Estimating time of a CAL module execution

Statistic under AI and its application to engineering sciences

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Abstract— **Abstract ...**

Keywords— **Machine learning, BalticLSC ...**

I. Introduction

Computation Application Language (CAL) is designed to write large scale application in due to perform big data processing. Each CAL program consists of modules that are separetely executed in sequence (with parallelization possibility) on virtual machines and sending the results futher to a next module of an application. CAL language is a part of the system developed under the Baltic LSC[1] project.

During the data processing within the application run, each module is executed with some input data. It could be different kind of data e.g. data frame or set of images. The execution of a module is invoke on a virtual machine with limited resources (RAM, mCPUs, GPUs). The details of an input data and the execution environment resources will be used to estimate the overall application execution time and price on a concrete cluster.

Baltic Large Scale Computing (BalticLSC[2]) project is using CAL language to perform data processing tasks. Each task is an execution of a CAL application. Each module can be used in many CAL applications. We can say that a single module is a one block (commonly as a docker image) and an application is the schema of executing a sequence of blocks. Figure **??** shows the example application that consits of a few modules to perform a kind of an image processing. Some of the modules (R, G and B *processors*) can be executed in parallel.

The aim of this project is to estimate the module execution time based on input data and limited resources of the execution. The choosen approach is to create machine learning models using historical data of the module executions times.

The WCET[1] execution time is a crucial feature of a real-time systems[3] when response should be guaranteed within a specified timing constraint or system should meet the specified deadline. In this project we do not strictly focus on providing an estimation of maximum execution time (WCET). We will try to estimate the average-case execution time (ACET) which is absolutely enought for this use case requirements.

II. Data

To estimate time of a CAL module execution we create a machine learning model for each module. With each execution of the module within some application of the Baltic LSC system, we will get another data point to train our model. We will use the following features (explanatory variables)[2] as an input data for a model:

1. mCPUs limit - called *mili cores* - the fraction of a physical CPU used to carry out the module execution,
2. total size of an input data in bytes,
3. max element size of an input data (if the input data is a set of files type it is the biggest part of data to be processed),
4. average size of an input element,
5. number of input data elements.

This last three features make clear sense only if an input data is a set of files. Otherwise, if data is just a single file, the features can be a sort of data features representation carrying more detailed information about the data then only a total size. For the data frame the number of input elements can be eqaul to the number of columns. The max element size will be a quotient of the total size and the number of columns, and the average size will be equal to that quotient as well.

Obviously, our dependent value (that we are going to estimate) is an execution time of a module.

We create two CAL applications based on 4 modules with a different types of an input data. The first application, consisting of 3 modules, take the movie as an input data, marks faces of people on each frame and return the movie with marked people faces as an output data. The second one consist of just a single one module and it do a search of the best hyperparameters of XGBoost algorithm within parameters grid. Table I describe the modules that we used in the research.

Tabla I: Modules that we used in the research.

ID (APP ID)	Name	Input data
1(1)	video_splitter	video file
2(1)	face_recogniser	image files
3(1)	images_merger	image files
4(2)	xgb_grid_search	CSV file

For each module we created set of 10 different input data. Next, we ran the modules with the mentioned datas using different mCPUs resources (from 0.5 mCPUs up to 4.0 mCPUs with 0.5 step).

[1] Worst-case execution time - the maximum amout of time that the execution can take.

[2] As a docker container that will be used to execute a module do not use SWAP memory, RAM is not colerated with execution time. In this program we will not use modules with GPU support. Summarazing, the GPUs and RAM resources limits are not taken into account for modeling.

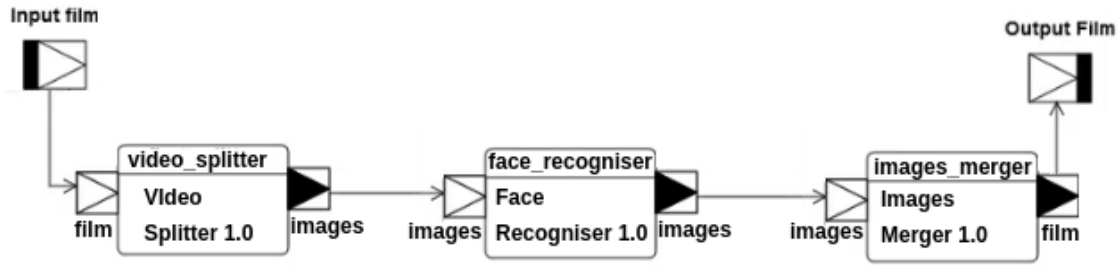


Fig. 1: *Face Recogniser* scheme. Application written in the CAL language.

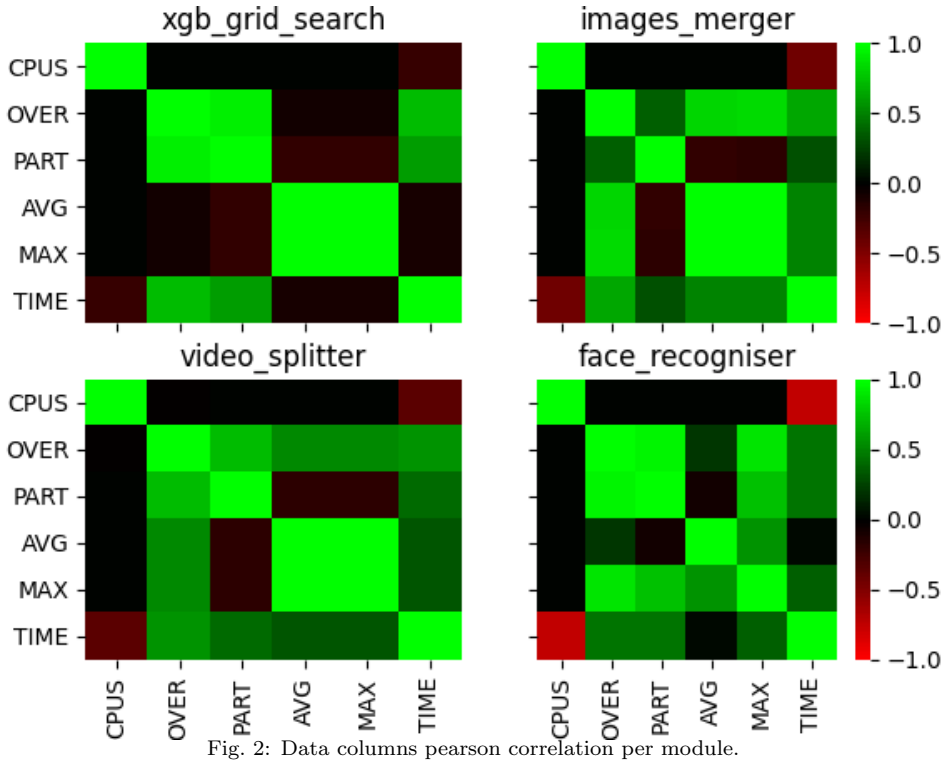


Fig. 2: Data columns pearson correlation per module.

Finally, we received the data frame with the number of 4 (number of modules) * 8 (different mCPUs resources) * 10 (number of input data sets) = 320 rows that will be used to train and validate our models which part of is presented in the table III.

III. Algorithms

A. Support Vector Regression

As a one of machine learning algorithms to estimate time of a CAL module execution we will use *Epsilon-Support Vector Regression* [4] (SVR) - it is based on Support Vector Machine (SVM, orginally named *support-vector networks*[5]).

We will use SVR model with a RBF kernel[6] which is the most known flexible kernel and it could project the features vectors into infinite dimensions. It uses Taylor expansion which is equivalent to use an infinite sum over the polynomial kernels. It allows to model any function that is a sum of unknown degree polynomials.

Using kernel, the resulting algorithm is formally similar, except that every dot product is replaced by a nonlinear kernel function. This allows the algorithm to fit the maximum-margin hyperplane in a transformed feature space. The RBF kernel have the following form:

$$K_{RBF}(\vec{x}, \vec{x}') = \exp\left(-\gamma||\vec{x} - \vec{x}'||\right) \text{, where:}$$

- $||\vec{x} - \vec{x}'||$ is the squared Euclidean distance between the two vectors of features,
- γ - hyperparameter described in more details below.

In the SVR algorithm we are looking for a hyperplane y in the following form:

$$y = \vec{w}\vec{x} + b, \text{ where:}$$

- $\vec{x}$ - vector of features,
- $\vec{w}$ - normal vector to the hyperplane y, using a kernel the $\vec{w}$ is also in the transformed space.

Training the original SVR means solving:

$$\frac{1}{2}||w||^2 + C\sum_{i}^{N}(\xi_i + \xi_i^*),$$

with the following constraints:

$$y_i - \vec{w}x_i - b \leq \epsilon + \xi_i$$

Tabla II: Part of the data frame for models training and validation.

Module ID	mCPUs	total size [B]	number of elements	max size [B]	average size [B]	time [s]
1	4.0	1703379	544	3131	3131	3.909
1	4.0	809881	548	1477	1477	1.981
1	4.0	1711796	1392	1229	1229	11.371
...	...	...	...	...	...	...

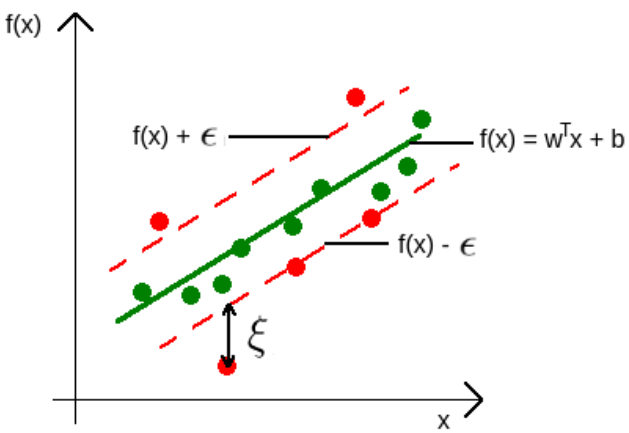
$$-y_i + \vec{w}x_i + b \leq \epsilon + \xi_i^*$$

$$\xi_i \xi_i^* \geq 0$$

Figure **??** shows the wanted hyperplane with marked ξ and ϵ parameters. As we already choosed the RBF kernel for the SVR algorithm, our modelling is simplified to just find the best values of the following hyperparameters[7]:

1. C -the weight of an error cost. The regularization[3] hyperparameer, have to be strictly positive. The example from the figure use l1 penalty (the library that we use to modelling use the squared epsilon-insensitive loss with l2 penalty). The strength of the regularization is inversely proportional to C. The larger value of C the more variance is introduced into the model.
2. *epsilon* - It specifies the epsilon-tube within which no penalty is associated in the training loss function with points predicted within a distance epsilon from the actual value. As it is shown of the figure 3 the green data points do not provide any penalty to the loss function because they are within the allowed epsilon range around the approximation[4].
3. *gamma* - The *gamma* hyperparameter can be seen as the inverse of the radius of influence of samples selected by the model as support vectors. Increasing the value of *gamma* hyperparameter causes the variance increase what is shown in the figure 4[4].

Fig. 3: Visualization of the SVR's epsilon and gamma parameters [8].

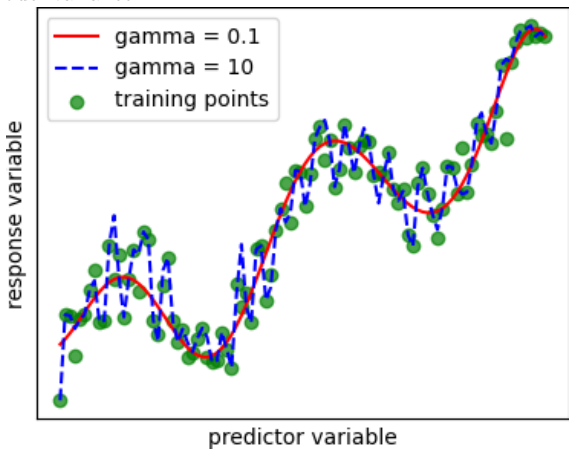


You can find detailed information about C and gamma params in sklearn library documentation[10].

[3]Regularization is a way to give a penalty to certain models (usually overly complex ones)

[4]The figure is based on some example data and it only shows the hyperparameter influence on model.

Fig. 4: SVR's gamma hyperparameter [9] influence on the model variance.



B. K-nearest Neighbors Regression

Another, examined algorithm used to estimating time of a module execution is a simple KNN[5] regression. Using the algorithm, a target is predicted by local interpolation of the targets associated of the nearest neighbors in the training set [11].In another words, the target assigned to a query point is computed based on the mean of the targets of its nearest neighbors.

To use the algorithm we have to define values of the following parameters:

1. k - number of the nearest neighbors
2. *weights* - weight function used in prediction. The basic nearest neighbors regression uses uniform weights: that is, each point in the local neighborhood contributes uniformly to the classification of a query point. Under some circumstances, it can be advantageous to weight points such that nearby points contribute more to the regression than faraway points. The weights can be calculated from the distances using any function for example the linear one.
3. *algorithm* - the procedure to calculate k-nearest neighbors for the query point. It does not have a direct impact to the final regression result, but the parameters of the algorithm surely have. For example, using the BallTree algorithm we have to choose the *metric* parameter that will be used to calculate the distance between data points. It could be, for example, the Minkowski [12] metric with the l2 (standard Euclidean [13]) distance metric or any function that will calculate the distance between two points.

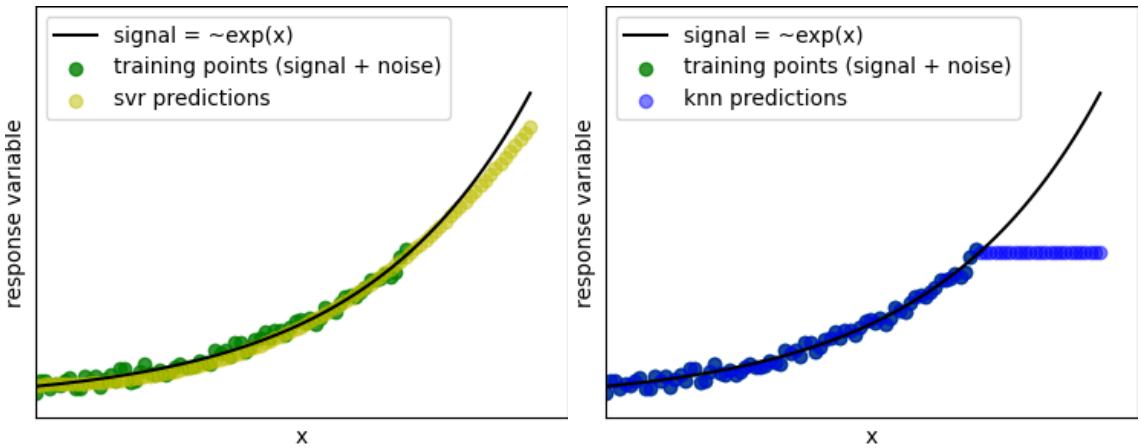


Fig. 5: Regression on the out of training range data.

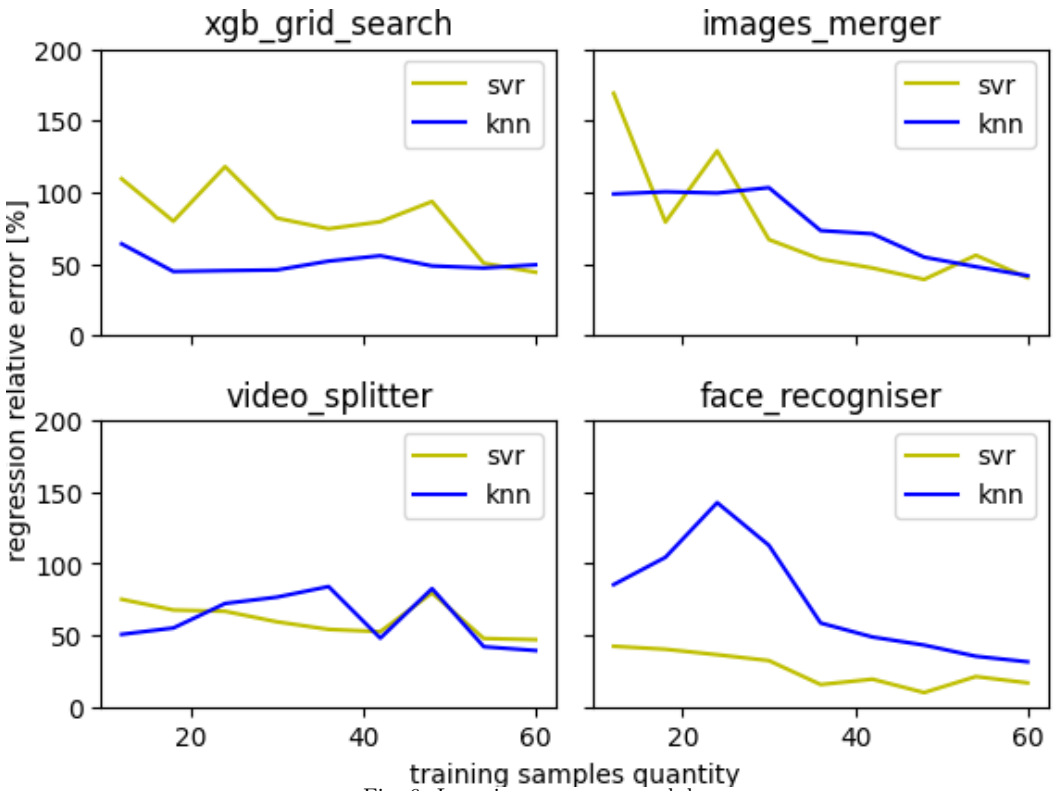


Fig. 6: Learning curve per module.

IV. Training and validation

The training pipeline for each module contains the following steps:

1. Having the 80 data points, we divide them into training and test data sets with 1:4 proportion.
2. Standardization of a data set is a common requirement for many machine learning estimators: they might behave badly if the individual features do not more or less look like standard normally distributed data (e.g. Gaussian with 0 mean and unit variance)[14]. We scale each column (feature) of the data set using the following formula:

$$\vec{x}'_f = \frac{\vec{x}_f - \mu_f}{\sigma_f}, \text{ where:}$$

- $\vec{x}_f$ - data set column f,
- μ_f - mean of the column f,
- σ_f - standard deviation of the column f.

3. Each algorithm have a few parameters that should be chosen wisely in order to the better results. It is hard to predict the best value of a continuous parameter. What we did is an exhaustive search over specified parameter values for an estimator from the given possible values. For each combination of the parameter values we validate the model using 5-fold cross validation (as it was mentioned in the first step). It is called a *grid search*[15].
4. Finally, we retrained our model using the full data set and the parameters that were found in the previous step.

A. Support Vector Regression

The parameters grid for the *SVR* algorithm is listed below:

[5] *KNN* - k-nearest neighbors

```
'gamma': [0.0001, 0.0002, 0.0004, 0.0008,
0.0016, 0.0032, 0.0064, 0.0128],
'epsilon': [1e-06, 2e-06, 4e-06, 8e-06,
1.6e-05, 3.2e-05, 6.4e-05, 0.000128,
0.000256, 0.000512, 0.001024],
'C': [1000.0, 2000.0, 4000.0, 8000.0,
16000.0, 32000.0, 64000.0, 128000.0,
256000.0, 512000.0, 1024000.0, 2048000.0]
```

B. K-nearest Neighbors

The parameters grid for the *KNN* algorithm is listed below:

```
'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8,
9, 10, 11],
'weights': ['uniform', 'distance'],
'p': [1, 2]
```

C. Final results

D. Training

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E. Validation

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V. Conclusiones

Conclusions ... `https://github.com/rasenjop/Plantilla-Jornadas-Sarteco`.

Thanks

Thanks for the help and support ...

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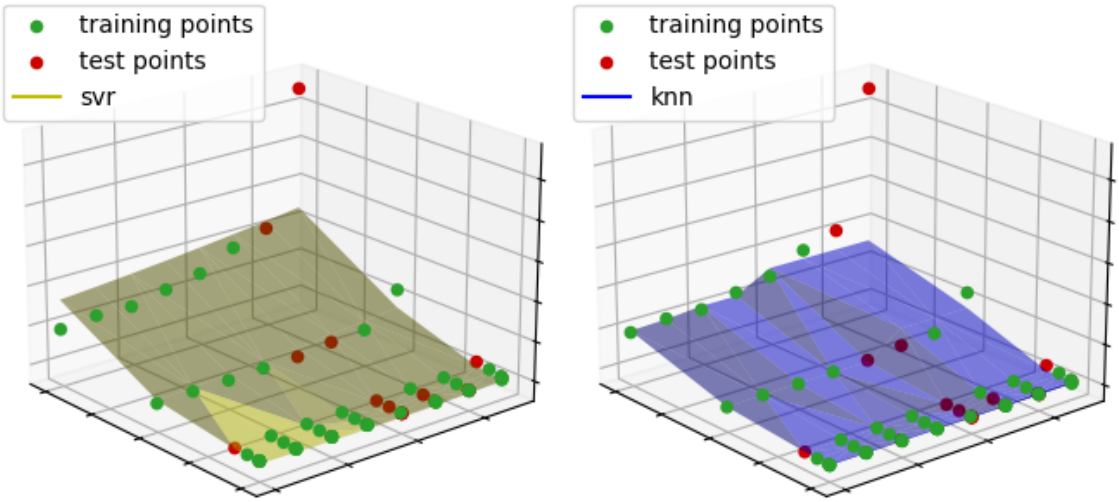

Fig. 7: Regression surfaces for *xgb_grid_search* module.

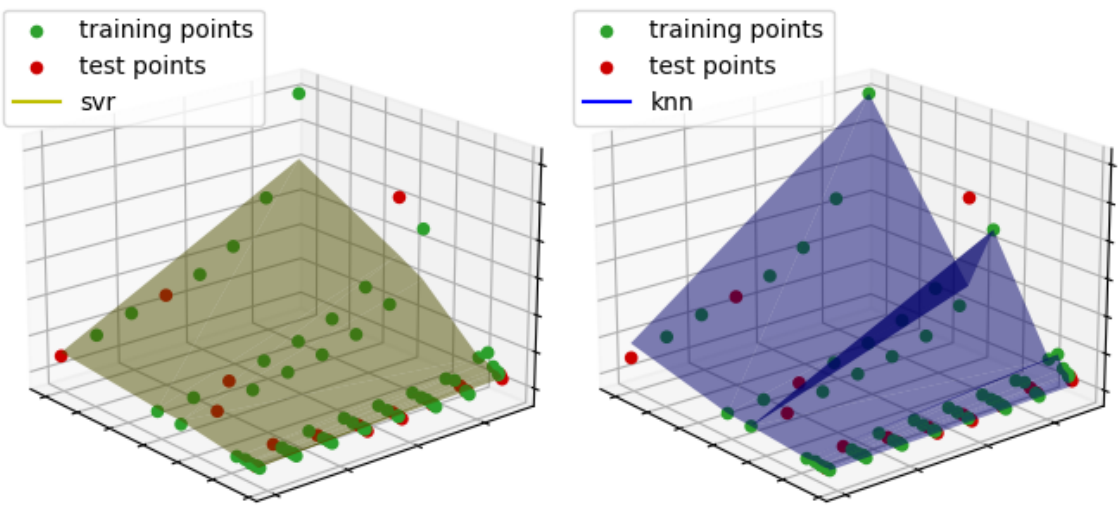

Fig. 8: Regression surfaces for *images_merger* module.

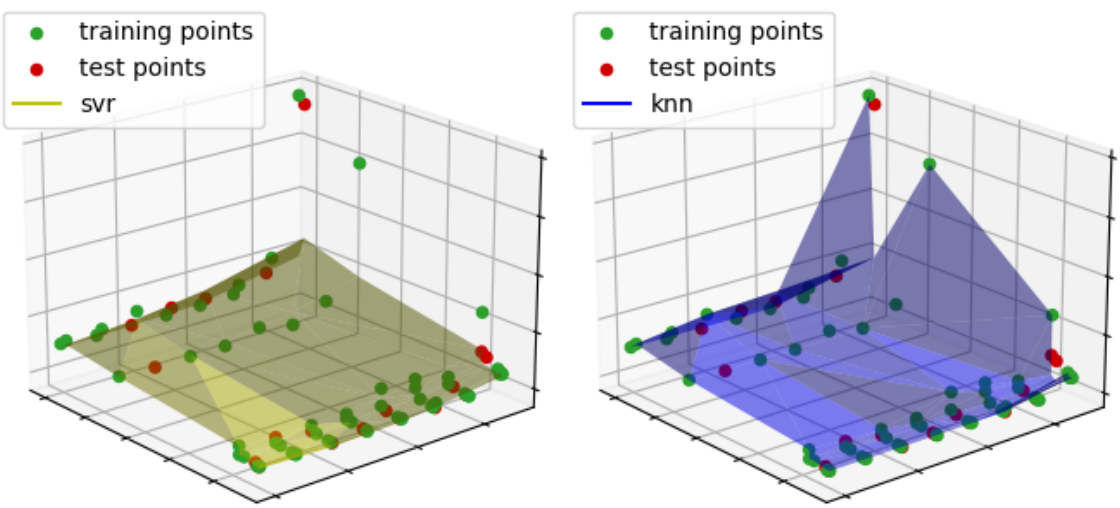

Fig. 9: Regression surfaces for *video_splitter* module.

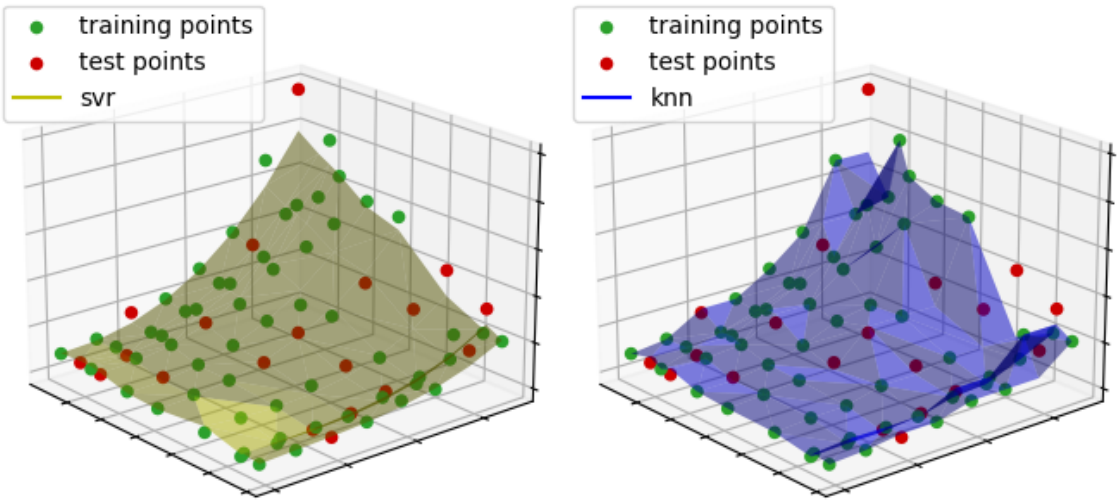

Fig. 10: Regression surfaces for *face_recogniser* module.

Tabla III: The final results.

Algorithm:	SVR		KNN	
	best params	relative error [%]	best params	relative error [%]
video_splitter	C: 256000.0, γ: 1e-04, ϵ: 2e-06	3131	n: 2, *weights*: 1e-04, p: 2e-06	3.909
face_recogniser	C: 256000.0, γ: 1e-04, ϵ: 2e-06	3131	n: 2, *weights*: 1e-04, p: 2e-06	3.909
xgb_grid_search	C: 256000.0, γ: 1e-04, ϵ: 2e-06	3131	n: 2, *weights*: *uniform*, p: 1	49.3
images_merger	C: 256000.0, γ: 1e-04, ϵ: 2e-06	3131	n: 2, *weights*: 1e-04, p: 2e-06	3.909