lib15x

- implements most supervised learning algorithms covered in Caltech machine learning classes CS155/156.
- written in C++, use template for better performance and easing implementation.
- provides **preprocessing tools** for data scaling, feature extraction.
- interfaces to higher level **aggregation method** such as bagging, random forest, boosting, etc.
- use external matrix library "[Eigen](#)" for data storage and basic linear algebra operations.
- threaded using openmp on higher level aggregation methods. (currently in development)

# Eigen Library Fundamentals

MATRIXD, VECTORD

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## declaring Matrix/Vector:

```
Eigen::MatrixXd mat{numberOfRows, numberOfCols}; mat.fill(value);  
Eigen::VectorXd vec{numberOfElements}; vec.fill(value);
```

## supported Matrix/Vector operations:

```
Eigen::MatrixXd mat = mat_0 + mat_1; //same for -, *  
Eigen::VectorXd vec = vec_0 + vec_1; //same for -  
Eigen::VectorXd vec = mat_0 * vec_0;  
double product = vec_0.dot(vec_1);  
...
```

## accessing elements:

```
mat(rowId, colId) = value; vec(id) = value;  
Eigen::VectorXd vec = mat.row(rowId);  
Eigen::VectorXd vec = mat.col(colId);  
mat.row(rowId) = vec;  
mat.col(colId) = vec;  
...
```

## linear algebra operations:

transpose, inverse, determinant, LU factorization, eigen value decomposition, QR decomposition, sparse LA ...

# Eigen Library Fundamentals

EIGEN::MATRIXXD MEMORY LAYOUT

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Eigen::MatrixXd are stored in **contiguous** memory:  
(different from std::vector<std::vector<double> >).

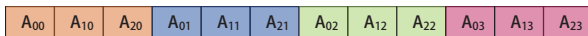
**row-major matrix:**

```
Eigen::Matrix<double, Eigen::Dynamic, Eigen::Dynamic, Eigen::RowMajor> A{3,4};
```



**column-major matrix:**

```
Eigen::Matrix<double, Eigen::Dynamic, Eigen::Dynamic> A{3,4};
```



by default Eigen::MatrixXd is typedefed as column-major.

Question: How are Eigen::MatrixXd::row(rowId) and Eigen::MatrixXd::col(colId) implemented? (becoming important later.)

# Eigen Library Fundamentals

EIGEN::MAP

Yingrui (Ray) Chang

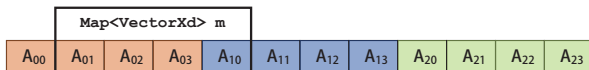
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- `Eigen::Map` : A matrix or vector expression mapping an existing array of data.
- usage: constructing a “Matrix/Vector” on existing data.

```
Eigen::MatrixXd A{3,4}; A.fill(1.);
Eigen::Map<Eigen::VectorXd> m(&A(0,1), 3);
A.fill(10.);
std::cout<<m.transpose()<<std::endl;
```

output: 10 10 10 10



- `Eigen::Map` can be implicitly converted to `Eigen::MatrixXd` or `Eigen::VectorXd`

```
Eigen::Map<VectorXd> m(&A(0,1), 3);
Eigen::VectorXd vec = m;
```

but usually involves copying data to create a new vector.

# Lib15x Basic Data Types

- data is stored in `Eigen::MatrixXd` with each sample corresponds to one row.
- labels type has corresponding enum associated to identify classification or regression for type safety.

```
enum class ProblemType {Classification, Regression};
```

```
struct Labels {  
    ProblemType _labelType;  
    Eigen::VectorXd _labelData;  
}
```

- each model defines its own problem type and loss function as static data members:

```
class ClassifierModel {  
public:  
    static const ProblemType ModelType = ProblemType::Classification;  
    static double LossFunction(const Labels&, const Labels&);  
    ...  
}
```

# Lib15x User Interfaces(1)

SUPPORT VECTOR MACHINE

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**import Lib15x namespace:**

```
#include <Lib15x.hpp>
using namespace Lib15x;
```

**defining learning model:**

```
using Kernel = Kernels::RBF;
using LearningModel = Models::LibSVM<Kernel>;
```

**model declaration:**

```
LearningModel learningModel{numberOfFeatures, numberOfClasses, Kernel{gamma}};
```

**training and predicting:**

```
learningModel.train(trainData, trainLabels);
Labels predictedLabels = learningModel.predict(trainData);
```

**compute in-sample accuracy:**

```
constexpr double (*LossFunction)(const Labels&, const Labels&) =
    LearningModel::LossFunction;
double accuracy = 1.0 - LossFunction(predictedLabels, trainLabels);
```

full example at *Lib15x/src/example/libsvm\_example.cc*





## Lib15x User Interfaces (2)

### CROSS VALIDATION, MULTI-CLASS CLASSIFICATION

**define multiclass with a binary class model:**

```
using Kernel = Kernels::RBF;  
using BinaryModel = Models::LibSVM<Kernel>;  
using MulticlassModel = Models::MulticlassClassifier<BinaryModel>;
```

**declare multiclass model:**

```
long numberOfClasses = 2;  
BinaryModel binaryModel{numberOfFeatures, numberOfClasses, C, Kernel{gamma}};  
MulticlassModel multiclassModel{numberOfFeatures, numberOfClasses, binaryModel};
```

**compute cross validation score:**

```
CrossValidation crossValidation{trainData, trainLabels, true};  
VectorXd losses = crossValidation.computeValidationLosses(&multiclassModel);
```

full example at *Lib15x/src/example/cross\_validation\_example.cc*

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# Inheritance & Virtual Functions

SUPPORT VECTOR MACHINE, KERNELS

## kernel interface:

```
class Kernel {  
public:  
    virtual double operator() (const VectorXd&, const VectorXd&) const = 0;  
};
```

## specific kernel implementations:

```
class KernelRBF : public Kernel {  
public:  
    explicit RBF(double gamma) : _gamma(gamma) {}  
    double operator() (const VectorXd& x, const VectorXd& y) const {  
        return exp(-_gamma*(x-y).squaredNorm());  
    }  
private:  
    double _gamma;  
};  
  
class KernelDot : public Kernel {  
public:  
    double operator()(const VectorXd& x, const VectorXd& y) const {  
        return x.dot(y);  
    }  
};
```



# Inheritance & Virtual Functions

SUPPORT VECTOR MACHINE, KERNELS

support vector machine:

```
class SupportVectorClassifier {
public:
    //...
    void train(const MatrixXd& trainData, const Labels& labels) {
        //at some point ...
        G(idI, idJ) = (*kernel)(trainData.row(idI), trainData.row(idJ));
    }
private:
    //...
    Kernel* kernel;
};
```



# Inheritance & Virtual Functions

SUPPORT VECTOR MACHINE, KERNELS

support vector machine:

```
class SupportVectorClassifier {
public:
    //...
    void train(const MatrixXd& trainData, const Labels& labels) {
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        G(idI, idJ) = (*kernel)(trainData.row(idI), trainData.row(idJ));
    }
private:
    //...
    Kernel* kernel;
};
```

implementation difficulties caused by pointer data member:

- choice of pointer (`std::unique_ptr`, `std::shared_ptr` or `raw *`);
- more implementation work:  
copy constructor, copy assignment operator, destructor,  
move constructor; move assignment operator (after C++11),  
`clone()`...
- exception safety ...

# Performance Issues Caused by Virtual Function

- an extra v-pointer (large data type: typically 8 bytes);
- tracing pointers (cache unfriendly);
- harmful to data alignment.
- impossible for function inlining.



## Performance Issues Caused by Virtual Function

- an extra v-pointer (large data type: typically 8 bytes);
- tracing pointers (cache unfriendly);
- harmful to data alignment.
- impossible for function inlining.

benchmark test designed by *crashwork*:

```
class TestVec {  
public:  
    float GetX() { return x; }  
    float SetX(float to) { return x=to; }  
    // GetY(), GetZ()45 SetY(), SetZ(), GetW(), SetW()  
private:  
    float x,y,z,w;  
};
```

test process:

- populate three arrays each with 1024 TestVec
- ran a loop that calls Get\*() and Set\*() to add each member to one another 1000 times.
- record average time used in each loop when Get\*() and Set\*() are *virtual*, *direct* and *inline*.

source code available at :

<http://assemblyrequired.crashworks.org/code-for-testing-virtual-function-speed/> (for Microsoft VS compiler)

[https://github.com/yingryic/performance\\_study/](https://github.com/yingryic/performance_study/) (for GCC compiler)

# Performance Issues Caused by Virtual Function

## testing results:

### test on my own machine:

compiler: g++-4.9  
cpu: Intel Core i7, 2.20GHz  
L1 cache size: 64KB

### average running time for a single loop:

- virtual: 75ms
- direct: 68ms
- inline: 2ms

### report by *crashwork*

compiler: Microsoft Visual Studio  
cpu: 3GHz  
L1 cache size: big enough to fit all the data

- virtual: 160ms
- direct: 68ms
- inline: 8ms



# Performance Issues Caused by Virtual Function

## testing results:

### test on my own machine:

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cpu: Intel Core i7, 2.20GHz  
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compiler: Microsoft Visual Studio  
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L1 cache size: big enough to fit all the data

- virtual: 160ms
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## take-home message:

- virtual function call cannot be faster than direct function call (usually slower because of the vpointer tracing mechanism).
- consider function inlining whenever possible.

# Template Alternative

SUPPORT VECTOR MACHINE

kernels are not derived from any class:

```
class KernelDot {  
public:  
    //...  
    double operator() (const VectorXd& x, const VectorXd& y) const {  
        return x.dot(y);  
    }  
};
```



# Template Alternative

## SUPPORT VECTOR MACHINE

kernels are not derived from any class:

```
class KernelDot {
public:
    //...
    double operator() (const VectorXd& x, const VectorXd& y) const {
        return x.dot(y);
    }
};
```

svm class contains a kernel object instead of pointer:

```
template<class Kernel>
class SupportVectorClassifier {
public:
    //...
    void train(const MatrixXd& trainData, const Labels& labels) {
        //...
        G(idI, idJ) = kernel(trainData.row(idI), trainData.row(idJ));
    }
private:
    //...
    Kernel kernel;
};
```

# Template vs Virtual Function

SUPPORT VECTOR MACHINE

## advantage of using template:

- no extra pointer and virtual function calls.
- can rely on the default copy/move constructor/assignment operator, destructor, etc.
- possible for function inlining (compiler can see the implementation).

# Template vs Virtual Function

SUPPORT VECTOR MACHINE

## advantage of using template:

- no extra pointer and virtual function calls.
- can rely on the default copy/move constructor/assignment operator, destructor, etc.
- possible for function inlining (compiler can see the implementation).

## advice from *Bjarne Stroustrup*:

- **Prefer a template** over derived classes when run-time efficiency is at a premium.
- Prefer derived classes over a template if adding new variants without recompilation is important.
- **Prefer a template** over derived classes when no common base can be defined.
- **Prefer a template** over derived classes when built-in types and structures with compatibility constraints are important.

*The C++ Programming Language, 3rd Edition, chapter 13.8*

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# Avoid Data Copying with Individual Sample

EIGEN::MAP

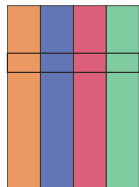
data forwarding problem:

```
Kernel::operator(const VectorXd&, const VectorXd&) const;
SupportVectorClassifier::train(const MatrixXd& trainData, const Labels& trainLabels) {
    //...
    G(idI, idJ)=kernel(trainData.row(sampleIdI), trainData.row(sampleIdJ));
}
```

question: what does `Eigen::MatrixXd::row(rowId)` return? possibly avoiding copying?

answer: cannot avoid copying since `Eigen::MatrixXd` is column major by default.

MatrixXd



data layout in memory:



MatrixXd::row(i)



MatrixXd::col(j)



but we should do better!



# Avoid Data Copying with Individual Sample

EIGEN::MAP

use row major matrix by default:

```
using MatrixXd = Eigen::Matrix<double, Eigen::Dynamic, Eigen::Dynamic, Eigen::RowMajor>;
```

MatrixXd

data layout in memory:

data_0
data_1
data_2
data_3
data_4

data_0	data_1	data_2	data_3	data_4
--------	--------	--------	--------	--------

possible to create “reference” to each data sample:

```
Map<VectorXd> vec_1(&trainData(1,0), numberOfCols)
```

forwarding Eigen::Map instead of vector to avoid data copying:

```
Kernel::operator()(const Eigen::Map<const VectorXd>&,
                  const Eigen::Map<const VectorXd>&) const;

SVM::train(const Eigen::MatrixXd& trainData, const Labels& trainLabels) {
    //...
    Eigen::Map<const VectorXd> dataI(&trainData(idI,0), numberOfFeatures);
    Eigen::Map<const VectorXd> dataJ(&trainData(idJ,0), numberOfFeatures);
    G(idI, idJ)=kernel(dataI, dataJ);
}
```



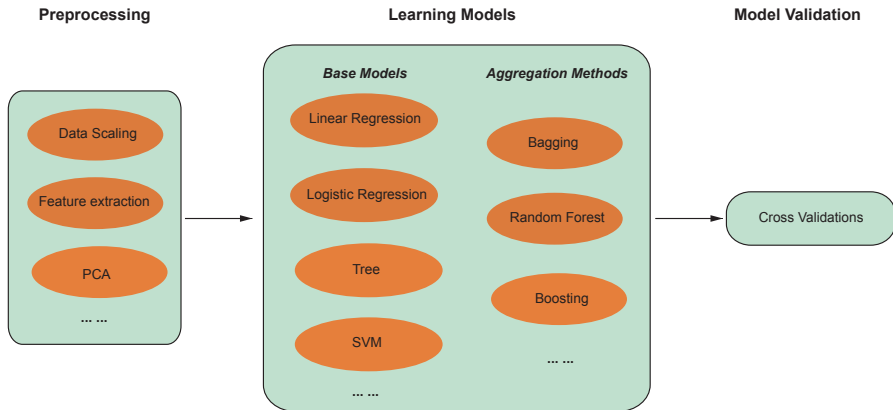
# Avoid Data Copying

INTERFACE DESIGN

training interface:

```
void train(const MatrixXd& trainData, const Labels& trainLabels);
```

problem: typical machine learning pipeline:





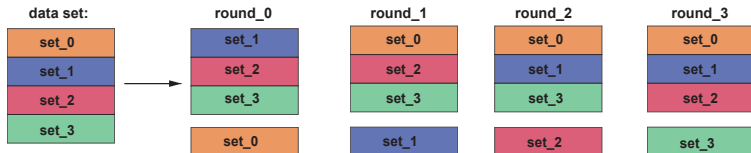
# Avoid Data Copying

INTERFACE DESIGN

training interface:

```
void train(const MatrixXd& trainData, const Labels& trainLabels);
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cross validation in action:





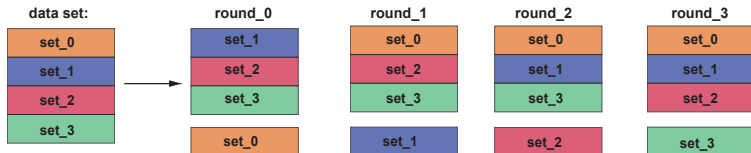
# Avoid Data Copying

INTERFACE DESIGN

training interface:

```
void train(const MatrixXd& trainData, const Labels& trainLabels);
```

cross validation in action:



implementation:

```
template<class LearningModel>
VectorXd CrossValidation::computeValidationLosses(LearningModel* learningModel) {
    //...
    for (long currentRoundId =0; ...) {
        //...
        MatrixXd trainDataOfThisRound{...};
        Labels trainLablesOfThisRound{...};
        //populate training and testing data
        learningModel->train(trainDataOfThisRound, trainLabelsOfThisRound);
        //do the same for testing ...
    }
};
```

# Index Based Training

inner training interface:

```
void train(const MatrixXd& trainData, const Labels& trainLabels,  
          const vector<long>& trainIndices) {  
    //train the model with the data identified by the trainIndices  
};
```



# Index Based Training

inner training interface:

```
void train(const MatrixXd& trainData, const Labels& trainLabels,
          const vector<long>& trainIndices) {
    //train the model with the data identified by the trainIndices
};
```

used by higher level classes:

- cross validation:

```
template<class LearningModel>
VectorXd CrossValidation::computeValidationLosses(LearningModel* learningModel) {
    for (long currentRoundId =0; ...) {
        //populate training data indices
        learningModel->train(_data, _labels, trainIndices);
    }
};
```

- bagging classifier:

```
BaggingClassifier::train(const MatrixXd& trainData, const Labels& trainLabels,
                        const vector<long>& trainIndices) {
    for (long modelId =0; ...) {
        //sample training data indices into trainIndices with replacement
        baseModels[modelId].train(_data, _labels, trainIndicesForThisModel);
    }
};
```

- Multi-class model, Random Forest, ... ..

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# Interfaces Summary

user interfaces:

```
void train(const MatrixXd& trainData, const Labels& trainLabels) {  
    //check user input  
    //populate trainIndices  
    train(trainData, trainLabels, trainIndices);  
}  
  
Labels predict(const MatrixXd& testData) {  
    //check user input  
    //populate testIndices  
    return predict(trainData, trainLabels, trainIndices);  
}
```



# Interfaces Summary

## user interfaces:

```
void train(const MatrixXd& trainData, const Labels& trainLabels) {  
    //check user input  
    //populate trainIndices  
    train(trainData, trainLabels, trainIndices);  
}
```

```
Labels predict(const MatrixXd& testData) {  
    //check user input  
    //populate testIndices  
    return predict(trainData, trainLabels, trainIndices);  
}
```

## interfaces for library developer:

```
void train(const MatrixXd& trainData, const Labels& trainLabels,  
           const vector<long>& trainIndices) {  
    //do training  
}  
  
Labels predict(const MatrixXd& trainData, const Labels& trainLabels,  
               const vector<long>& trainIndices) {  
    //do predicting  
}
```





# Implementation Difficulties

## user interfaces:

```
void train(const MatrixXd& trainData, const Labels& trainLabels);  
Labels predict(const MatrixXd& testData);
```

## interfaces for library developer:

```
void train(const MatrixXd& trainData, const Labels& trainLabels,  
           const vector<long>& trainIndices);  
Labels predict(const MatrixXd& trainData, const Labels& trainLabels,  
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```

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Labels predict(const MatrixXd& trainData, const Labels& trainLabels,  
               const vector<long>& trainIndices);
```

## template awkward:

same user interface implementations for every model, but template requires every model implementing all the interfaces.



# Implementation Difficulties

## user interfaces:

```
void train(const MatrixXd& trainData, const Labels& trainLabels);  
Labels predict(const MatrixXd& testData);
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## interfaces for library developer:

```
void train(const MatrixXd& trainData, const Labels& trainLabels,  
           const vector<long>& trainIndices);  
Labels predict(const MatrixXd& trainData, const Labels& trainLabels,  
               const vector<long>& trainIndices);
```

## template awkward:

same user interface implementations for every model, but template requires every model implementing all the interfaces.

## solution:

need to explore class hierarchy to ease implementation but without using virtual functions.



# Curiously Recurring Template Pattern (CRTP)

## BASIC IDEA

base model:

```
template<class DerivedModel>
class BaseModel {
public:
    void train(const MatrixXd& trainData, const Labels& trainLabels) {
        //do all the checking
        //populate indices for all training data
        static_cast<DerivedModel*>(this)->train(trainData, trainLabels, trainIndices);
    }
};
```



# Curiously Recurring Template Pattern (CRTP)

## BASIC IDEA

### base model:

```
template<class DerivedModel>
class BaseModel {
public:
    void train(const MatrixXd& trainData, const Labels& trainLabels) {
        //do all the checking
        //populate indices for all training data
        static_cast<DerivedModel*>(this)->train(trainData, trainLabels, trainIndices);
    }
};
```

### derived model:

```
class SVM : public BaseModel<SVM> {
public:
    using BaseModel<SVM> train;
    void train(const MatrixXd& trainData, const Labels& trainLabels) {
        //do the actual training
    }
};

template<typename ImpurityRule>
class TreeClassifier : public BaseModel<TreeClassifier<Impurityrule> > {...};
```



# Curiously Recurring Template Pattern (CRTP)

## BASIC IDEA

### base model:

```
template<class DerivedModel>
class BaseModel {
public:
    void train(const MatrixXd& trainData, const Labels& trainLabels) {
        //do all the checking
        //populate indices for all training data
        static_cast<DerivedModel*>(this)->train(trainData, trainLabels, trainIndices);
    }
};
```

### derived model:

```
class SVM : public BaseModel<SVM> {
public:
    using BaseModel<SVM> train;
    void train(const MatrixXd& trainData, const Labels& trainLabels) {
        //do the actual training
    }
};

template<typename ImpurityRule>
class TreeClassifier : public BaseModel<TreeClassifier<Impurityrule> > {...};
```

### user code:

```
SVM model{...}; model.train(trainData, trainLabels);
TreeClassifier<Gini> model{...}; model.train(trainData, trainLabels);
```



## Example: Lib15x BaseClassifier

```
template<class DerivedClassifier>
class _BaseClassifier {
public:
    static const ProblemType ModelType = ProblemType::Classification;
    static constexpr const char* ModelName=DerivedClassifier::ModelName;
    static double LossFunction(const Labels& predictedLabels, const Labels& testLabels) {...};
```

```
    long getNumberOfFeatures() const {...};
    long getNumberOfClasses() const {...};
    VerboseFlag& whetherVerbose();
protected:
    long _numberOfFeatures;
    long _numberOfClasses;
    VerboseFlag _verbose = VerboseFlag::Quiet;
};
```

Every model should implement:

- `train(...)`;
- `predictOne(...)`;
- `_clearModel()`;

*Lib15x/src/include/internal/\_BaseClassifier.hpp*



## Example: Lib15x BaseClassifier

```
template<class DerivedClassifier>
class _BaseClassifier {
public:
    static const ProblemType ModelType = ProblemType::Classification;
    static constexpr const char* ModelName=DerivedClassifier::ModelName;
    static double LossFunction(const Labels& predictedLabels, const Labels& testLabels) {...};
    void train(const MatrixXd& trainData, const Labels& trainLabels) {
        //...
        static_cast<DerivedModel*>(this)->train(trainData, trainLabels, trainIndices);
    }
    Labels predict(const MatrixXd& testData) const {...};
    Labels predict(const MatrixXd& testData, const vector<long>& testIndices) const {
        //...
        for (auto testDataId : testIndices){
            Map<const VectorXd> instance(&testData(testDataId, 0), _numberOfFeatures);
            predictedLabels._labelData(testDataId) =
                static_cast<const DerivedClassifier*>(this)->predictOne(instance);
        }
        return predictedLabels;
    }
    void clear() {
        static_cast<DerivedClassifier*>(this)->_clearModel();
    }
    long getNumberOfFeatures() const {...};
    long getNumberOfClasses() const {...};
    VerboseFlag& whetherVerbose();
protected:
    long _numberOfFeatures;
    long _numberOfClasses;
    VerboseFlag _verbose = VerboseFlag::Quiet;
};
```

Every model should implement:

- train(...);
- predictOne(...);
- \_clearModel();

*Lib15x/src/include/internal/\_BaseClassifier.hpp*



## Example: TreeClassifier



```
template<double (*ImpurityRule)(const vector<long>&) = gini>
class TreeClassifier : public _BaseClassifier<TreeClassifier<ImpurityRule> > {
public:
    using BaseClassifier = _BaseClassifier<TreeClassifier<ImpurityRule> >;
    using BaseClassifier::train;
    static constexpr const char* ModelName = "TreeClassifier";
    static constexpr double (*LossFunction)(const Labels&, const Labels&) = BaseClassifier::LossFunction;

private:
    long _minSamplesInALeaf;
    long _minSamplesInANode;
    long _maxDepth;
    long _maxNumberOfLeafNodes;
    _ClassificationTree _tree;
};
```

*Lib15x/src/include/models/TreeClassifier.hpp*



## Example: TreeClassifier

```
template<double (*ImpurityRule)(const vector<long>&) = gini>
class TreeClassifier : public _BaseClassifier<TreeClassifier<ImpurityRule> > {
public:
    using BaseClassifier = _BaseClassifier<TreeClassifier<ImpurityRule> >;
    using BaseClassifier::train;
    static constexpr const char* ModelName = "TreeClassifier";
    static constexpr double (*LossFunction)(const Labels&, const Labels&) = BaseClassifier::LossFunction;

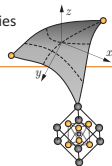
    void train(const MatrixXd& trainData, const Labels& trainLabels, const vector<long>& trainIndices) {
        //...
    }
    double predictOne(const Map<const VectorXd>& instance) const {
        //...
    }
    void _clearModel() {
        //...
    }

private:
    long _minSamplesInALeaf;
    long _minSamplesInANode;
    long _maxDepth;
    long _maxNumberOfLeafNodes;
    _ClassificationTree _tree;
};
```

*Lib15x/src/include/models/TreeClassifier.hpp*



Graduate Aerospace Laboratories  
Kochmann Research Group



**Thank you for your interest!**

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**References::**

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