Feature selection and classification of acoustic emission signals

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Contents

Goals

- Comparison of two approaches to signal classification
  - Classification using feature representation
  - Direct signal classification
- Automated feature extraction tools
- Methods for dimensionality reduction
- Direct signal classification methods

Experiment 1

- 4 sensors
- Burst acoustic emission
- AE induced by impact
- brousek, kulička, ořech, patrona, řezák
- 1000 events from all objects

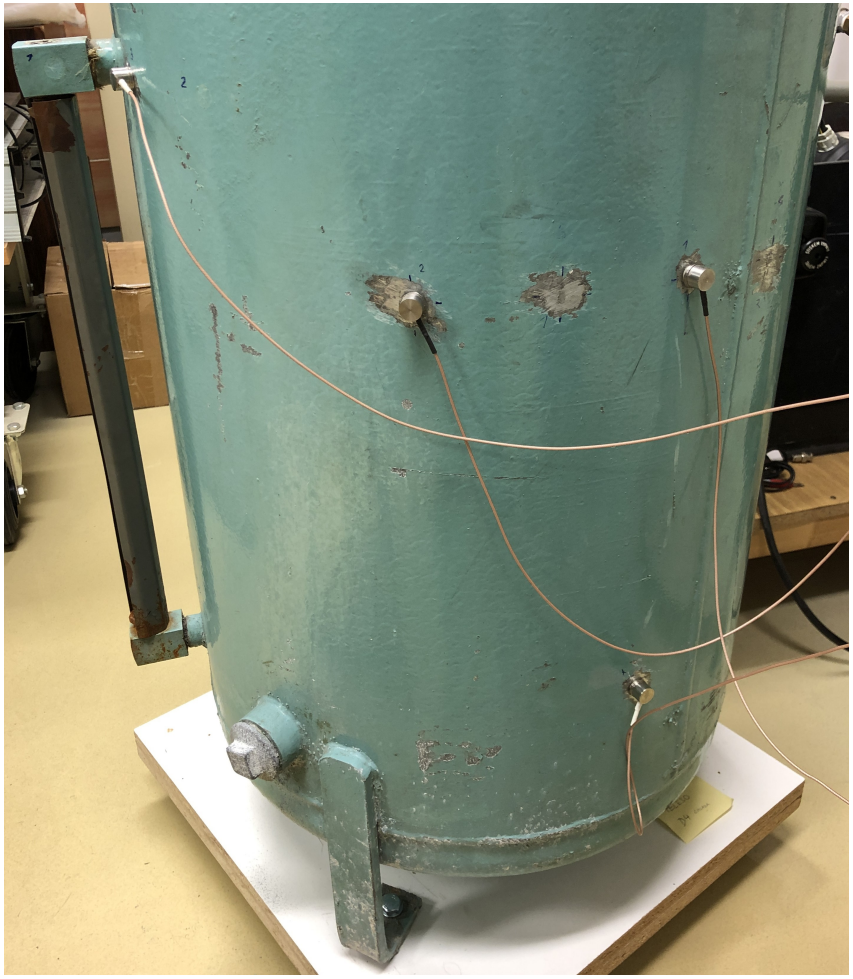
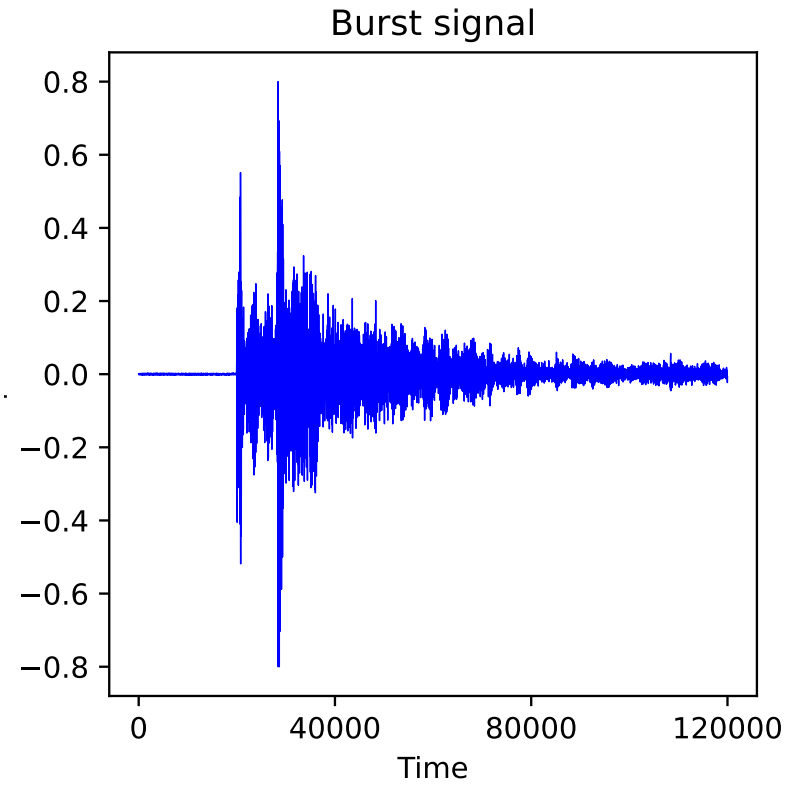


Figure: Pressure canister

Experiment 1



(a) Burst AE signal

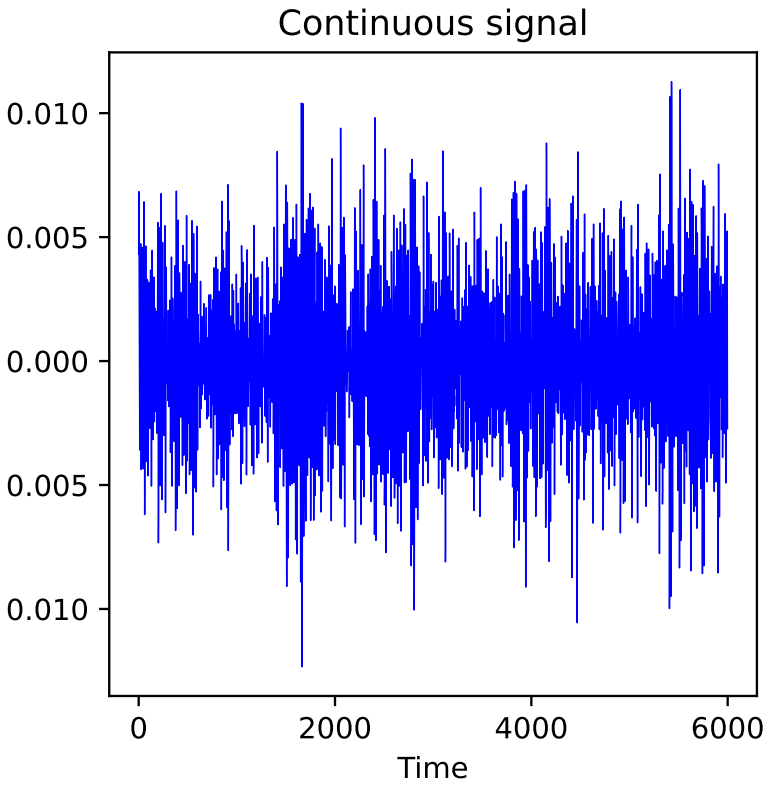
(b) Used objects

Experiment 2

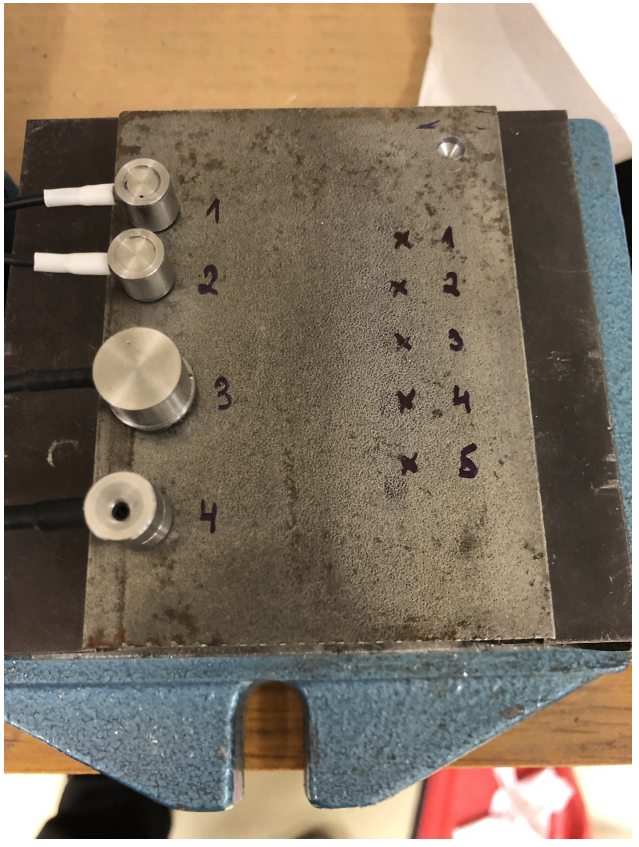
- 4 sensors
- Continuous acoustic emission
- 5 levels of drill bluntness
- 5 different holes
- Selection of shorter samples from continuous signal of AE

Figure: Drilling rig

Experiment 2



(a) Continuous AE signal



(b) Drilling block

Feature extraction

- Time Series FeatuRe Extraction on basis of Scalable Hypothesis (TSFresh)
- Database of 794 features
- Discriminability of the features is estimated

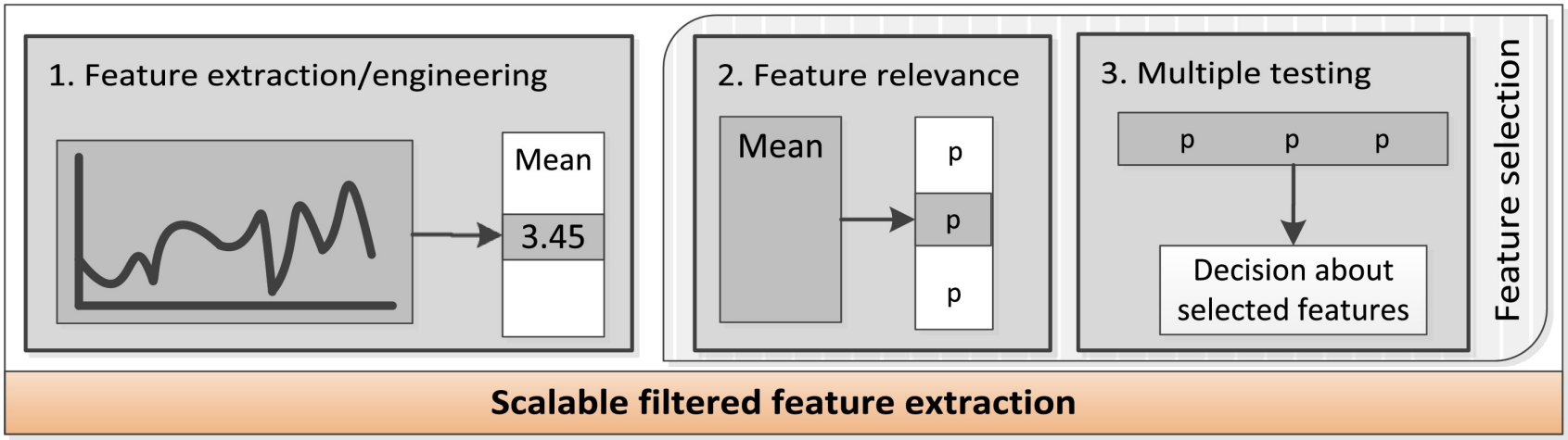


Figure: Feature extraction using TSFresh

dimensionality reduction

- Sequential feature selection - accuracy as criterion
- Principal component analysis
- Kernel PCA - modification using kernel trick

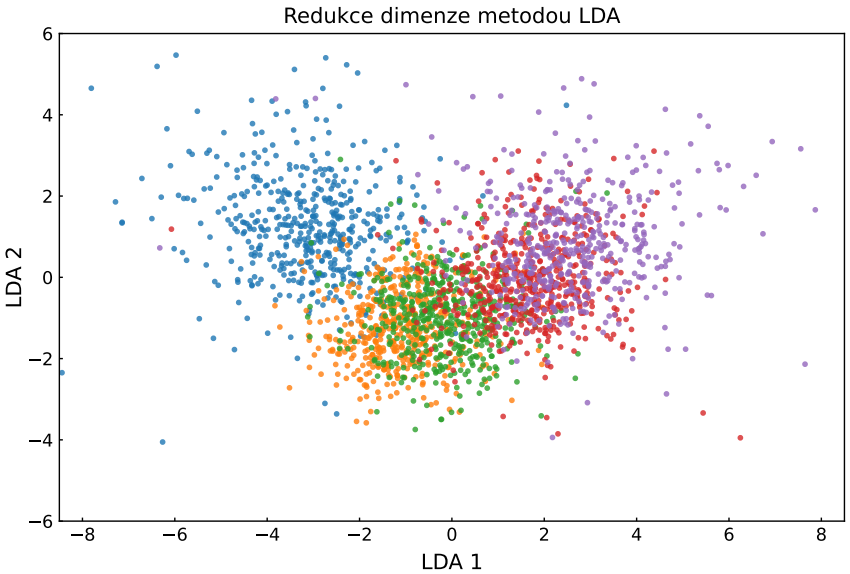
$$\text{transformation} \Phi(x) \qquad \Phi(x_i)^T \Phi(x_j) = k(x_i, x_j)$$

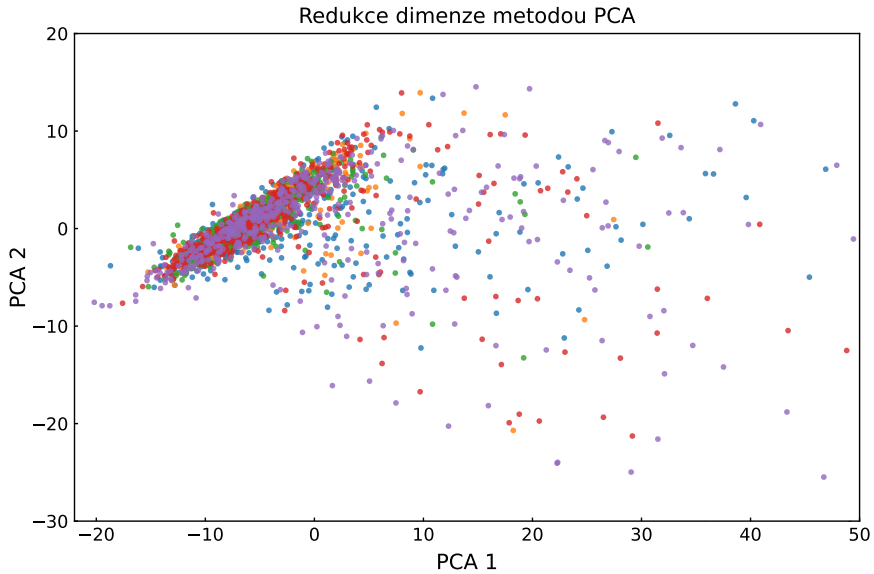
- Linear discriminant analysis - supervised, data transformed as

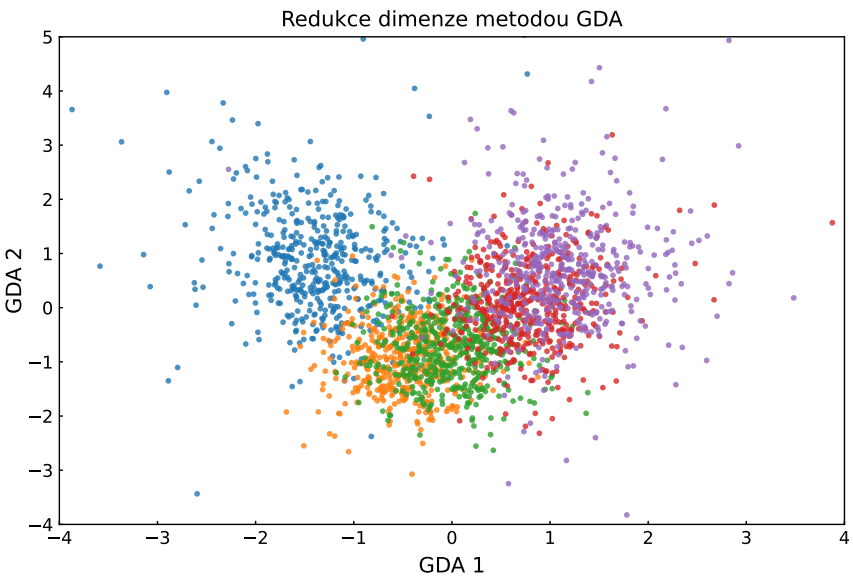
$$Z = Xa, \text{ where} \qquad \text{a} = \arg\max_a \left(\frac{\boldsymbol{a}^T \Sigma_B \boldsymbol{a}}{\boldsymbol{a}^T \Sigma_W \boldsymbol{a}} \right)$$

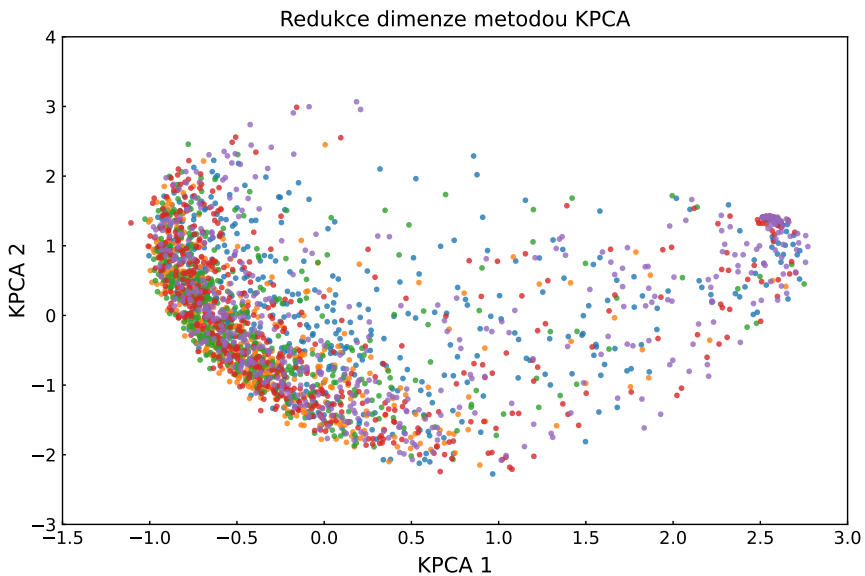
- Generalized discriminant analysis - modification of LDA using kernel trick

Dimensionality reduction









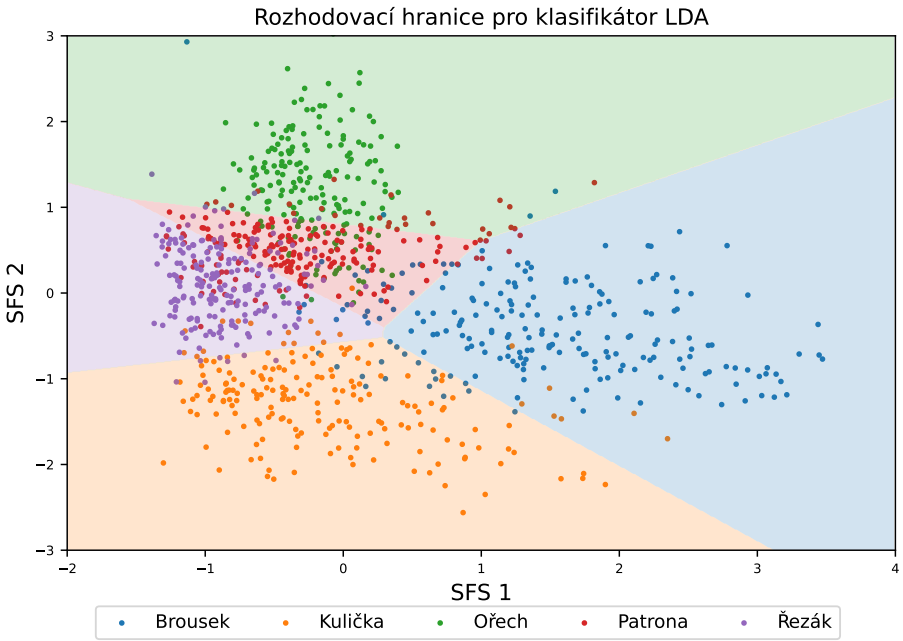
Classification methods - in feature space

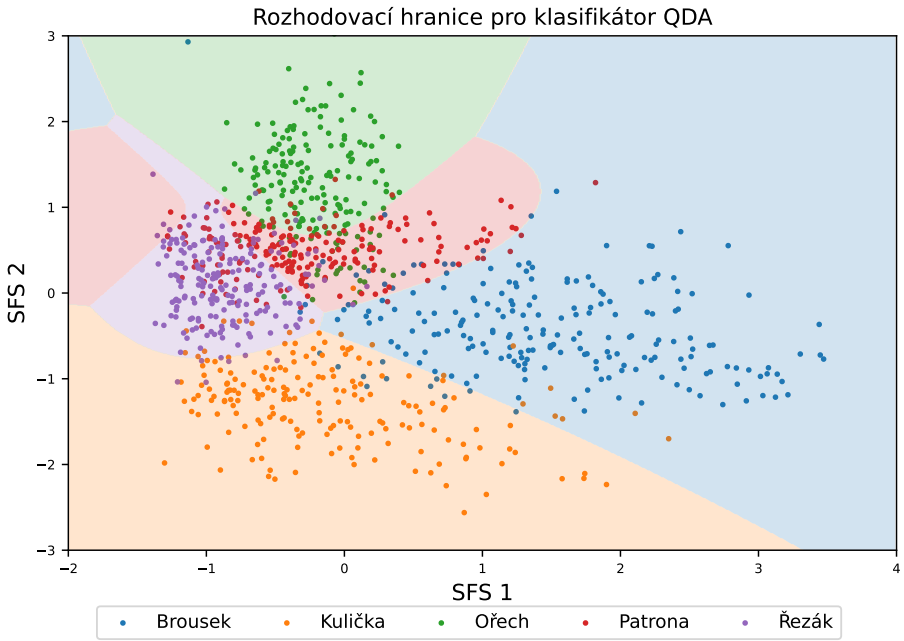
- Bayessian classifiers - LDA, QDA

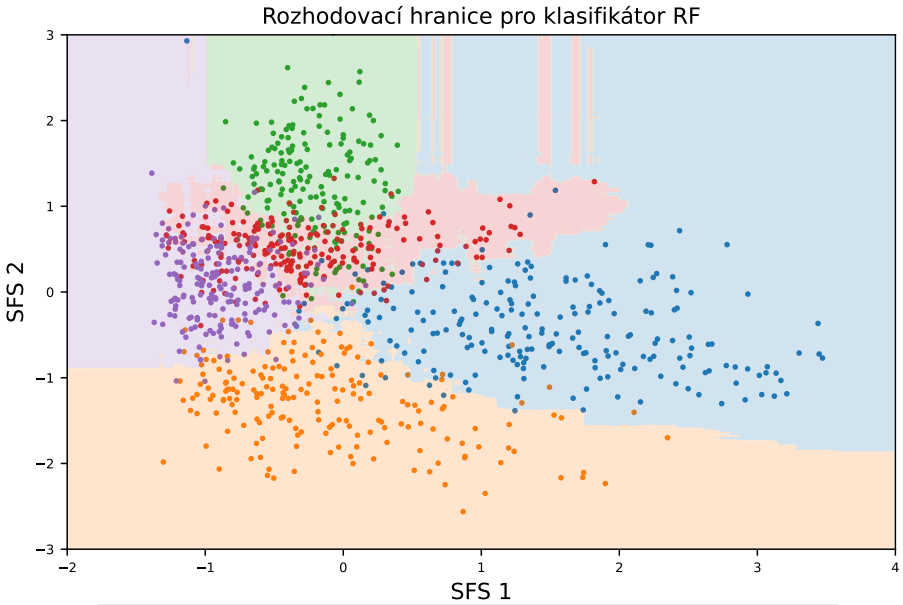
$$P(y = k|\boldsymbol{x}) = \frac{f_k(\boldsymbol{x})P(y = k)}{\sum_{j=1}^{p} f_j(\boldsymbol{x})P(y = j)}.$$

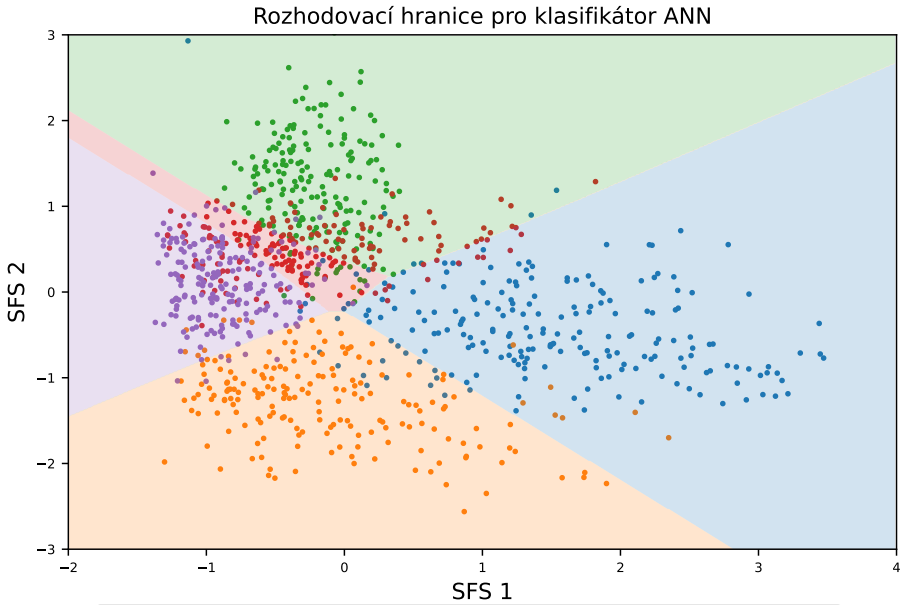
- Decision tree - CART
- Random forest
- Fully-connected neural networks

Classification methods - in feature space









Classification methods - directly on signals

- Order dependent, unlike feature vector
- Sensitive to signal shifts
- Convolutional neural networks

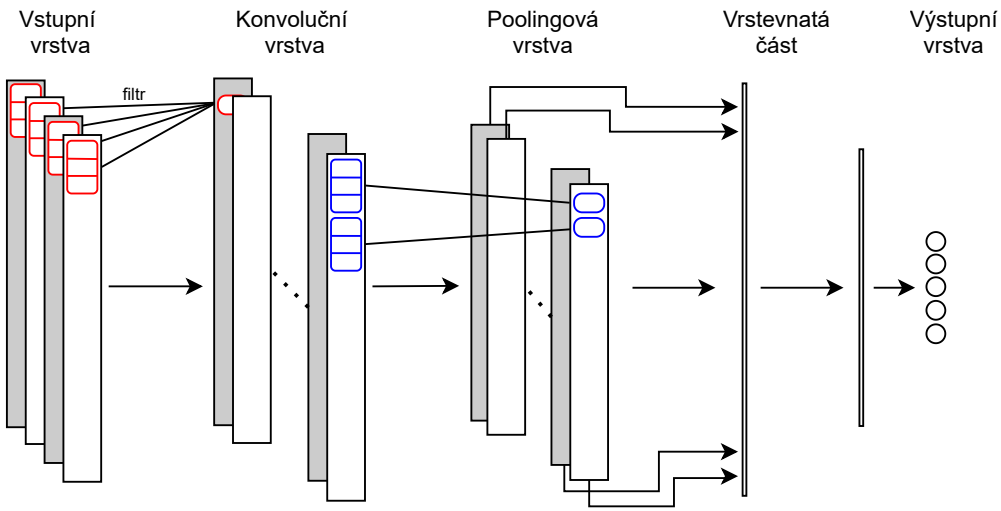


Figure: Convolutional neural network architecture

Results - Experiment 1

- Classification in reduced, 4-dimensional space

		Dimensionality reduction method				
		SFS	PCA	KPCA (cosine)	LDA	GDA (cosine)
Classifier	LDA	92,3%	71,4%	74,3%	99,4%	99,4%
	QDA	94,5%	76,3%	76,7%	99%	99,4%
	DT	89,8%	77,6%	77,9%	97,8%	98,4%
	RF	93,4%	84,5%	84,5%	98,9%	99,2%
	ANN	93,7%	85%	79,9%	99,4%	99,1%

Results -Experiment 1

- Classification in complete feature space (dim 2921)

Classifier	RF	ANN
Accuracy	99,3%	99,7%

- Classification directly on signals
  - Accuracy of trained CNN: 99,6%

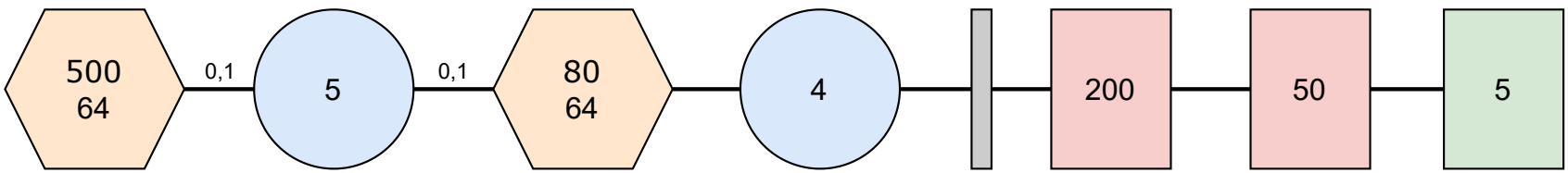


Figure: Used CNN architecture

Results - Experiment 2

- Classification in reduced, 4-dimensional space

		Dimensionality reduction method				
		SFS	PCA	KPCA (rbf)	LDA	GDA (rbf)
Classifier	LDA	40,8%	28,2%	28,4%	72,8%	75,7%
	QDA	38,5%	25%	28,2%	73,9%	75,5%
	DT	35%	25,3%	24,6%	64,8%	69,2%
	RF	41,9%	28%	29,7%	72,8%	74,2%
	ANN	45,3%	27,9%	29,9%	73,9%	75,7%

Results - Experiment 2

- Classification in complete feature space (dim 1161)

Classifier	RF	ANN
Accuracy	67,4%	76%

- Classification directly on signals
  - Same CNN architecture used as in experiment 1
  - Accuracy of trained CNN: 78,9%

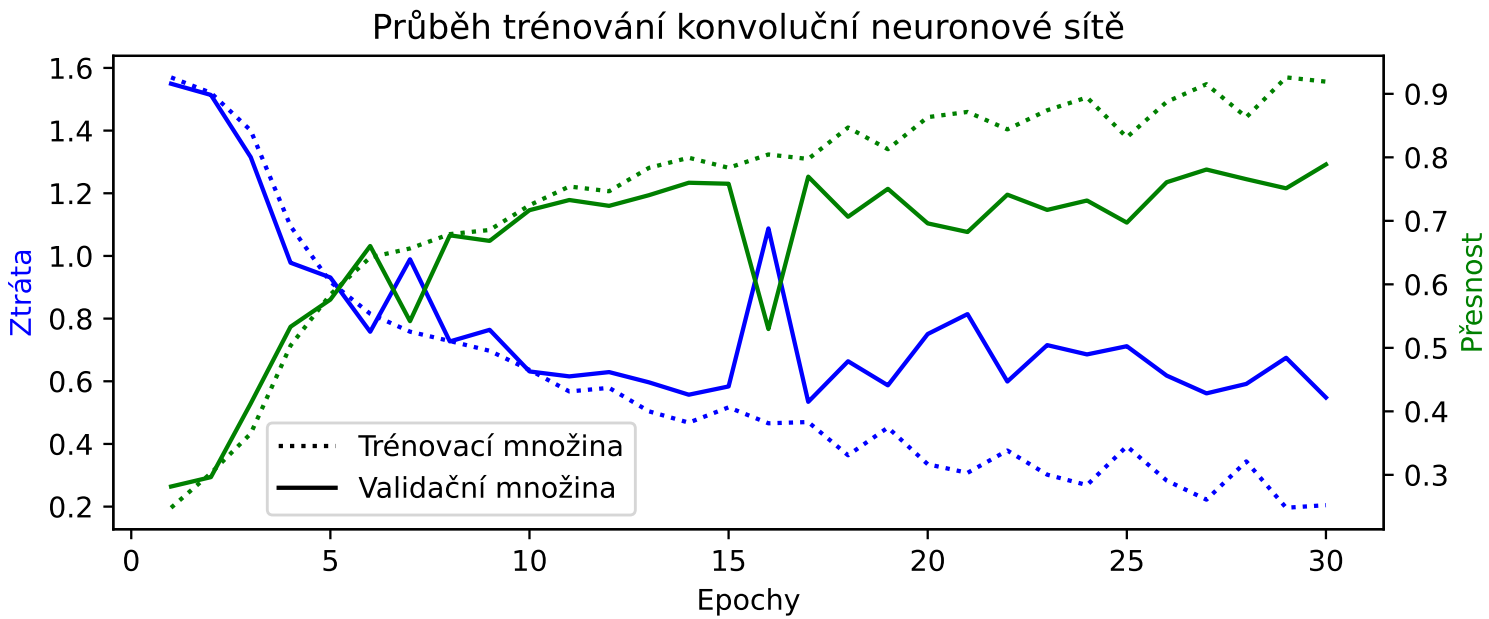


Figure: CNN learning development

Thanks for the attention