A practical guide to Support Vector Machine and the Kernel Based Learning Platform (KeLP)

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Support Vector Machines

- Let us consider a binary classification problem where example are represented in a "input" space $X \subseteq \mathcal{R}^n$ and the output space $Y = \{-1, 1\}$
  - Training set $S = \{(x_1, y_1), \ldots (x_l, y_l)\} \in (X \times Y)$
- We want to derive a relation binding X and Y
- In a classification problem, we want to induce a decision function f that, given a new example x, produces a label -1 or +1, depending on the assigned class

Support Vector Machines

- A binary classifier is can be implemented considering the function
- f: $X \subseteq \mathcal{R}^n \rightarrow \mathcal{R}$:
  - if $f(x) \geq 0$ $+1$
  - if $f(x) < 0$ -1
- And the final classification function is:
  - $sign(f(x))$

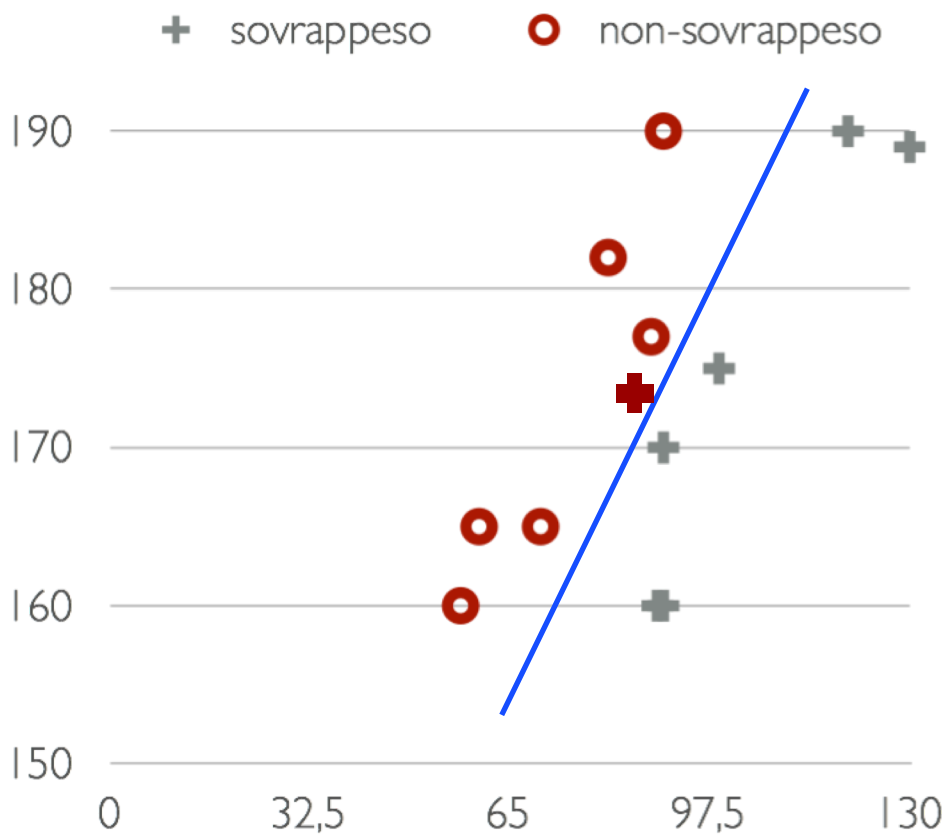
SVM Optimization: trade-off between training error and margin

The soft-margin SVM allows classification errors in the training set

- The regularization parameter C need to appropriately chosen
- A very high value of C corresponds to the hard margin SVM

$$\text{Minimize:} \quad \frac{1}{2}||\vec{w}||^2 + C\sum_k \xi_k$$

$$\text{subject to:} \quad \forall k : y_k[\vec{w} \cdot \vec{x_k} + b] \geq 1 - \xi_k$$



SVM OPTIMIZATION: Adjusting the cost of false positives vs. false negatives

- As we can deal with unbalanced numbers of positive and negative examples, two different cost factors $\mathbf{C_+}$ and $\mathbf{C_-}$ are employed.

$$\begin{aligned} &\text{Minimize:} && \frac{1}{2}||\vec{w}||^2 + C_+ \sum_{i:y_i=1} \xi_i + C_- \sum_{j:y_j=-1} \xi_j \\ &\text{subject to:} && \forall k : y_k[\vec{w} \cdot \vec{x_k} + b] \geq 1 - \xi_k \end{aligned}$$

- They allow to adjust the cost of false positives vs. false negatives

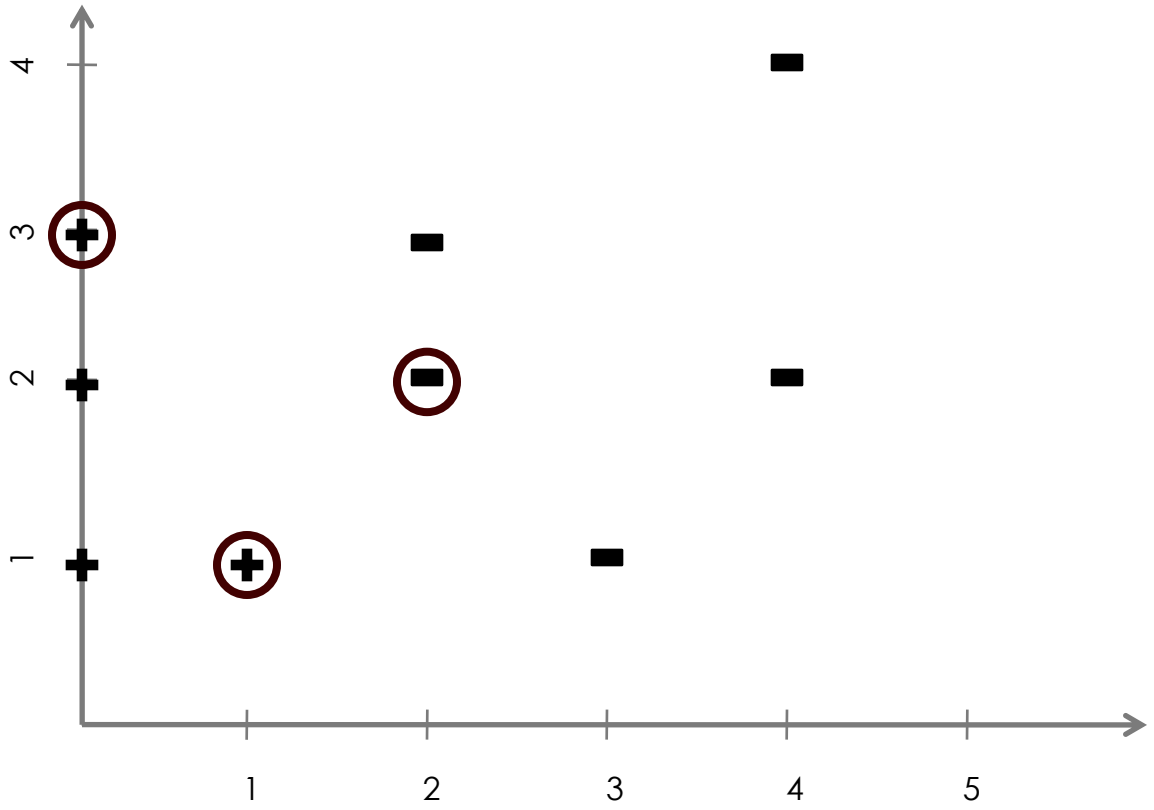
A practical example

Positive Ex.

a1 (1,1)
a2 (0,1)
a3 (0,2)
a4 (0,3)

Negative Ex.

b1 (3,1)
b2 (2,2)
b3 (2,3)
b4 (4,2)
b5 (4,4)



We apply the SVM learning algorithms

	a_i	COORD
sv_1	0.222	(0,3)
sv_2	0.889	(1,1)
sv_3	-1.111	(2,2)
b	3	

A practical example

	α_i	COORD
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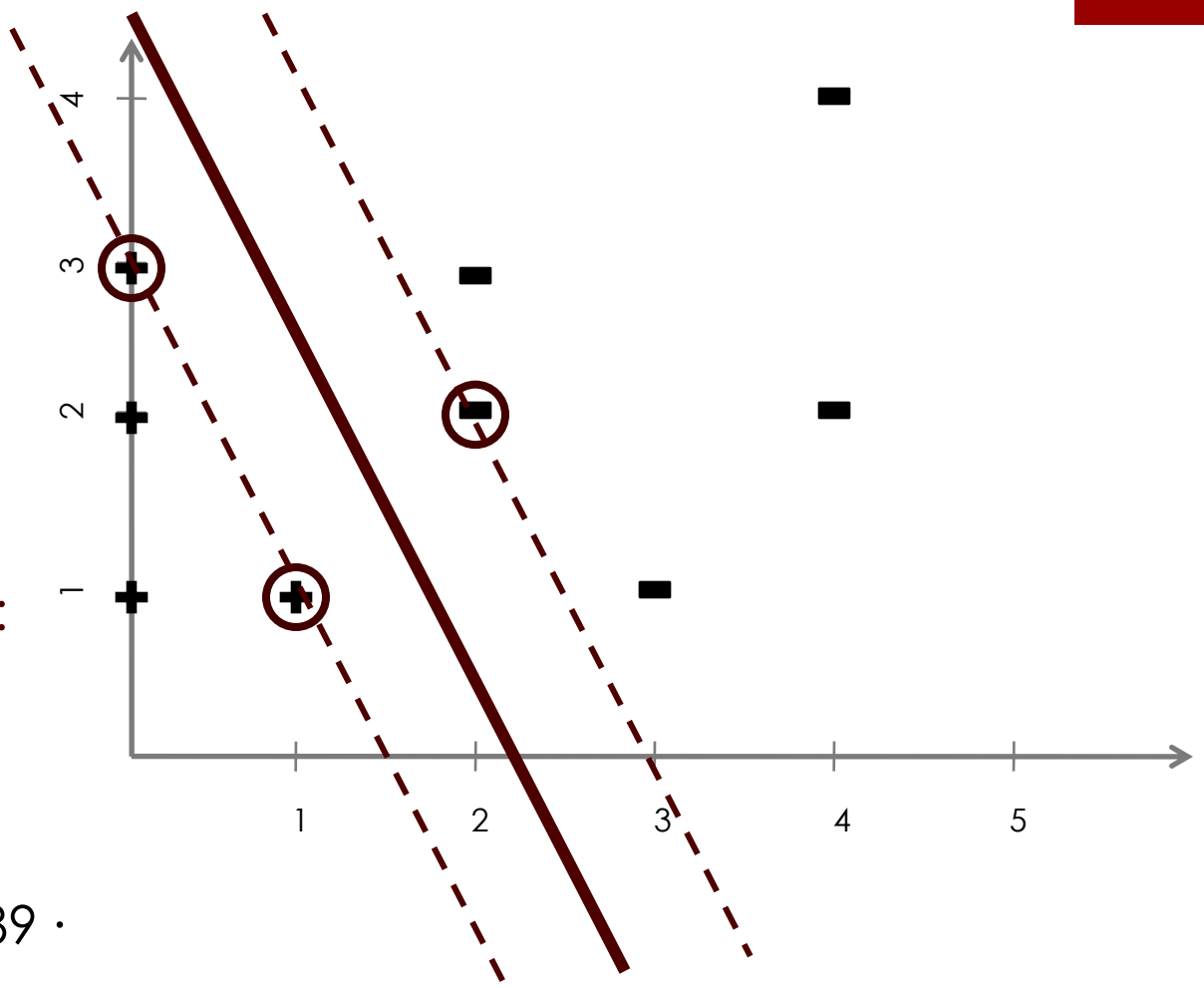


Hyperplane Equation:
$w \cdot x + b = 0$

$w = \sum a_i \cdot sv_i =$

$w = 0.222 \cdot (0,3) + 0.889 \cdot (1,1) - 1.111 \cdot (2,2)$

$w = (-1.3334 , -0.6667)$

$-1.3334 \cdot x_1 - 0.6667 \cdot x_2 + 3 = 0$

A ***Ke***rnel-based ***L***earning ***P***latform

- **KeLP** is a Java *open source* Machine Learning platform focusing on Kernel machines
  - http://www.kelp-ml.org
- Kernel are decoupled from learning algorithms, through the definition of specific interfaces
  - Support for the following learning tasks, e.g. Classification, Regression, Learning over sequences, Clustering…
  - Several learning algorithms are implemented for
    - **Batch Learning**: SVM, Pegasos, …
    - **Online Learning**: Perceptron, Passive-Aggressive, …

Kelp and Maven

- You can import the KeLP library via Maven
  - Instructions are available at:

  http://www.kelp-ml.org/?page_id=170

- The source code is open-source and you can download it from

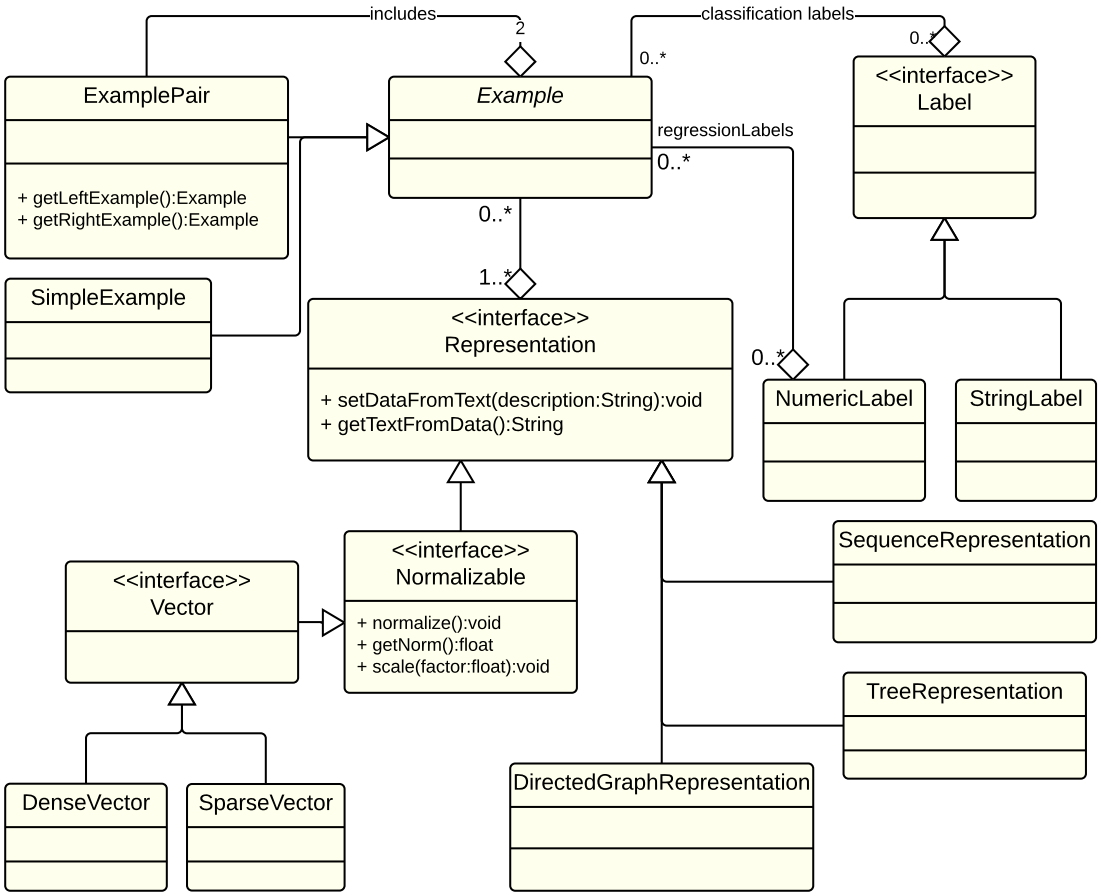
  https://github.com/SAG-KeLP

- KeLP is divided in four java projects
  - `kelp-core`: it contains the core interfaces and classes for algorithms, kernels and representations. (It contains the stands SVM)
  - `kelp-additional-kernels`: it contains additional kernel functions, such as the Tree Kernels.
  - `kelp-additional-algorithms`: it contains additional learning algorithms
  - `kelp-full`: it aggregates via Maven all the above projects.

Examples/Representation/Algorithms and Java Objects

- Each example is stored in the `Example` object and it is characterized by
  - A set of `Label`s reflecting one or more classes
  - A list of `Representation`s each identified by a `String`
- Examples are collected in `Dataset`s
- Several `LearningAlgorithm`s have been implemented
  - `BinaryCSvmClassification` implements the SVM learning algorithm seen in previous lessons

A Class Diagram of main objects



Input Data

- A dataset can be stored in a textual file (this is not true for graphs)
  - Each row of a dataset represents an `Example` according to the following format

label1 ... labelN |B*type1*:*name1*| *descrip.* |E*type1*| |B*type2*:*name2*| *descrip.* |E*type2*|

- The list of strings label1 ... labelN identifies the classes
- An example can be represented through multiple representations, whose type must be specified:
  - V: Vector (default is sparse vector)
  - DV: Dense Vector
  - T: Tree
  - S: String
  - SQ: Sequence
- Each representation has a name used by the kernel function for a proper selection
  - A representation starts with a tab B (e.g., BV) and is closed with a tag E (e.g., EV)

Let us consider the Question Classification task…

- Question classification consists in assigning a question to a class reflecting the intention of the question.

  Example: "*What is the width of a football field?*" → `Number`

- A QC dataset is available at:

  http://cogcomp.cs.illinois.edu/Data/QA/QC/

  - Train dataset: 5,452 questions
  - Test dataset: 500 questions

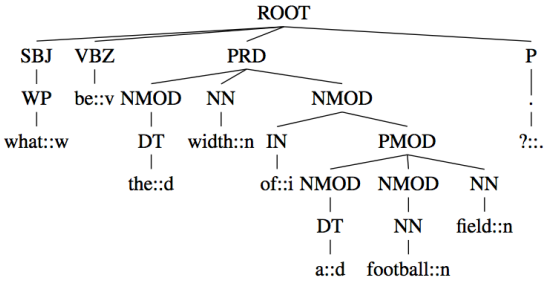
- Two settings:
  - Coarse-Grained: 6 classes ← We will focus on this setting
  - Fine-grained: 50 classes

[1] Xin Li, Dan Roth, Learning Question Classifiers. COLING'02, Aug., 2002.

Multiple ways to represent a question

```
NUM |BV:bow| _what__w:1.0 _a__d:1.0 _field__n:1.0 _football__n:1.0
_the__d:1.0 _be__v:1.0 _width__n:1.0 _of__i:1.0 _?__.:1.0 |EV| |BT:grct|
(SYNT##root(POS##WP(LEX##what::w))(SYNT##cop(POS##VBZ(LEX##be::v)))(SYNT##nsu
bj(SYNT##det(POS##DT(LEX##the::d)))(POS##NN(LEX##width::n))(SYNT##prep_of(SYN
T##det(POS##DT(LEX##a::d)))(SYNT##nn(POS##NN(LEX##football::n)))(POS##NN(LEX#
#field::n))))))|ET|
|BS:quest| What is the width of a football field ?|ES|
```

- NUM is the class assigned to the question
- |BV:bow| _what__w:1.0 _a__d:1.0 ... |EV|
  it is a vector (V) called bow (do you remember the Bag-of-word representation?)
- |BT:grct| (SYNT##root(POS##WP(LEX##what::w)) ... |EV|
  it is a tree (T) derived from the dependency parsing of the question written in parenthetic form
- |BS:quest| What is the width of a football field ?|ES|
  It is a string (S). It is not used by kernel functions but it can be used to comment examples.



Grammatical Relation Centered Tree (GRCT)

see Danilo Croce, Alessandro Moschitti, Roberto Basili: *Structured Lexical Similarity via Convolution Kernels on Dependency Trees*. In proceedings of EMNLP 2011: pages 1034-1046

Handling datasets

- Given a dataset in a file, we can load the dataset with

```
String datasetFilePath="qc_train.klp"
SimpleDataset trainingSet = new SimpleDataset();
trainingSet.populate(datasetFilePath);
```

- We can access the examples and representations

```
for(Example e: trainingSet.getExamples()){
   Representation rep = e.getRepresentation("bow");
}
```

- We can shuffle the dataset

```
SimpleDataset shDataset = trainingSet.getShuffledDataset();
```

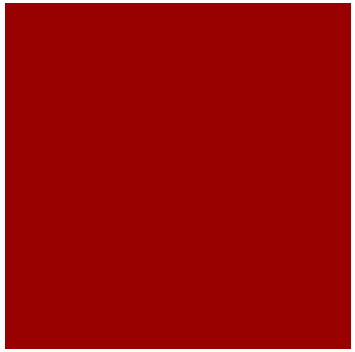
- We can split the dataset in two datasets according to a split rate

```
float splitRate=0.8f;
SimpleDataset[] split = trainingSet.split(splitRate);
```

- Check if an example is associated to a class

```
StringLabel stringLabel = new StringLabel("NUM");
boolean isNum = e.isExampleOf(stringLabel);
```

Kernels



- KeLP implements the following kernels seen in the previous lessons
- Linear Kernel

```
String vectorRepName = "bow";
Kernel linearKernel = new LinearKernel(vectorRepName);
```

- Polynomial Kernel

```
String vectorRepName = "bow";
int exp=2;
Kernel linearKernel = new LinearKernel(vectorRepName );
Kernel polynKernel = new PolynomialKernel(exp, linearKernel);
```

Kernels (2)

- Tree kernel (Vishwanathan and Smola, 2003)

```
String treeRepresentationName = "grct";
float lambda = 0.4f;
Kernel tkgrct = new SubSetTreeKernel(lambda,
treeRepresentationName);
```

- Linear combination

```
String vectorRepresentationName = "bow";
String treeRepresentationName = "grct";
float lambda = 0.4f;

Kernel linearKernel = new LinearKernel(vectorRepresentationName);
Kernel tkgrct = new SubSetTreeKernel(lambda,
treeRepresentationName);

LinearKernelCombination combination = new LinearKernelCombination();
combination.addKernel(0.7, linearKernel);
combination.addKernel(0.3, tkgrct);
```

Kernels (2)

- Kernel Normalization

```
Kernel linearKernel = new LinearKernel(vectorRepName);
Kernel normLinearKernel = new NormalizationKernel(linearKernel);
```

- Kernel Normalization and Combination

```
Kernel linearKernel = new LinearKernel(vectorRepName);
Kernel normLinearKernel = new NormalizationKernel(linearKernel);

Kernel treeKernel = new SubSetTreeKernel(lambda, treeRepName);
Kernel normTreeKernel = new NormalizationKernel(treeKernel);

LinearKernelCombination comb = new LinearKernelCombination();
comb (0.7, normLinearKernel );
comb (0.3, normTreeKernel );
```

Binary Learning Algorithms

```
// define the positive class
StringLabel positiveClass = new StringLabel("+1");
// instantiate a learning algorithm
BinaryCSvmClassification learningAlgo = new
BinaryCSvmClassification();
// indicate to the learner what is the positive class
learningAlgo.setLabel(positiveClass);
// set the regularization parameters
learningAlgo.setCp(c);
learningAlgo.setCn(c);

// set the kernel function
Kernel linearKernel = new LinearKernel("repr_name");
learningAlgo.setKernel(linearKernel);

// learn and get the prediction function
learningAlgo.learn(trainingSet);
Classifier classifier = learningAlgo.getPredictionFunction();
```

From binary to multi-class classifiers

- When multiple classes are involved, we can combine several binary classifiers to build a multi-class classifier
- We adopt the **One-VS-All classification** schema
  - We adopt in competition as many classifiers as involved classes
- **Training**: at turn, a binary classifier is trained over the training set, with the set of examples of a class considered as positive examples
  - The remaining examples are considered negative examples
- **Test**: the example is classified with each binary classifier and the class associated to the classifier with the maximum classification score is selected

Multiclass classification function The One Vs All Schema

```
List<Label> labels = trainingSet.getClassificationLabels();
// instantiate the basic binary learning algorithm.
// NO need of setting the labels
BinaryCSvmClassification baseAlgo = new BinaryCSvmClassification();
// set the regularization parameters
baseAlgorithm.setCp(c);
baseAlgorithm.setCn(c);
// set the kernel function
Kernel linearKernel = new LinearKernel("repr_name");
baseAlgorithm.setKernel(linearKernel);

OneVsAllLearning ovaLearning=new OneVsAllLearning();
// set the binary classification function
ovaLearning.setBaseAlgorithm(baseAlgorithm);
// set the targeted classes
ovaLearning.setLabels(labels);
// learn and get the prediction function
ovaLearning.learn(trainingSet);
// get the classification function
OneVsAllClassifier ovaCl = ovaLearning.getPredictionFunction();
```

Caching kernel evaluations

- The running time of some kernel-based learning algorithm can be almost $O(n^2)$
- These algorithms evaluate the kernel function between two examples multiple times
- To reduce the learning time we can save some kernel computations

```
KernelCache cache=new FixIndexKernelCache(cacheSize);
usedKernel.setKernelCache(cache);
```

  - Useful in the training phase
  - In testing it is not useful for binary classification but it can be useful for Multi-class classification
  - Be careful when using the cache during training over datasets with hundred of thousands examples

- To switch the cache off: `usedKernel.disableCache();`

Prediction Functions

- Binary Classifier

```
ClassificationOutput p = classifier.predict(testExample);
float getClassificationScore=p.getScore(positiveClass);
if(getClassificationScore>0)
      ...
```

- Multi Class Classifier

```
ClassificationOutput pred = ovaClassifier.predict(testExample);
List<Label> predictedClasses = pred.getPredictedClasses();
Label predictedLabel = predictedClasses.get(0);
      ...
```

Evaluators

- To support the evaluation phase, KeLP implements evaluators for:
  - The binary scenario
  - The multi-class scenario

```
//Building the evaluation function
BinaryClassificationEvaluator evaluator = new
BinaryClassificationEvaluator(positiveClass);

// Classify examples and compute the accuracy
for (Example e : testSet.getExamples()) {
        ClassificationOutput p = classifier.predict(e);
        evaluator.addCount(e, p);
}
// Get evaluation metrics
float accuracy = evaluator.getAccuracy();
float precision = evaluator.getPrecision();
float recall = evaluator.getRecall();
float f1 = evaluator.getF1();
```

Evaluators for the Multi-class classification schema

```
//Building the evaluation function
List<Label> labels = trainingSet.getClassificationLabels();
MulticlassClassificationEvaluator evaluator = new
        MulticlassClassificationEvaluator(labels);

// Classify examples and compute the accuracy
for (Example e : testSet.getExamples()) {
        ClassificationOutput p = classifier.predict(e);
        evaluator.addCount(e, p);
}

// Get evaluation metrics
float accuracy = evaluator.getAccuracy();
for (Label label : labels) {
        float precision = evaluator.getF1For(label);
        float recall = evaluator.getF1For(label);
        float f1 = evaluator.getF1For(label);
}
```

Saving/Loading the model

- Once the classifier has been learned it can be saved into a file

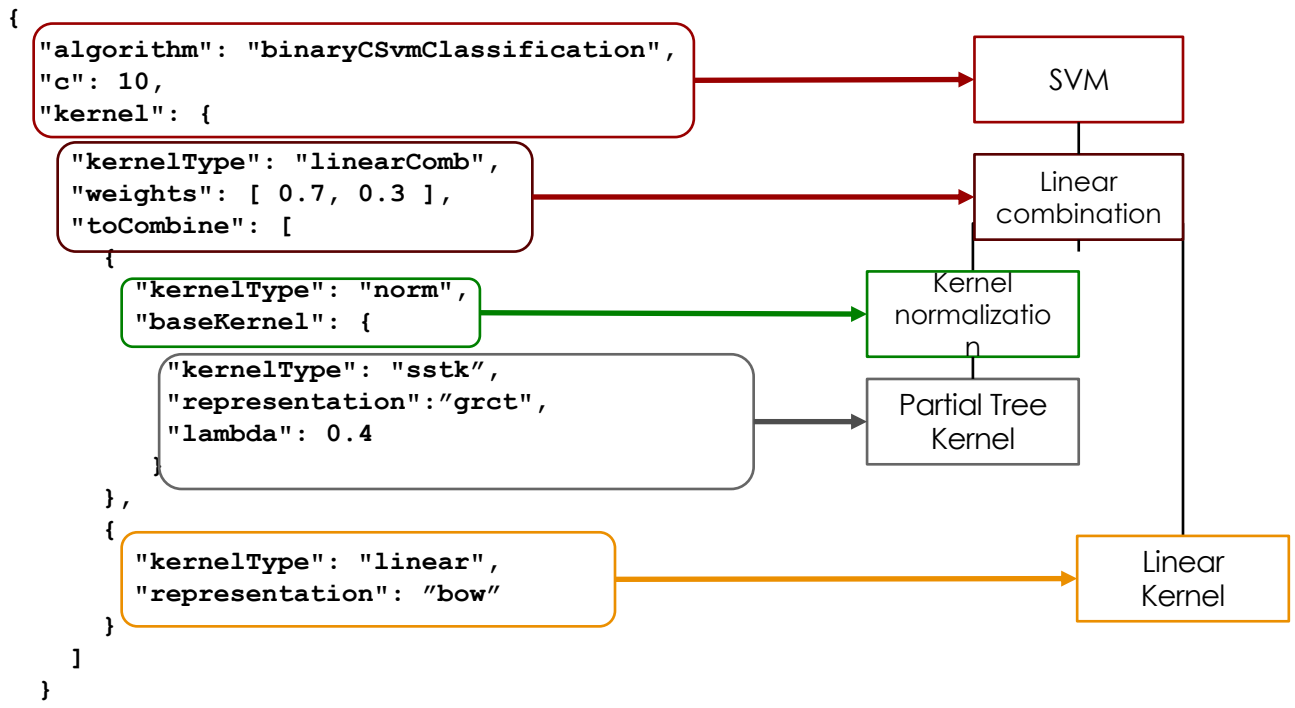
```
JacksonSerializerWrapper serializer = new JacksonSerializerWrapper();
serializer.writeValueOnFile(classifier, "classifer_file_name.klp");
```

- And it can be also loaded

```
File inputFile=new File("classifer_file_name.klp");
Classifier classifier=serializer.readValue(inputFile, Classifier.class);
```

- *But also kernel functions and learning algorithms can be serialized on file*
- *It means that you can build and tune the kernel/classifier without reading a single line of JAVA code*

A learning algorithm in Json



Homework

- In the folder you will find a README with the instructions to compile and execute the JAVA code
- For Homework you are required to:
  1. parameterize the kernel functions with a 5-fold schema
  2. learn the classifier maximizing the F1 metrics for the HUMAN class
     - No restriction on the tuning policy
     - Hint: you should use the `BinaryCSvmClassification class`
  3. evaluate the classifiers without a direct use of the evaluators
     - You should make explicit TPs, FPs, TN…