Pattern Recognition Lab

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FACULTY OF ENGINEERING

Deep Learning for Orca Call Type Identification – A Fully Unsupervised Approach

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Introduction – Killer Whale *(Orcinus Orca)* Communication

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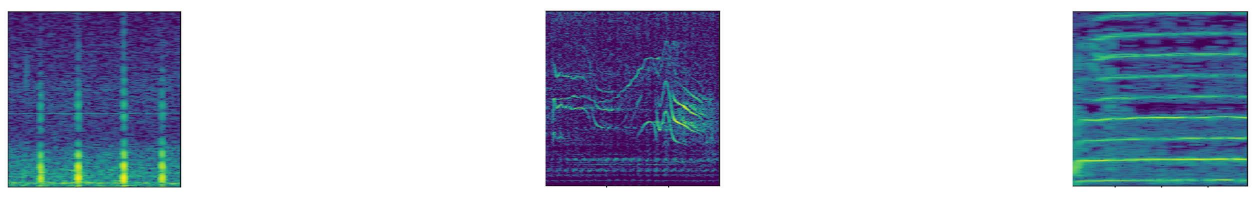
- **Largest member** of the **dolphin family** with complex and well-studied vocal structures [1] **producing three different sound types** [2]:



a) Echolocation Clicks **b)** Whistle **c)** Pulsed Call

- Pulsed calls are besides whistles and echolocation clicks the most common type of killer whale vocalization (discrete, variable, aberrant)
- **Pulsed calls (call types)** have sudden and patterned shifts in frequency with a pulse repetition rate between 250 and 2,000 Hz [2]
- Various pods (socializing matrilines) have **distinct vocal repertoires** (mixture of unique and shared discrete call types) $\rightarrow$ **Dialects**

Motivation – Fully Unsupervised Call Type Identification

- Current understanding of killer whale vocalizations refer to the **human classified killer whale sound type catalog** by Ford in **1987** [3]

a) A5 N09 **b)** A12 N09 **c)** A24 N09 **d)** A36 N09

- Huge **inter- but also intra-pod signal variations** even within one single human-labeled call type
- Fully unsupervised multi-step machine- and data-driven approach to address issues such as: (1) labor-intensive and **missing data annotation**, (2) **human** perception-based **classification**, (3) **human error-proneness**, (4) analysis of **large (bioacoustic) audio archives**

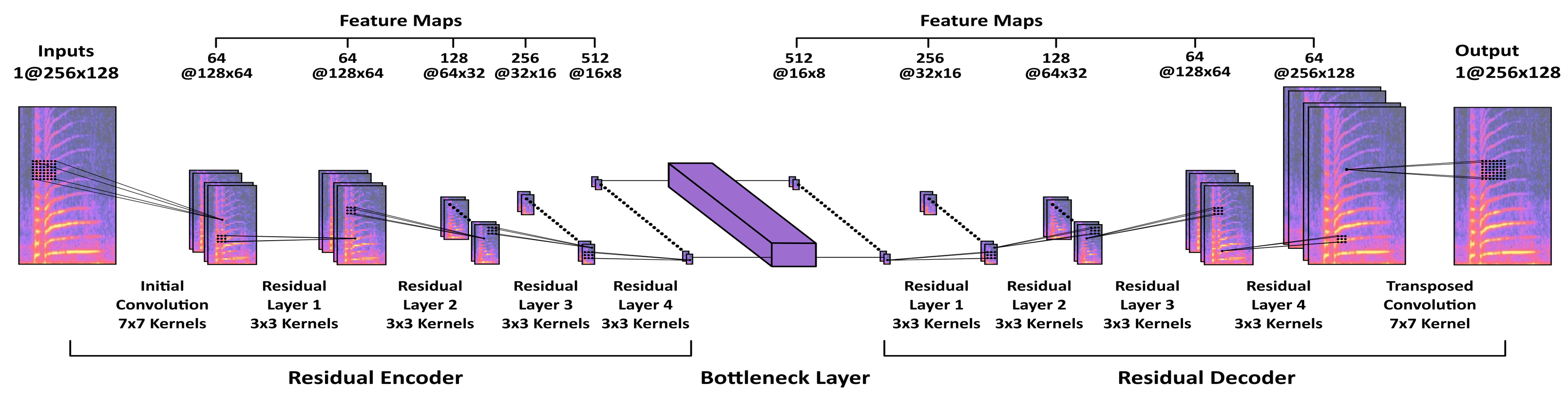
Methodology – Approach, Data Material, Network Models

- **Approach:** (1) Unsupervised killer whale **feature learning** using a **convolutional undercomplete ResNet18-autoencoder** trained on machine-annotated orca data, and (2) **Spectral clustering** of killer whale signals utilizing compressed **orca feature representations**
- **Orca Segmented Data (OSD):** 19,211 samples (100.0 %), Training: 13,443 samples (70.0 %), Validation: 2,902 samples (15.1 %), Test: 2,866 (14.9 %) (ResNet18-based orca/noise segmenter [4, 5])
- **Call Type Data:** 514 samples (100.0 %), Training: 363 samples (70.6 %), Validation: 72 samples (14.0 %), Test: 79 (15.4 %) [4]

Orca Call Type/ Corpus	N01	N02	N03	N04	N05	N07	N09	N12	N47	el	whistles	ns	SUM
CCS	33	10	—	21	14	18	26	16	—	—	—	—	**138**
CCN	36	—	56	60	—	31	70	—	33	—	—	—	**286**
EXT	—	—	—	—	—	—	—	—	—	30	30	30	**90**
SUM	**69**	**10**	**56**	**81**	**14**	**49**	**96**	**16**	**33**	**30**	**30**	**30**	**514**

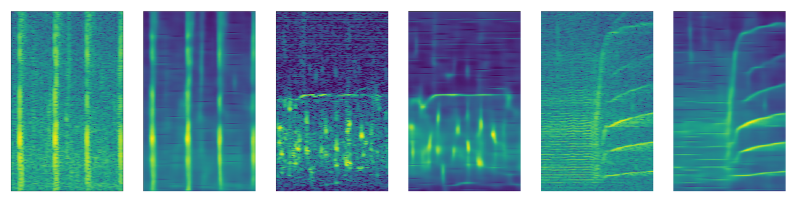
- **Network models:** (1) **Orca/Noise Segmenter** (CNN, 2-classes, cross-entropy loss) [4, 5], **Call Type Classifier** (CNN, 12-classes, cross-entropy loss) [4], and **convol. undercomplete Autoencoder** (mean squared error loss) are all based on ResNet18 [6]

Experiments – Data Preprocessing, Training, Setup

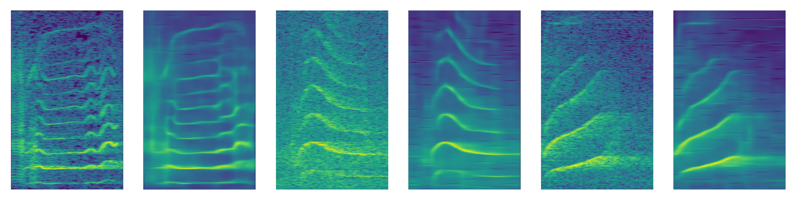


- **Data Preprocessing:** power spectrum, dB-conversion, augmentation, linear frequency compression (256 bins), noise augmentation, dB-normalization, subsampling/padding (1.28 s) $\rightarrow 1 \times 256 \times 128$
- **Network Training:** implemented in PyTorch, Adam optimizer, $\alpha = 10^{-5}$, $\beta_1 = 0.5$, $\beta_2 = 0.999$, batch size of 32 (Segmentation/Feature Learning) and 4 (Call Type Classification), α decay of 0.5 after 4 epochs and training stopped after 10 epochs without improvements on the validation set
- **Experimental Setup:** (1) Autoencoder feature learning using the automatic pre-segmented OSD dataset combined with a subsequent spectral clustering (gap statistic) using $4 \times 16 \times 8$ bottleneck features of the call type dataset, (2) Identifying potential call type sub-classes and human-misclassifications for all 514 human-labeled orca signals, and (3) Supervised [4] vs. Unsupervised Call Type Classification

Result – Reconstructions

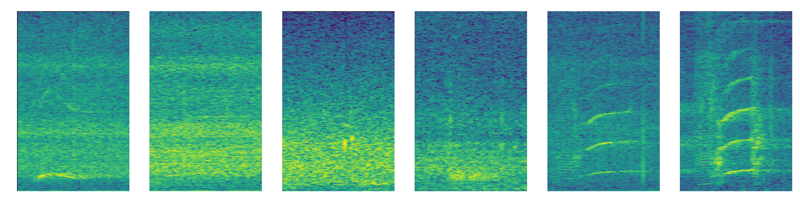


echo clicks whistle N09

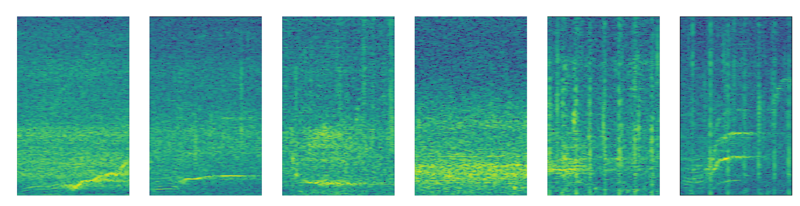


N01 N04 N47

Result – Misclassifications

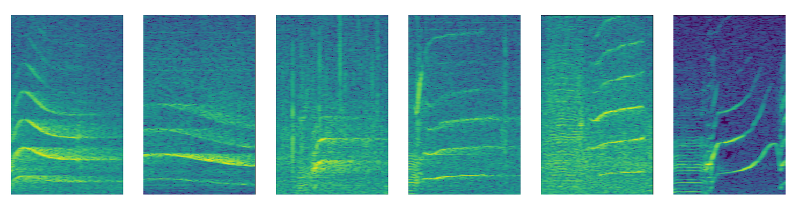


cl.a) N04/N09 **cl.b)** ns/el **cl.c)** N07/N09

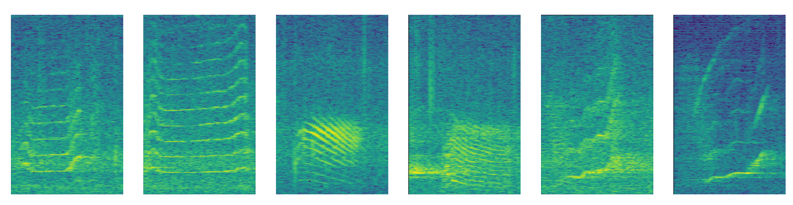


cl.d) N47/N09 **cl.e)** N03/ns **cl.f)** el/N07

Result – Sub-Call Types

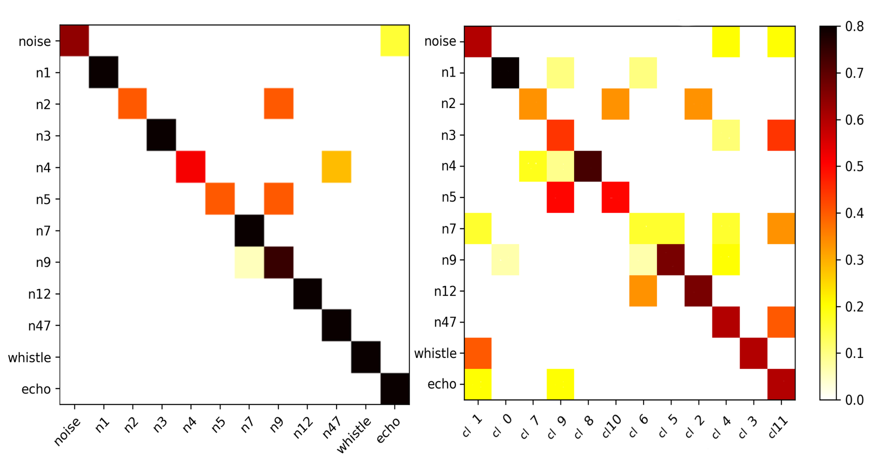


N04 cluster N07 cluster N09 cluster



N01 cluster N03 cluster N47 cluster

Result – Superv./Unsuperv.



hypothesis [4] hypothesis

Conclusion and Future Work

- Robust analysis of large datasets, no labeled data required, less susceptibility to human errors, human perception eliminated, derivation of new, previously unknown (sub-)call types
- Process entire Orchive [7] to derive totally new insights/possibilities

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