

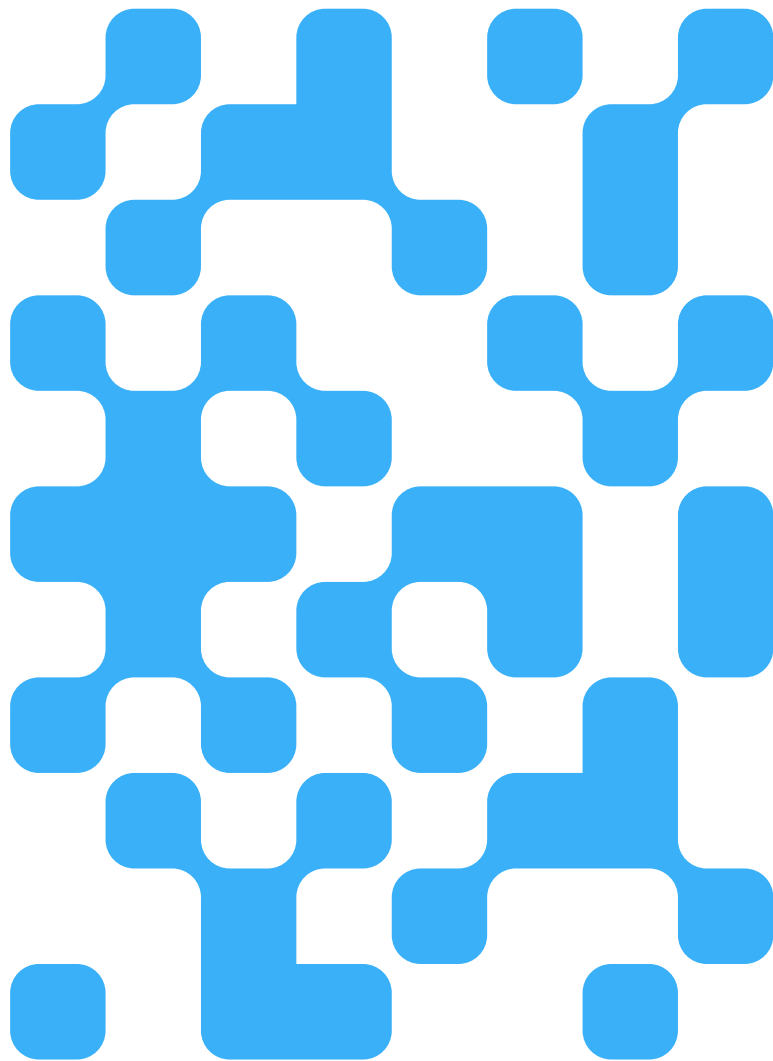


Machine Learning

2024 (ML-2024)

Lecture 4. Quality metrics. Tips & tricks in ML: data splitting, cross-validation, regularization, batches

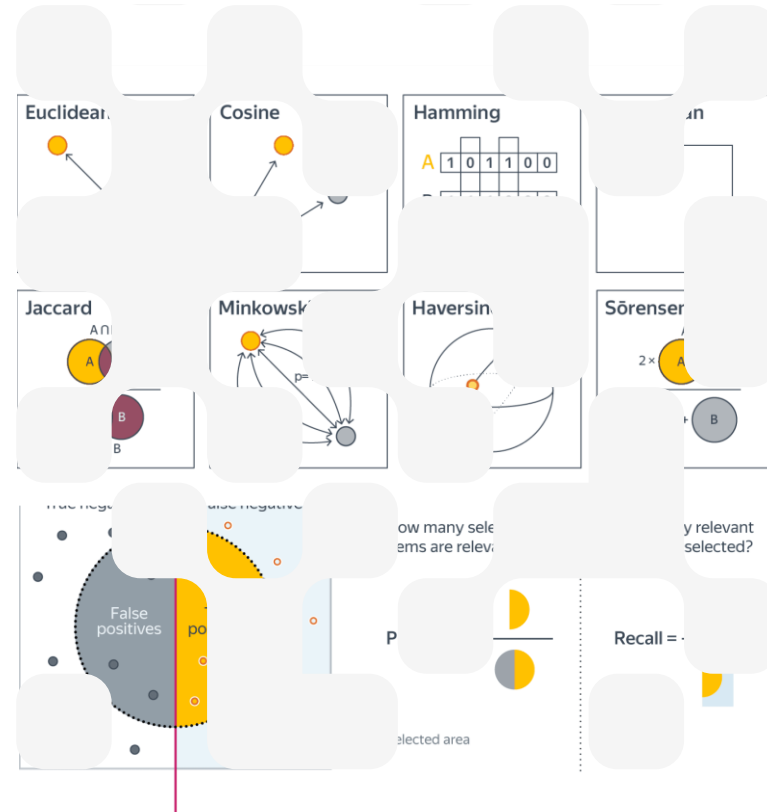
by Alexei Valerievich Kornaev, Dr. habil. in Eng. Sc.,
Researcher at the RC for AI, Assoc. Prof. of the Robotics and CV
Master's Program, [Innopolis University](#)
Researcher at the RC for AI, [National RC for Oncology n.a. NN Blohin](#)
Professor at the Dept. of Mechatronics, Mechanics, and Robotics,
[Orel State University](#)



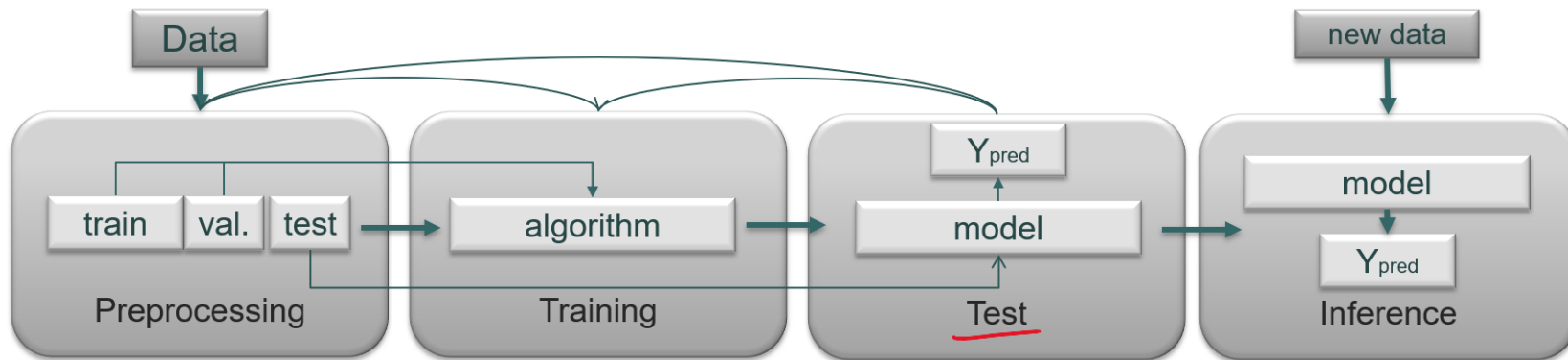
Agenda

- I. Quality metrics in ML
- II. Data splitting, cross-validation
- III. Regularization
- IV. Batches

All models are wrong, but some are useful.
/George Box/

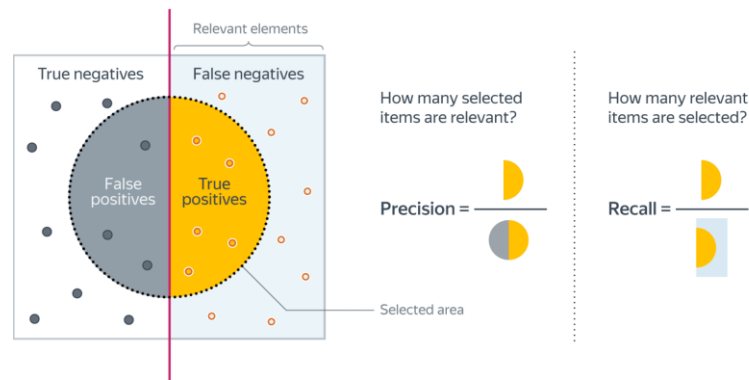
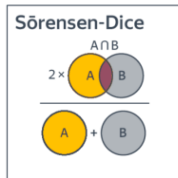
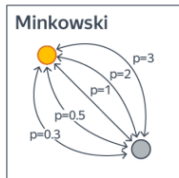
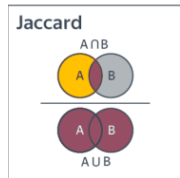
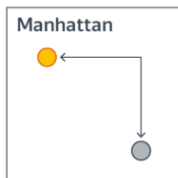
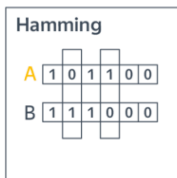
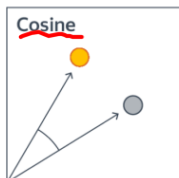
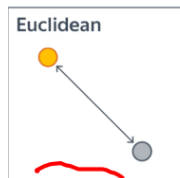
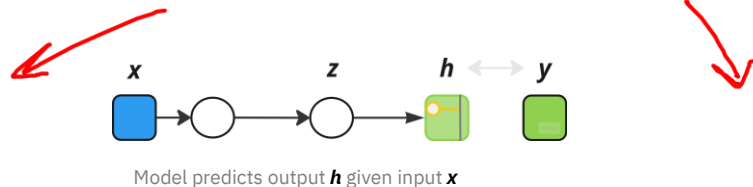


Flowchart for an ML model design



Is the model good enough?

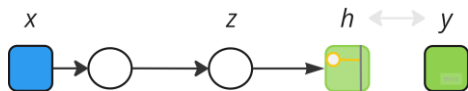
Metrics can be used both in learning (metric learning) and in estimating a model's quality



[Metrics from the Yandex Handbook](#)

[Classification metrics from the Yandex Handbook](#)

Metrics that estimate model's quality. Binary classification



Model predicts output \mathbf{h} given input \mathbf{x}

1. Accuracy: $acc(\mathbf{h}, \mathbf{y}) = \frac{1}{m} \sum_{i=1}^m (\mathbf{h}^{(i)} == \mathbf{y}^{(i)})$, or (and) error rate: $error\ rate = 1 - acc(\mathbf{h}, \mathbf{y})$

$$acc(\mathbf{h}, \mathbf{y}) = \frac{TP+TN}{TP+TN+FP+FN}$$

$acc = 0.8$

Predicted	True
1	0
0	0
1	1
0	0
1	0
0	0
0	0
1	1
0	0
0	0

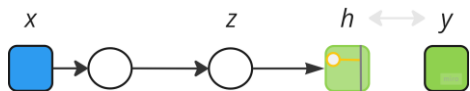
$acc = 0.8$

Predicted	True
0	1
0	0
0	0
0	0
0	1
0	0
0	0
0	0
0	0
0	0

Predicted class		
Positive	Negative	
TP	FN	Positive
FP	TN	Negative
		True class

[Confusion matrix](#)

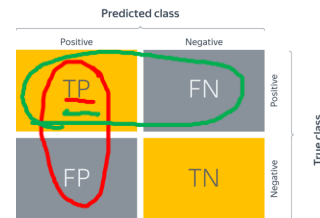
Metrics that estimate model's quality. Binary classification



Model predicts output h given input x

$$2. \text{Precision} = \frac{TP}{TP+FP}, \text{Recall} = \frac{TP}{TP+FN}, F_1 = \frac{\text{Recall} \cdot \text{Precision}}{\text{Recall} + \text{Precision}}. \quad \text{F}_1 \text{ score}$$

1 - rare class



$pr =$ $re =$ $F_1 =$

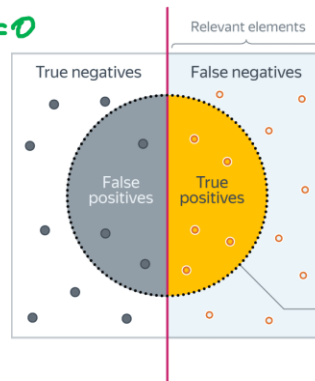
Predicted	True
1	0
0	0
1	1
0	0
1	0
0	0
0	0
1	1
0	0
0	0

FP
...

$pr = 0$ $re = 0$ $F_1 = 0$

Predicted	True
0	1
0	0
0	0
0	0
0	1
0	0
0	0
0	0
0	0
0	0

TP=0



How many selected items are relevant?

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}}$$

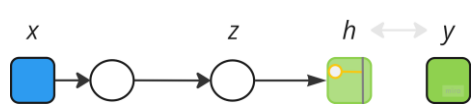
Selected area

How many relevant items are selected?

$$\text{Recall} = \frac{\text{True positives}}{\text{True positives} + \text{False negatives}}$$

[Precision, recall, F1-score intuition](#)

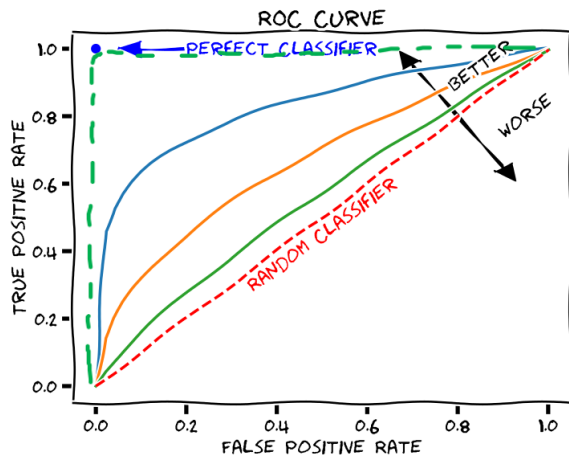
Metrics that estimate model's quality. Binary classification



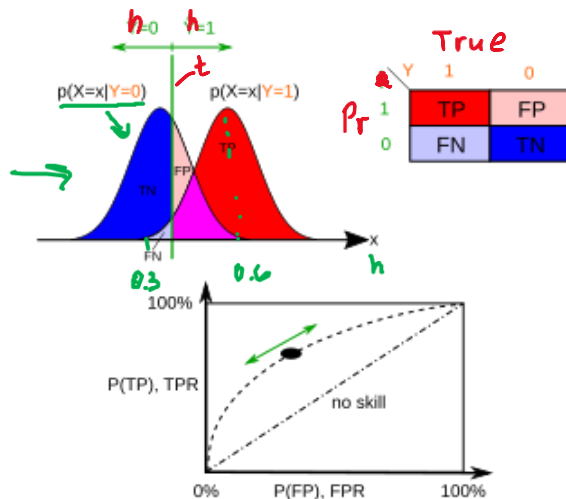
$h < t \rightarrow 0$; t is threshold - a tunable param.
 $h > t \rightarrow 1$;

Model predicts output h given input x

1. True positive rate $TPR = Recall = \frac{TP}{TP+FN}$, false positive rate $FPR = \frac{FP}{FP+TN}$, Receiver operating characteristic (ROC), area under curve AUC.



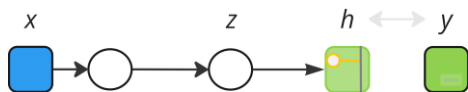
[ROC curve intuition](#)



Overall, the optimization of precision and recall proceeds as follows:

- train the model on a loss function;
- obtain metric graphs depending on the threshold using real predictions on the validation set, by iterating over different thresholds from 0 to 1;
- select the desired combination of precision and recall.

Metrics that estimate model's quality. Fitting



Model predicts output h given input x

1. Mean squared error (MSE):

2. Mean absolute error (MAE): $MAE = \frac{1}{m} \sum_{i=1}^m |h^{(i)} - y^{(i)}|;$

3. Root MSE (RMSE):

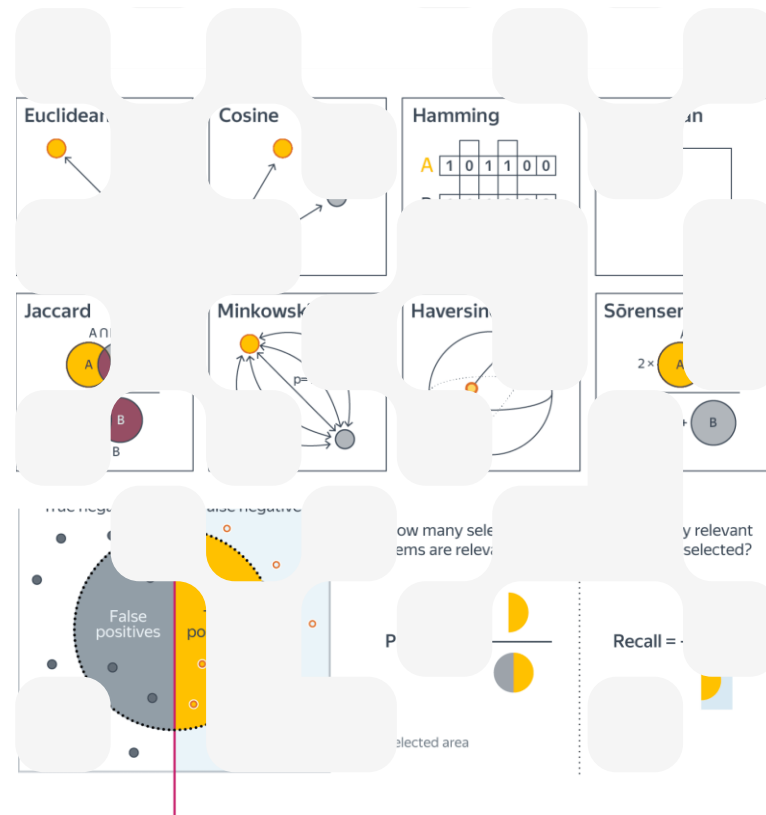
$$MSE = \frac{1}{m} \sum_{i=1}^m (h^{(i)} - y^{(i)})^2;$$

$$RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^m (h^{(i)} - y^{(i)})^2}.$$

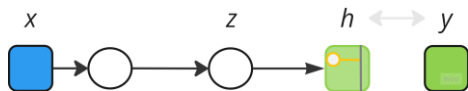
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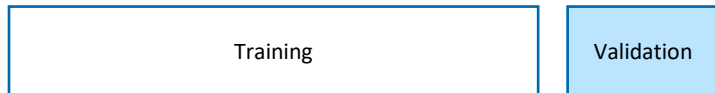
Overfitting intuition and data splitting



Model predicts output h given input x

Model *parameters* are determined during the solution of the ML problem, e.g. model weights. *Hyperparameters* are set by the user, usually not in a single way, and their values affect the values of the sought parameters.

Training data splitting by default: training set, validation set



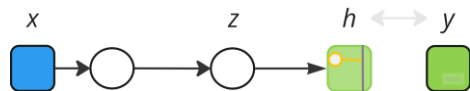
K-Fold splitting (normally used when the dataset is small)



Algorithm. The dataset is divided into k equal parts. Next, k iterations occur, during each of which one fold serves as the validation set, and the union of the remaining folds serves as the training set. The model is trained on $k-1$ folds and tested on the remaining one. The final score of the model is obtained either by averaging the resulting test results or by measuring it on a held-out test set that did not participate in cross-validation.

Testing procedure: the accuracy of the selected trained model is checked on a new (test set)!!!

Overfitting intuition and data splitting



Model predicts output h given input x

$$h = \theta_j x^j, (j = 0, \dots, d)$$

$$L = \frac{1}{2m} \left[\sum_{i=1}^m (h^{(i)} - y^{(i)})^2 \right] \Rightarrow \min.$$

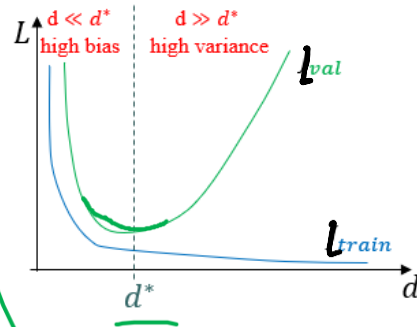
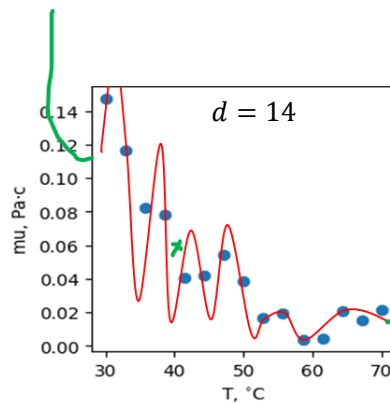
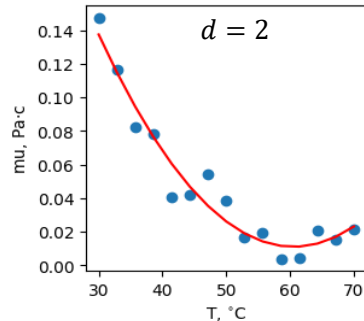
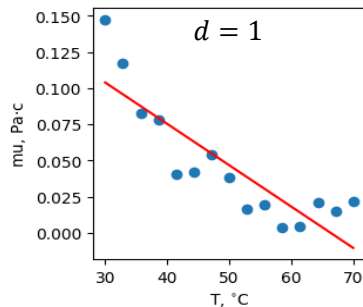
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Training $\{(x_i, y_i)\}$

validation

test

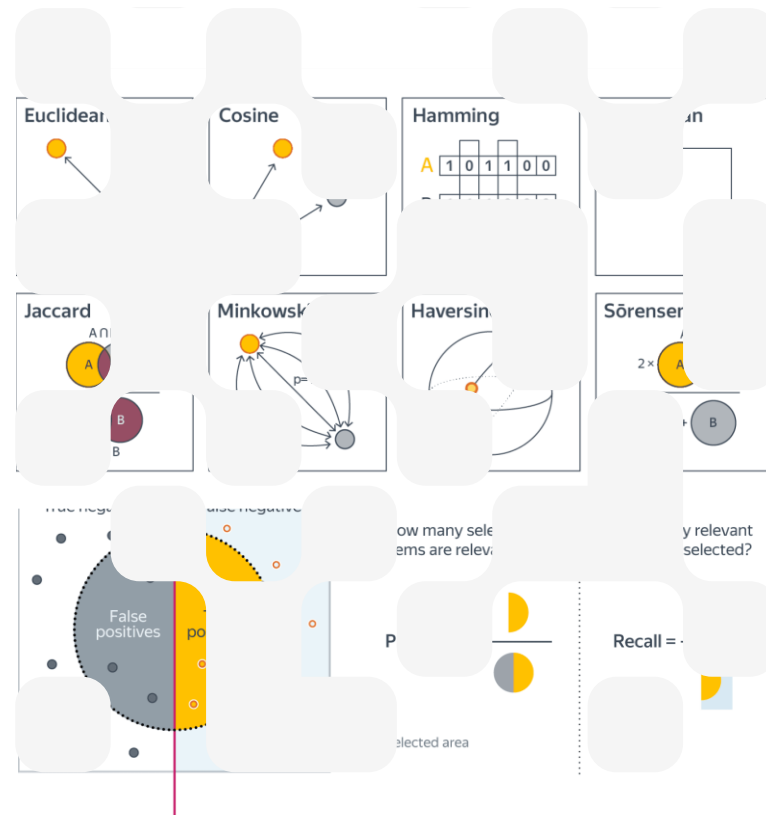
d



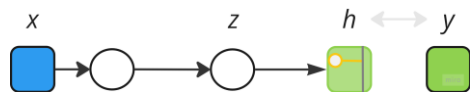
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Overfitting intuition and regularization (L2)



Model predicts output h given input x

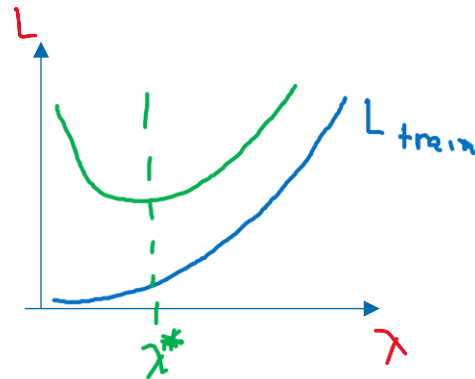
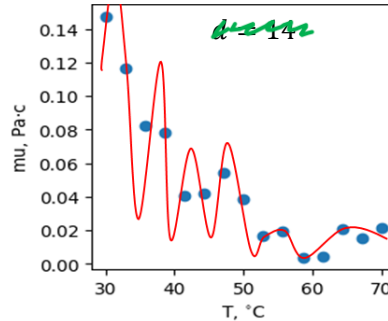
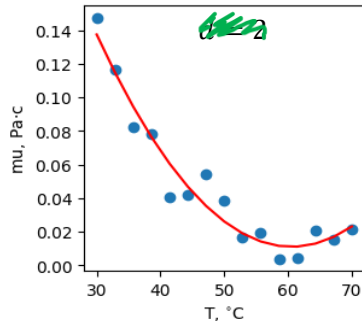
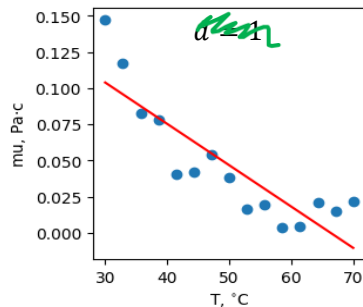
Model *parameters* are determined during the solution of the ML problem. For example, in regression problems, the parameters are the components of the matrix of weights ϕ . *Hyperparameters* are set by the user, usually not in a single way, and their values affect the values of the sought parameters.

1. Feature Scaling
2. Learning Rate
3. Error and # of iterations
4. **Regularization (L2)**



$$L = \frac{1}{2m} \left[\sum_{i=1}^m (h^{(i)} - y^{(i)})^2 + \lambda \sum_{j=1}^n \phi_j^2 \right] \Rightarrow \min.$$

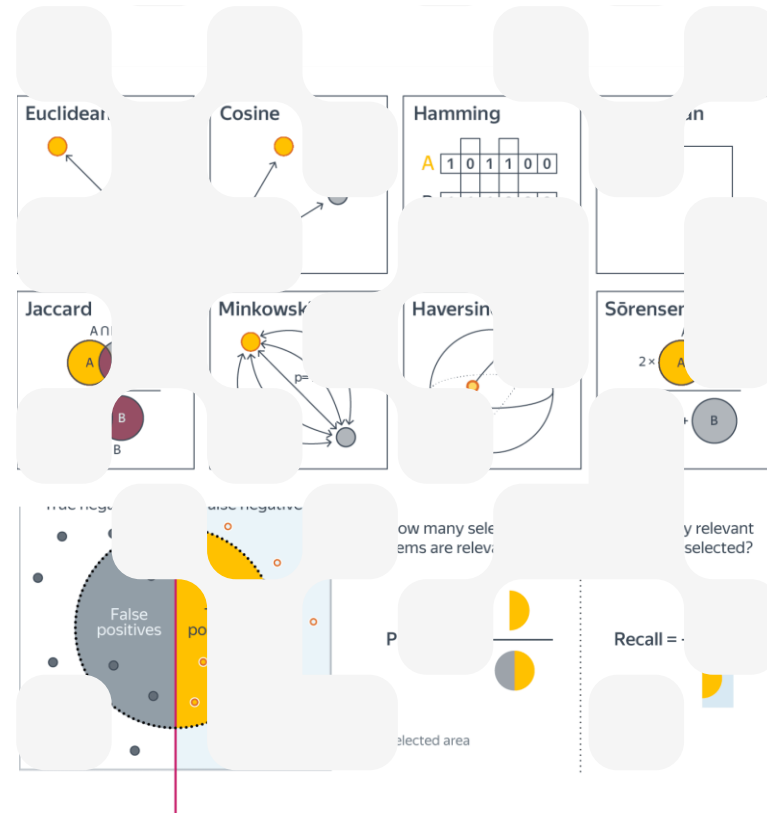
$$h(x) = \theta_j x^j, (j = 0, \dots, d)$$



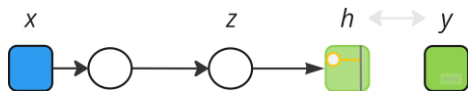
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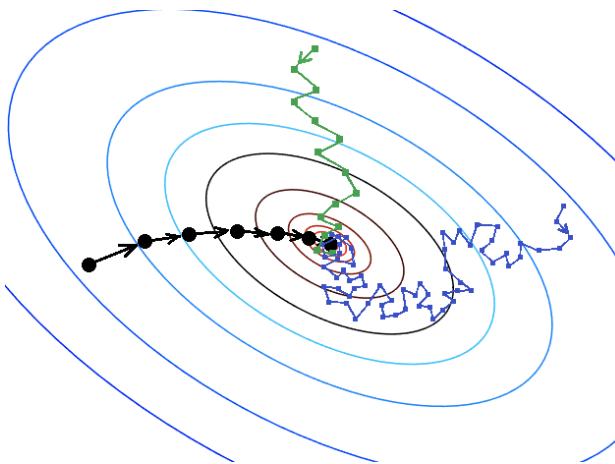


Overfitting intuition and data splitting



Model predicts output h given input x

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Batch GD

- Slowest
- Perfect gradient

Stochastic GD

- Fastest
- Rough-estimate grad

Mini-batch GD

- Compromise

<https://dragonnotes.org/MachineLearning/Optimization>

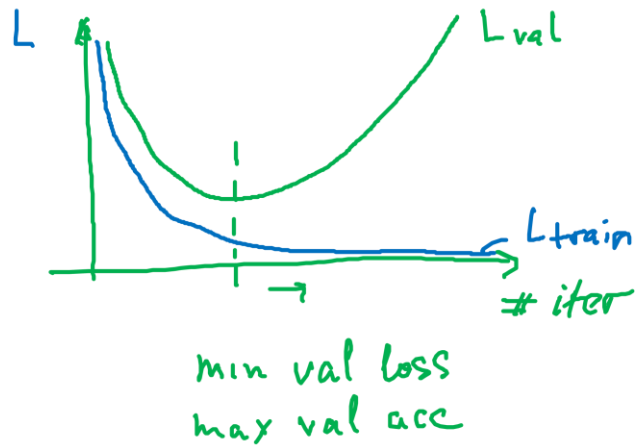


Benedict Minibatch

Thank you for your attention!

a.kornaev@innopolis.ru, [@avkornaev](#)





$$L = \frac{1}{2m} \left[\sum_{i=1}^m (h^{(i)} - y^{(i)})^2 + \lambda \sum_{j=1}^n \phi_j^2 \right] \Rightarrow \min.$$

