Comparing Three Machine Learning Algorithms for the Classification of Risso's Dolphins and Cuvier's BW

8th DCLDE Workshop

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Outline

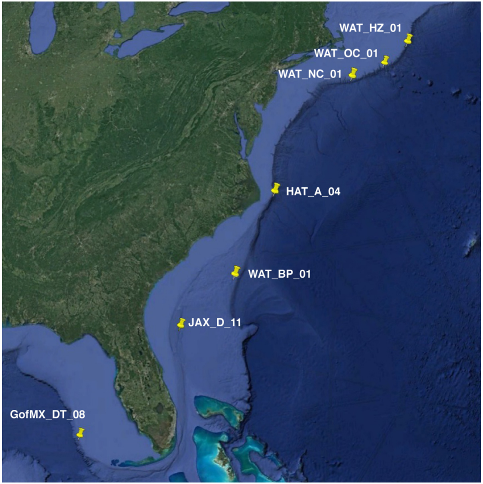
Motivation

- ML class final project
- DCLDE 2018 challenge

Approach

- Classify Risso's dolphins (*Gg*) against Cuvier BWs (*Zc*)
- Single set of features
- Compare 3 Machine Learning algorithms

Dataset



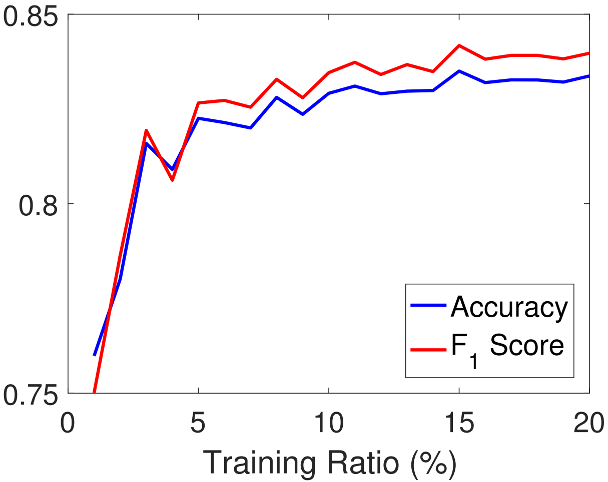
http://sabiod.univ-tln.fr/DCLDE/challenge.html

Training data

56	GofMX	DT	Gg	2014-10-10T10:56:00.0		2014-10-10T10:57:27.6	GofMX_DT08_141010_105230.x					210	297.6
59	GofMX	DT	Gg	2014-10-10T11:49:00.0		2014-10-10T11:50:19.7	GofMX_DT08_141010_113000.x					1140	1219.7
60	GofMX	DT	Zc	2014-10-10T12:42:30.0		2014-10-10T13:01:15.0							
61	GofMX	DT	Zc	2014-10-10T13:06:15.0		2014-10-10T13:08:45.0	GofMX_DT08_141010_124500.x					1275	1425
62	GofMX	DT	Zc	2014-10-10T13:22:30.0		2014-10-10T13:23:45.0							
63	GofMX	DT	Zc	2014-10-10T19:21:15.0		2014-10-10T19:36:15.0							
64	GofMX	DT	Zc	2014-10-10T21:03:45.0		2014-10-10T21:13:45.0							
65	GofMX	DT	Zc	2014-10-10T23:18:45.0		2014-10-10T23:35:00.0							
82	GofMX	DT	Zc	2014-10-12T17:25:00.0		2014-10-12T17:30:00.0	GofMX_DT08_141012_171500.x					600	900
83	GofMX	DT	Zc	2014-10-12T17:42:30.0		2014-10-12T17:43:45.0						1650	1725

- Filter by species
- Find 10 encounters with each species
- Extract clicks

Effect of Training Ratio



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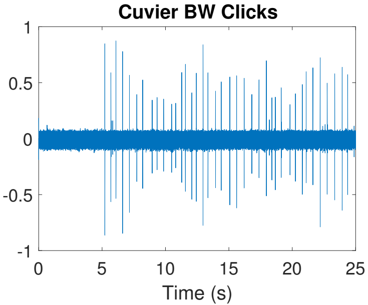
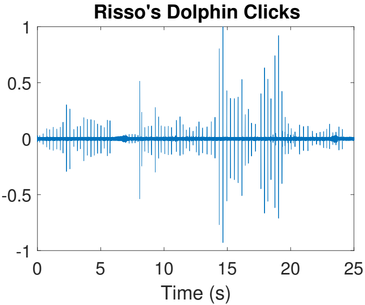
- Filter by species
- Find 10 encounters with each species
- Extract clicks
- 200 for training, 30 for testing (87/13 ratio)

Click extraction



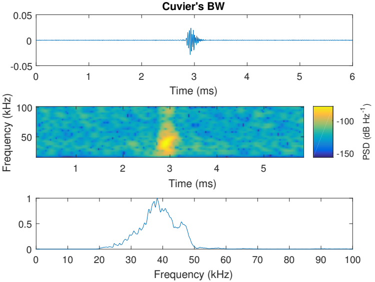


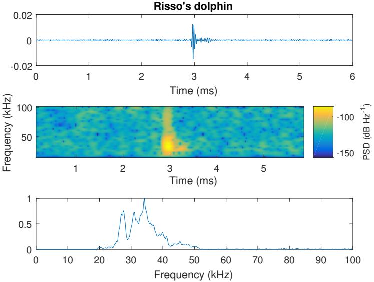
- Teager-Kaiser energy operator

$$\Psi(x[n]) = x^2[n] - x[n+1]x[n-1]$$

V. Kandia & Y. Stylianou (2006), *Detection of sperm whale clicks based on the Teager-Kaiser energy operator.* Applied Acoustics, 67(11-12), 1144-1163.

Click extraction





Feature 1: spectral banding patterns

Risso's Dolphin

- Peaks: 22, 25, 31, 39 kHz
- Notches: 20, 28, 36 kHz

Cuvier's BW

- Peaks: 17, 23, 40 kHz
- Notch: 26 kHz

Feature

Area under PSD curve (25-27 kHz)

M. Soldevilla et al. (2017) *Geographic variation in Risso's dolphin echolocation click spectra* JASA 142(2), 599-617

W. Zimmer et al. (2005) *Echolocation clicks of free-ranging Cuviers beaked whales* JASA 117(6), 3919-3927

Feature 2: Inter-click Interval (ICI)

Risso's Dolphin

ICI: 40-200 ms

Cuvier's BW

ICI: 337 (94, 491) ms

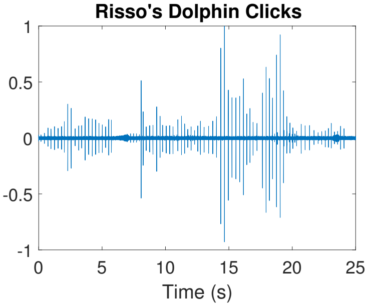
M. Roch et al. (2008) *Comparison of machine learning techniques for the classification of echolocation clicks from three species of odontocetes* Canadian Acoustics, 36(1), 41-47.

S. Baumann-Pickering et al. (2013) *Species-specific beaked whale echolocation signals* JASA, 134(3), 2293-2301.

Feature 2: Inter-click Interval (ICI)

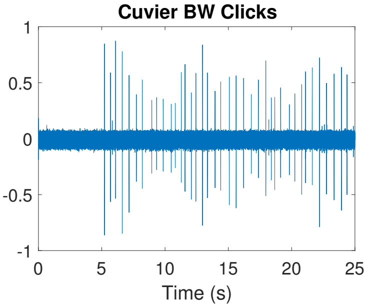
Risso's Dolphin

ICI: 40-200 ms



Cuvier's BW

ICI: 337 (94, 491) ms



I Gaussian Discriminative Analysis

- Estimate μ, Σ of features
- Model distribution of [Gg] features

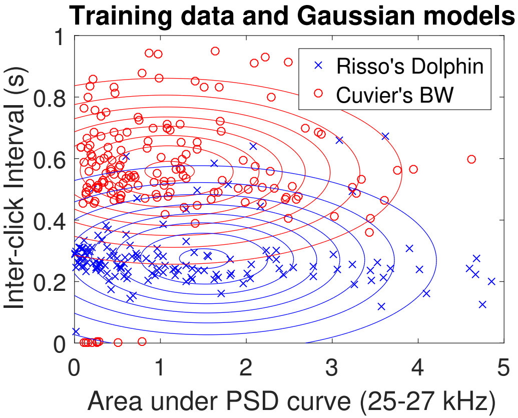
$$p(\vec{x}|y=1) = \frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(\vec{x}-\vec{\mu_1})^T|\Sigma|^{-1}(\vec{x}-\vec{\mu_1})\right)$$

- Use Bayes rule to classify test example

$$p(y|x_{test}) = \frac{p(x_{test}|y)p(y)}{p(x_{test})}$$

A. Ng *CS229 - Machine Learning Stanford Lecture Notes*
https://see.stanford.edu/course/cs229

I GDA - Results



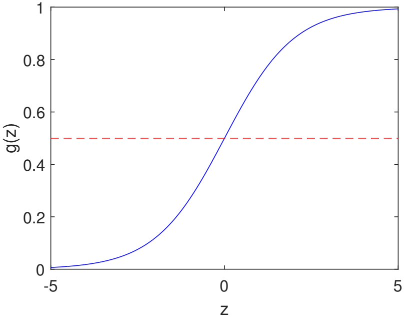
- Model accuracy: 92.1% (cross-validation), 92.2% (testing)

II Logistic Regression

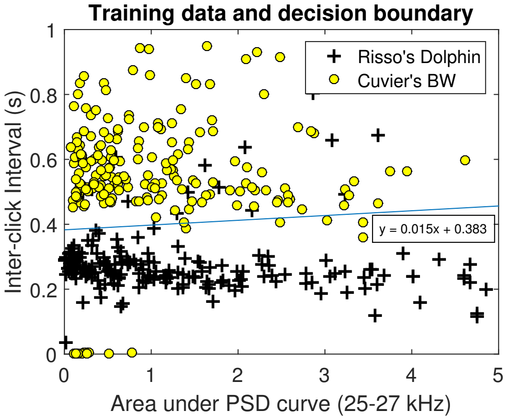
- Minimize cost function by gradient descent

$$J(\vec{\theta}) = -\frac{1}{m}\left[\sum_{i=1}^{m} y^{(i)} \log h_{\vec{\theta}}(\vec{x}^{(i)}) + (1 - y^{(i)}) \log (1 - h_{\vec{\theta}}(\vec{x}^{(i)}))\right]$$

$$h_{\theta}(x) = g(\vec{\theta}^{T} \cdot \vec{x}) = \frac{1}{1 + e^{-\vec{\theta}^{T} \cdot \vec{x}}}$$

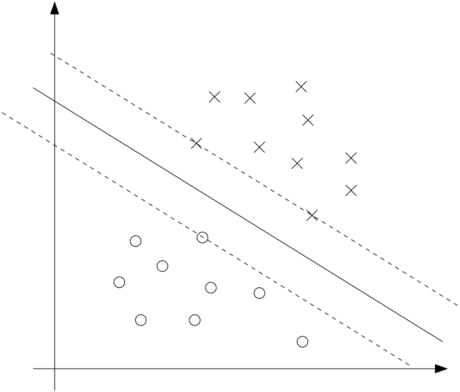


II LR Results



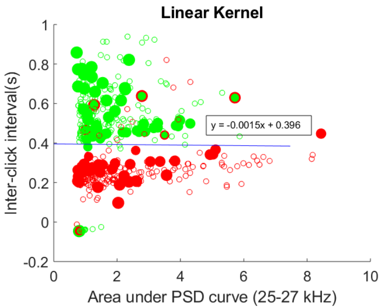
- Model accuracy: 92.5% (cross-validation), 91.7% (testing)

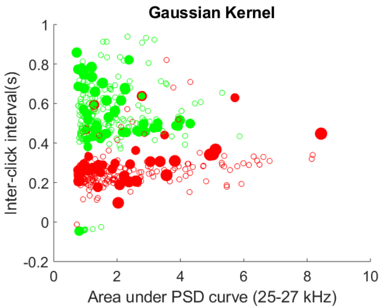
III Support Vector Machine



- Consider linear and Gaussian kernels
- *libsvm* package

III SVM Results





- 92.4% (testing)
- 94.8% (cross-validation), 96.7% (testing)

Metrics used

- Accuracy

$$A = \frac{TP + TN}{m}$$

- Precision

$$P = \frac{TP}{TP + FP}$$

- Recall

$$R = \frac{TP}{TP + FN}$$

- F_1 score

$$F_1 = 2\frac{PR}{P + R}$$

Algorithm Comparison

Algorithm	**Accuracy (%)**	**Precision**	**Recall**	F_1 **score**
GDA	92.2	0.878	0.927	0.900
LR	91.7	0.964	0.870	0.915
SVM (Linear)	92.4	0.954	0.891	0.921
SVM (Gaussian)	96.7	1	0.935	0.966

Conclusion

- GDA, LR, SVM (Linear) comparable
- SVM (Gaussian) in the lead
- Data efficient but features have to be well-defined

Thank you!