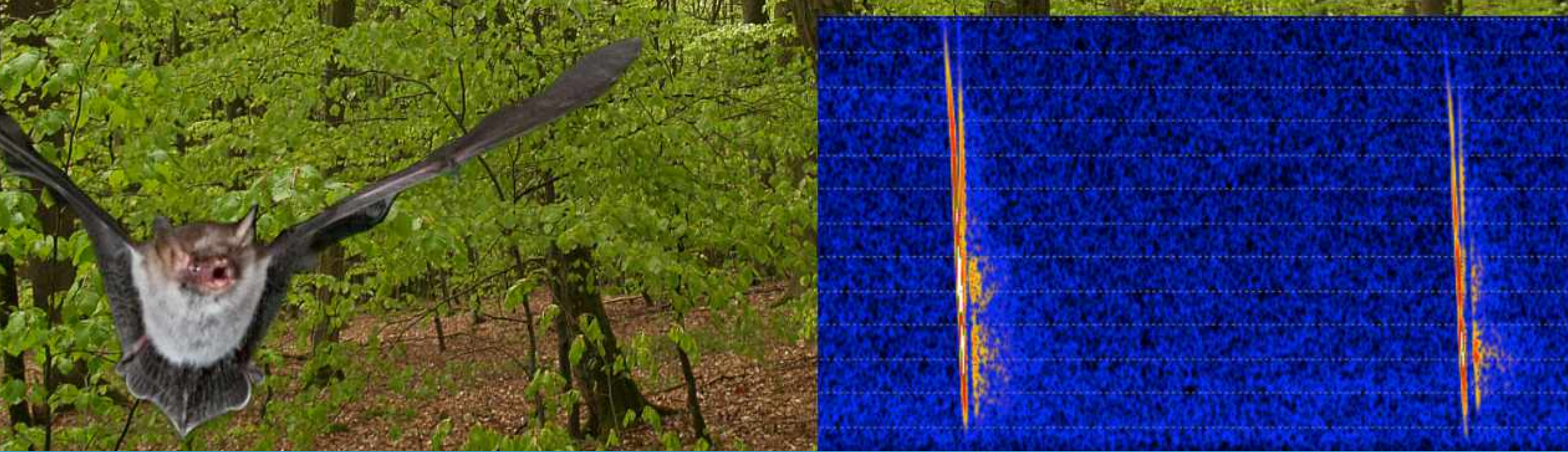




KI - FLUCH ODER SEGEN ?

KÜNSTLICHE INTELLIGENZ VS HUMAN BRAIN POWER

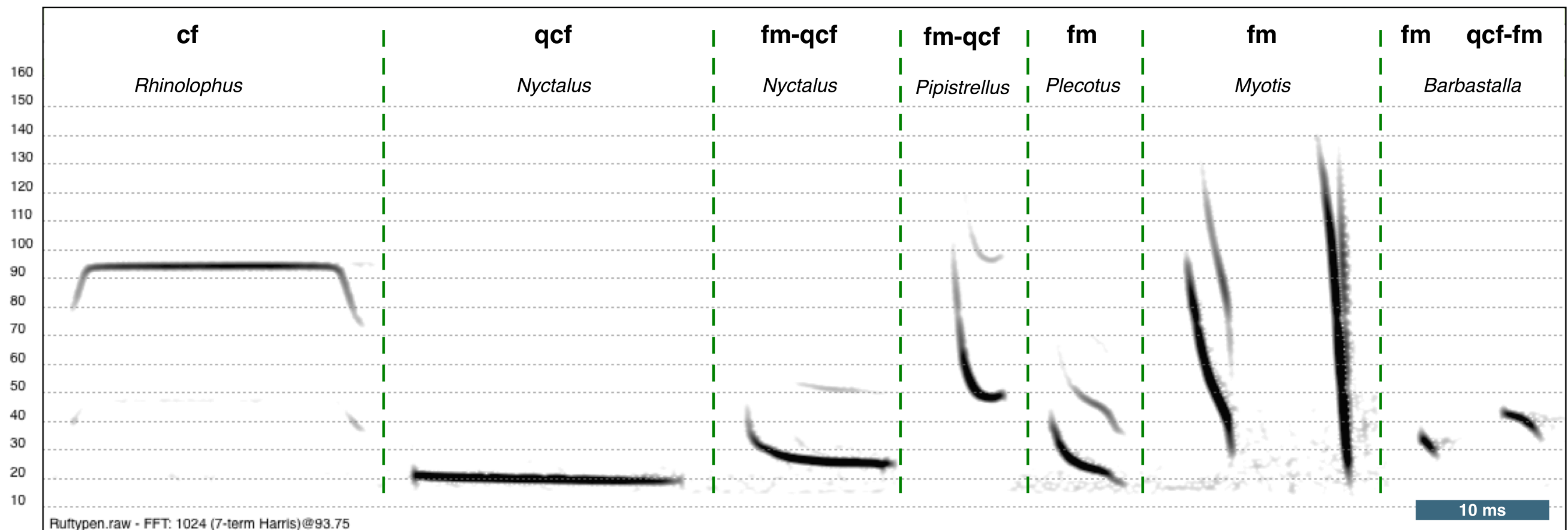
A photograph of a bat in flight against a dark background. The bat's wings are spread, and its body is illuminated. Overlaid on the image is a sonar visualization consisting of three vertical yellow lines and three corresponding blue and yellow speckled areas at the bottom, representing the bat's echolocation pulses and returning echoes.

FLEDERMAUS

RUFE BESTIMMEN

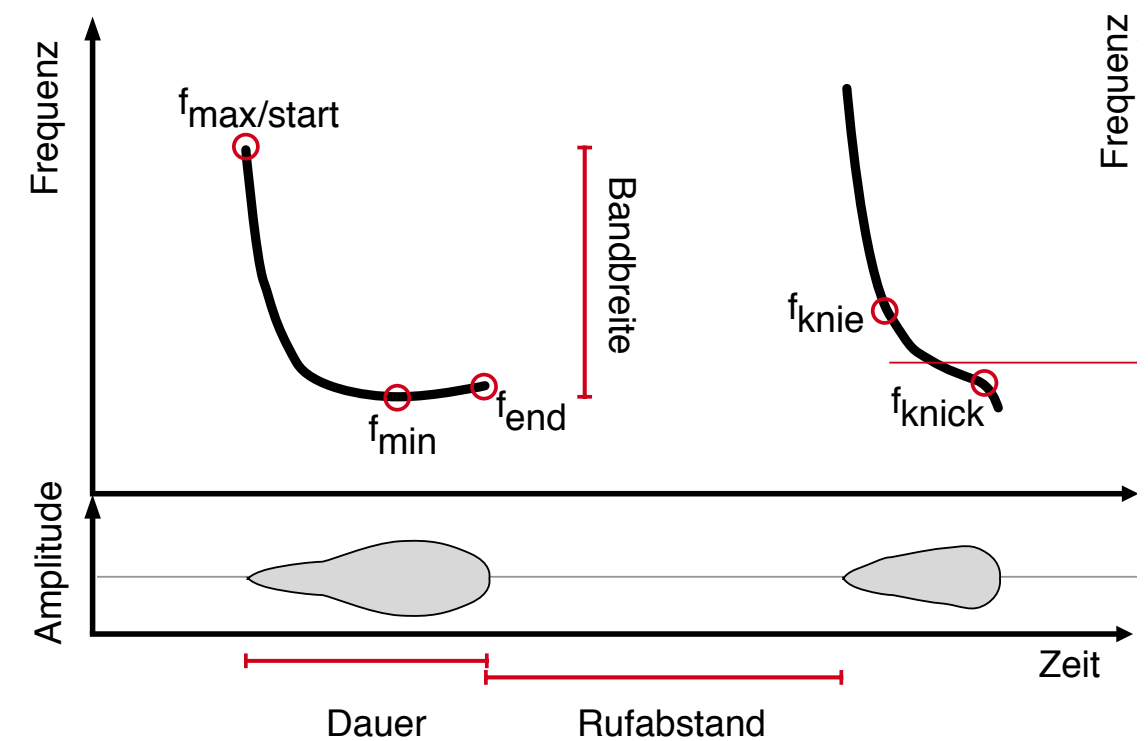
RUFTYPEN

- ▶ >50 Arten in Europa
- ▶ ~25 Arten in Deutschland aus 9 Gattungen

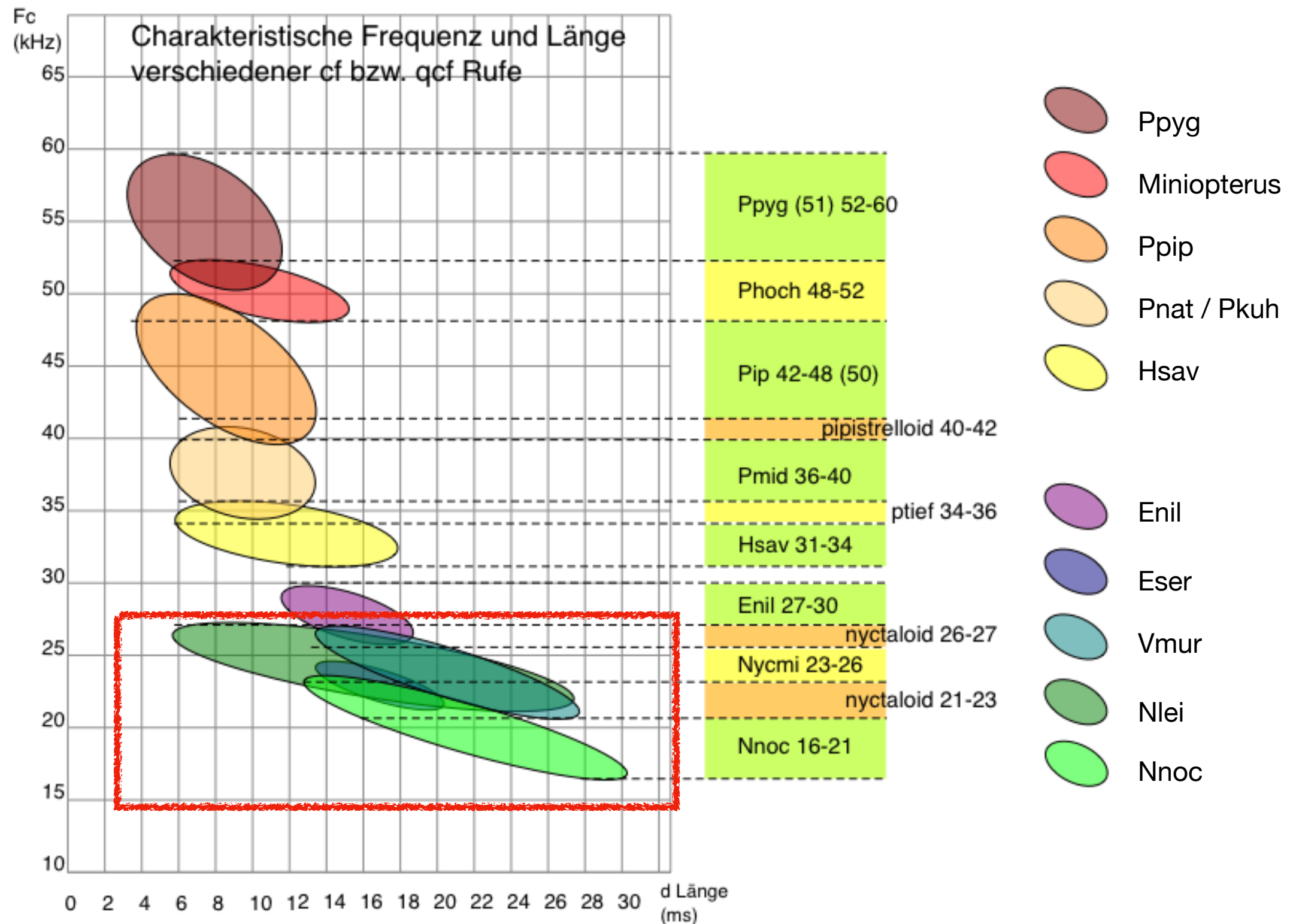


IDENTIFIKATION VON ARTEN: MESSWERTE

- ▶ Einfache Parameter
 - ▶ Rufdauer, Startfrequenz, ...
 - ▶ meßbar durch Menschen
- ▶ Überlappung mancher Arten

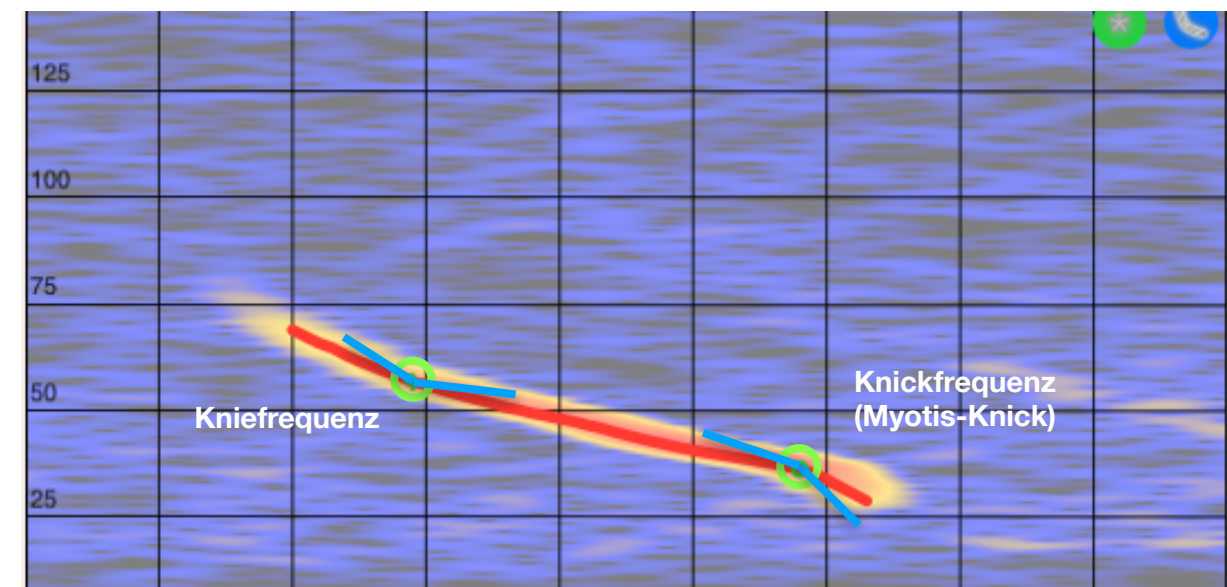
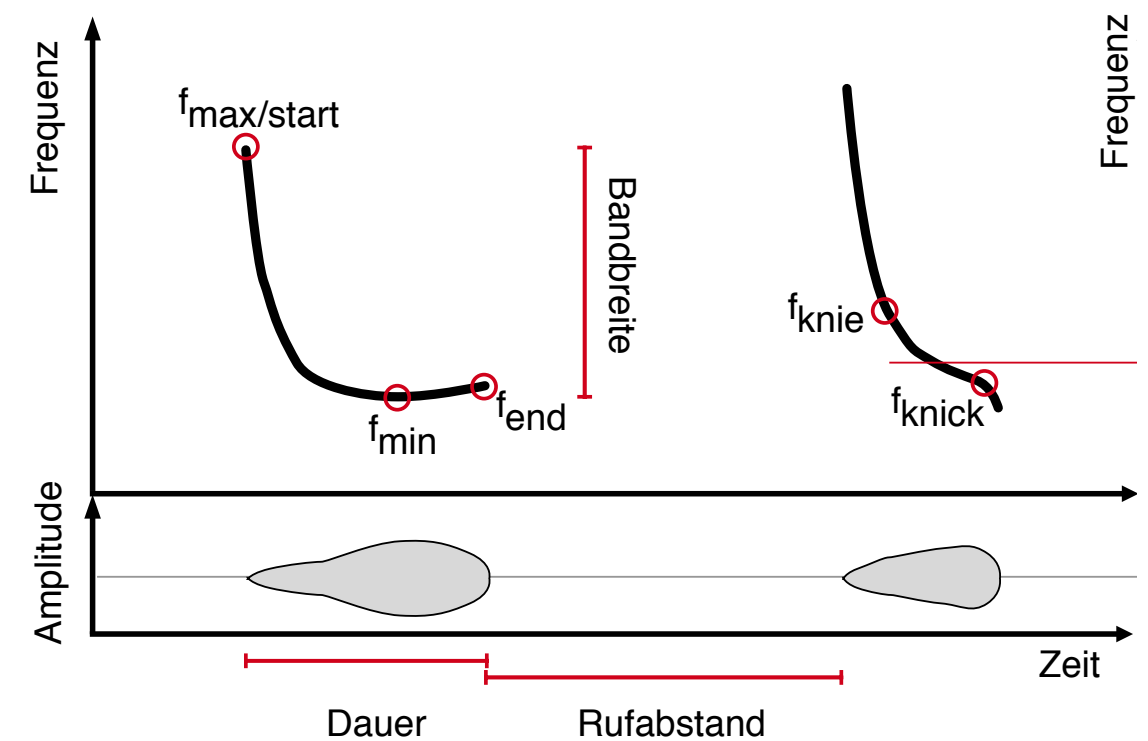


VARIABILITÄT UND ÜBERLAPPUNG



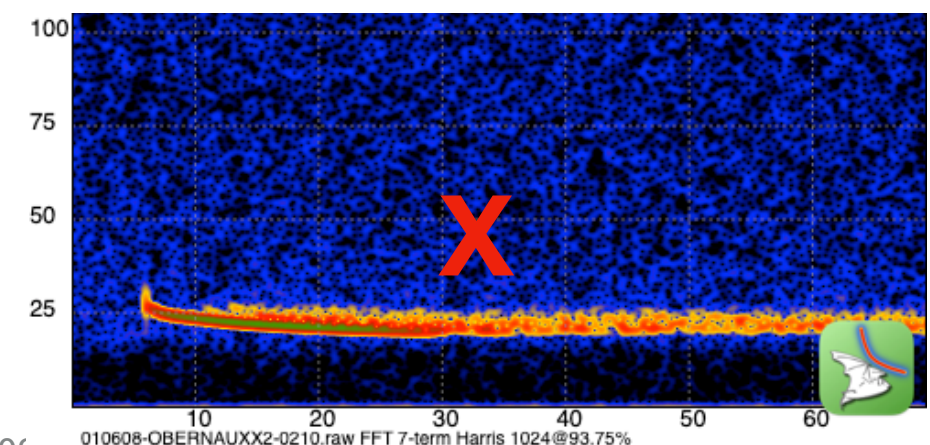
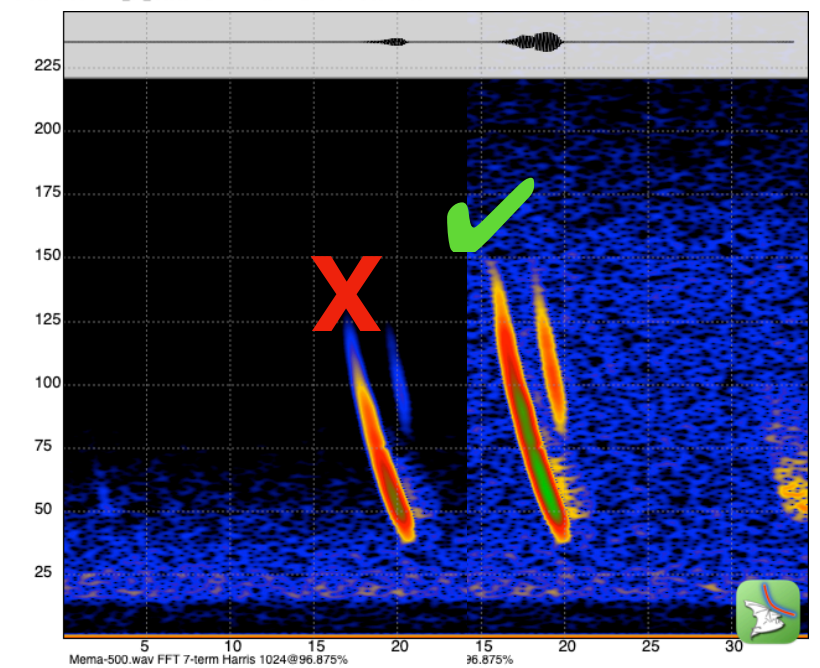
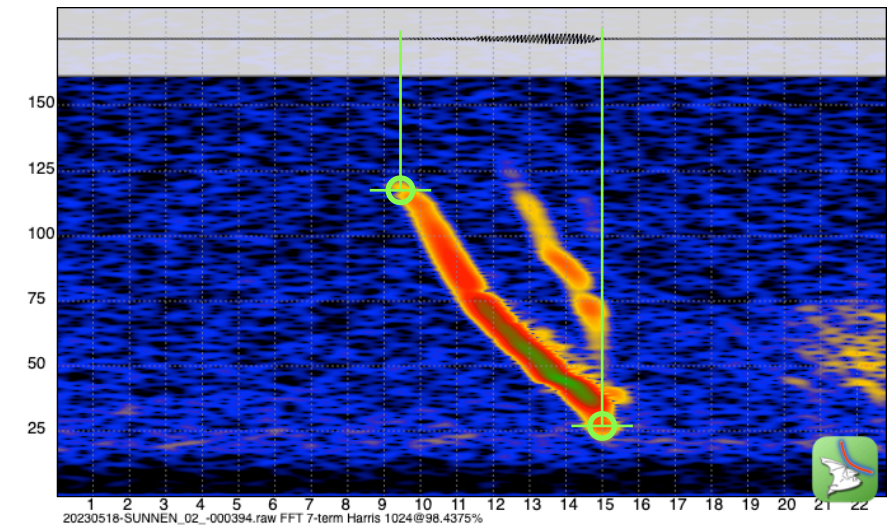
IDENTIFIKATION VON ARTEN: MESSWERTE

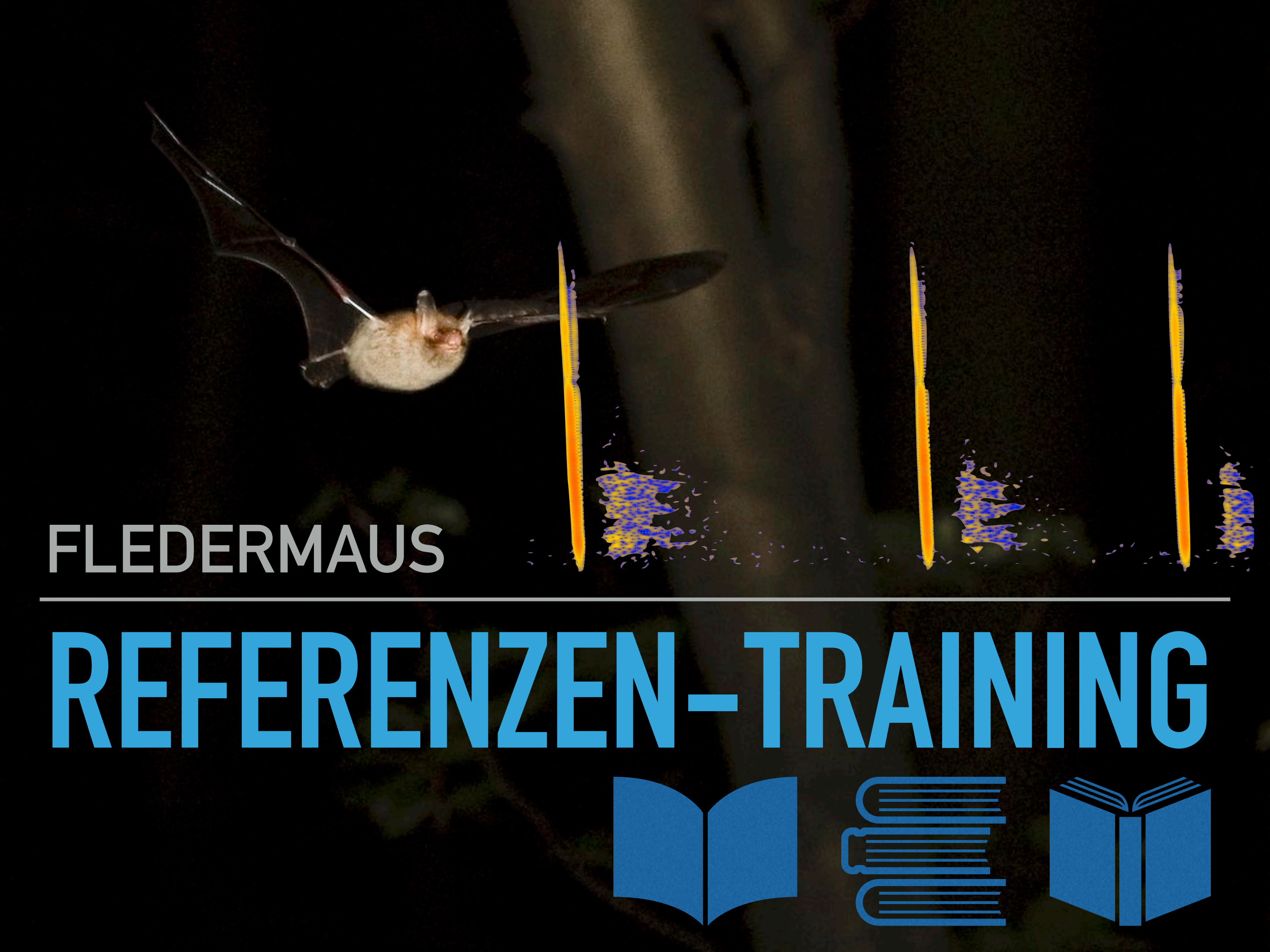
- ▶ Einfache Parameter
 - ▶ Rufdauer, Startfrequenz, ...
 - ▶ meßbar durch Menschen
- ▶ Überlappung mancher Arten
 - ▶ Kombination von Parametern
 - ▶ zusätzlich abgeleitete Messwerte
 - ▶ Vermessung teils schwierig



IDENTIFIKATION VON ARTEN: VERMESSUNG

- ▶ Messung
 - ▶ Sonagramm: Frequenzen/Zeit
 - ▶ Spektrum: Frequenzen
- ▶ „Bildqualität“ ist stark korreliert mit Aufnahmequalität
 - ▶ schlechte Aufnahme, schlechtes Sonagramm
 - ▶ großer Einfluß der Technik (Hardware und Software)



A bat is shown in flight against a dark background. A vertical beam of light illuminates the scene. Three vertical yellow lines are positioned on the right side of the image.

FLEDERMAUS

REFERENZEN-TRAINING

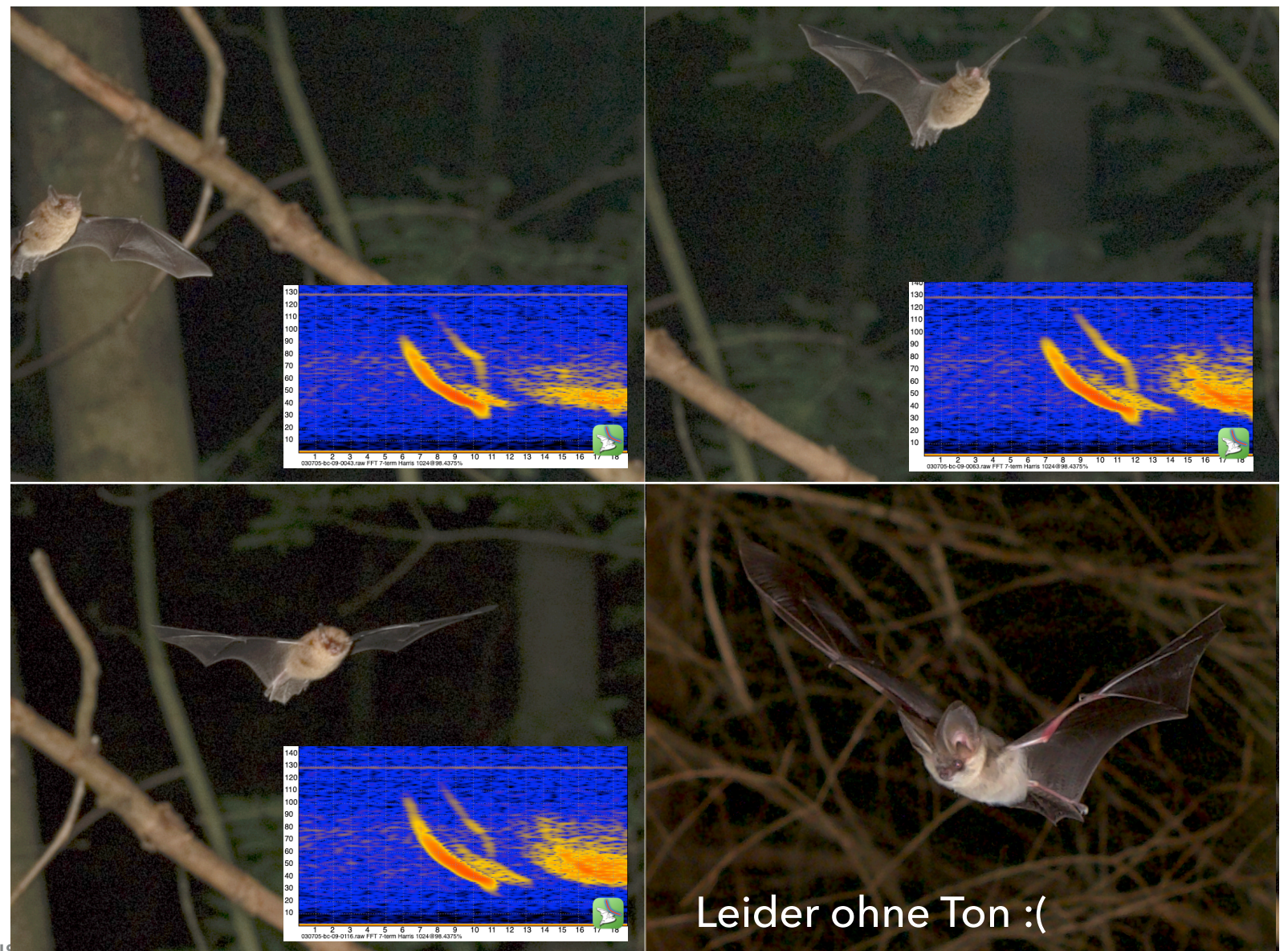


RUF-REFERENZEN UND KI-TRAINING

- ▶ Referenz-Rufe oder auch *ground truth*
 - ▶ manuelle Auswahl, gute Qualität
 - ▶ „typische“ Rufe des gesamten Rufspektrums
- ▶ Generelle Probleme
 - ▶ Woher kommen die Rufe?
 - ▶ Wie stellt man Art bei Freiland-Rufen sicher?
 - ▶ Ist das Rufspektrum gut abgebildet?
- ▶ Gefahr
 - ▶ Zirkelschlüsse bei der sicheren Artbestimmung
 - ▶ Messmethode nicht eindeutig

TRAINING – REFERENZRUFE

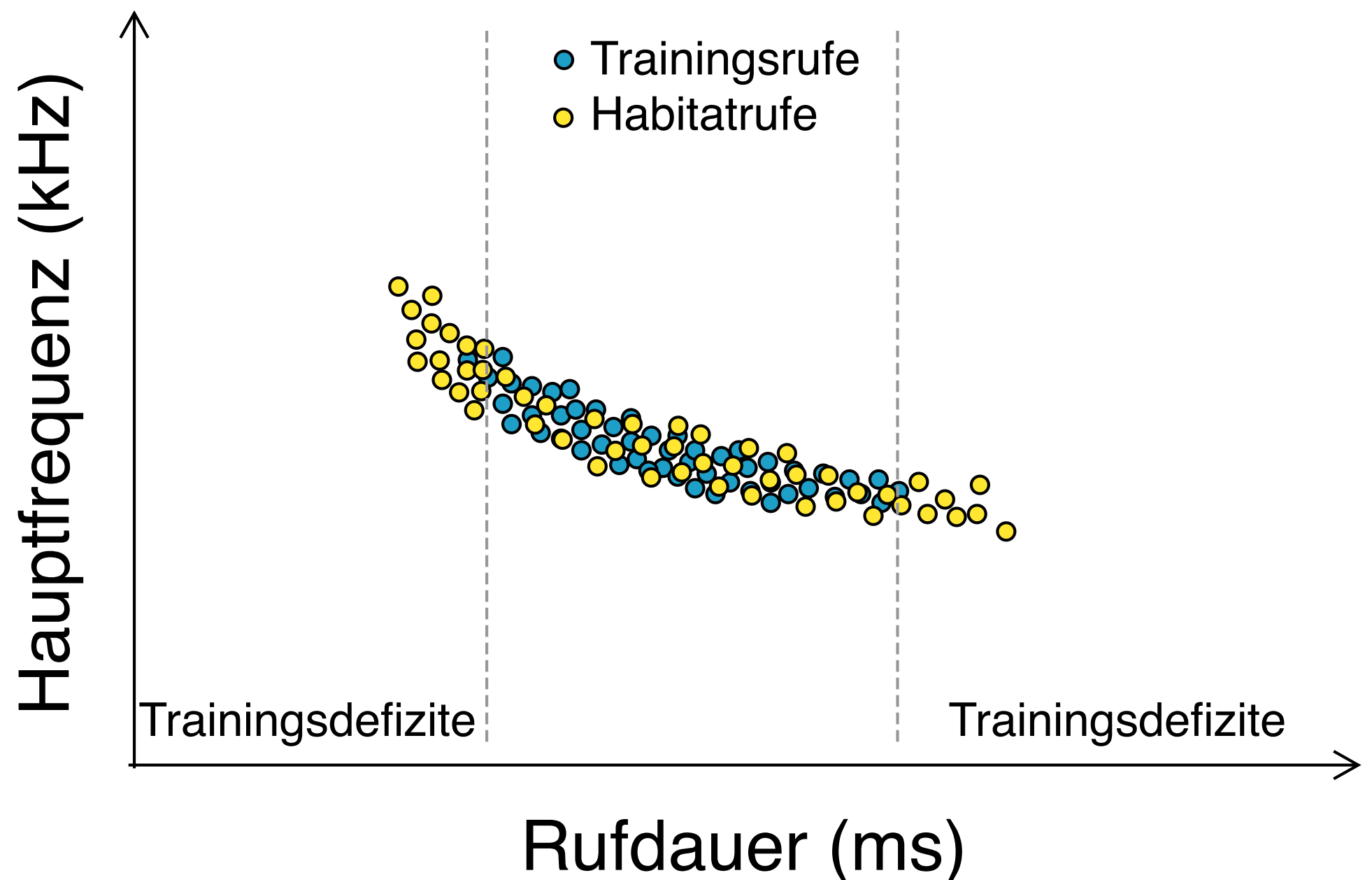
- ▶ Sammlung von typischen Rufen im Freiland
 - ▶ nicht nur oder nur wenig: Netzfang, Quartierausflug



Leider ohne Ton :(

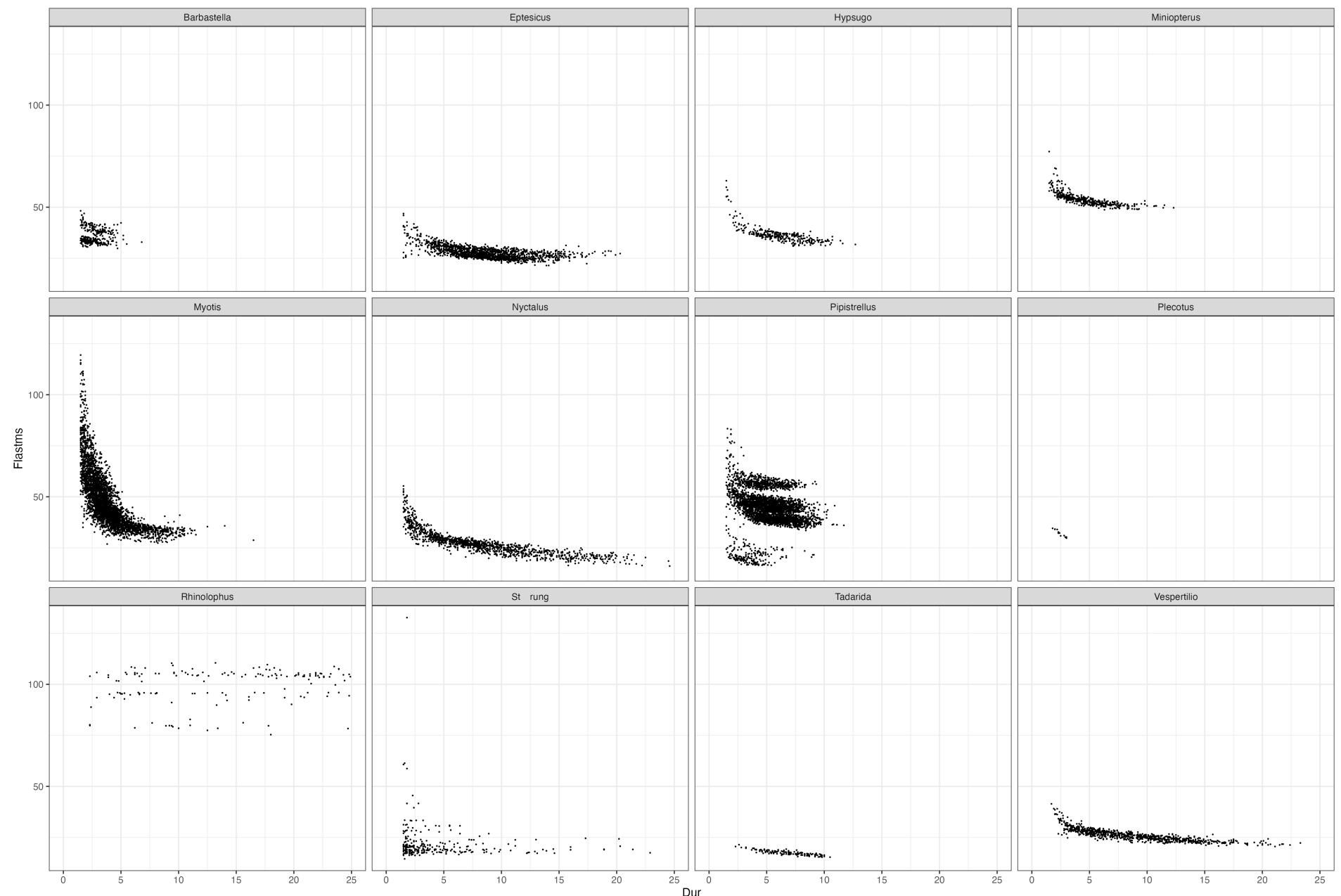
TRAINING – REFERENZRUF

► Vollständiges Rufspektrum?



TRAINING – REFERENZRUFE

► Vollständiges Rufspektrum?



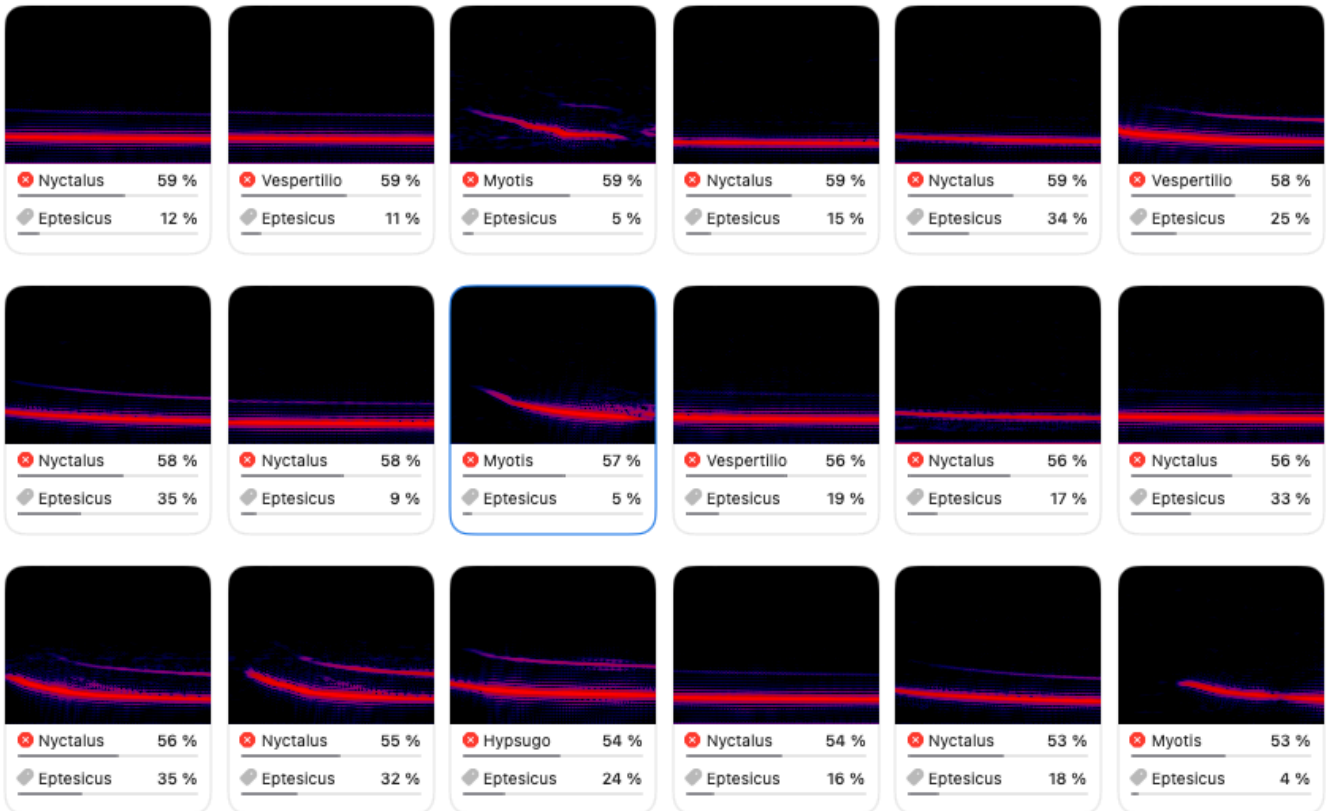


TRAINING – REFERENZRUFE

- ▶ Training
- ▶ Training
- ▶ Training
- ▶ Ergebnis:
KI-Modell
oder
Nachschlagetabelle

Class	Count	Correct	False Positives	False Negatives	Precision	Recall	F1 Score
Barbastella	102	64	14	38	82 %	63 %	0,71
Eptesicus	423	339	116	84	75 %	80 %	0,77
Hypsugo	154	99	29	55	77 %	64 %	0,7
Myotis	1147	1095	121	52	90 %	95 %	0,93
Nyctalus	409	305	74	104	80 %	75 %	0,77
Pipistrellus	611	589	49	22	92 %	96 %	0,94
Plecotus	72	44	3	28	94 %	61 %	0,74
Stoerung	43	36	8	7	82 %	84 %	0,83
Vespertilio	183	119	40	64	75 %	65 %	0,7

84 images labeled as 'Eptesicus' were incorrectly classified



A photograph of a bat in flight against a dark background. The bat's wings are spread, and its body is visible. Overlaid on the image is a heatmap visualization of echolocation data. Three vertical yellow lines represent the primary echolocation calls, with blue and purple speckled areas below them indicating the returning echoes. The bat is positioned to the left of the first call.

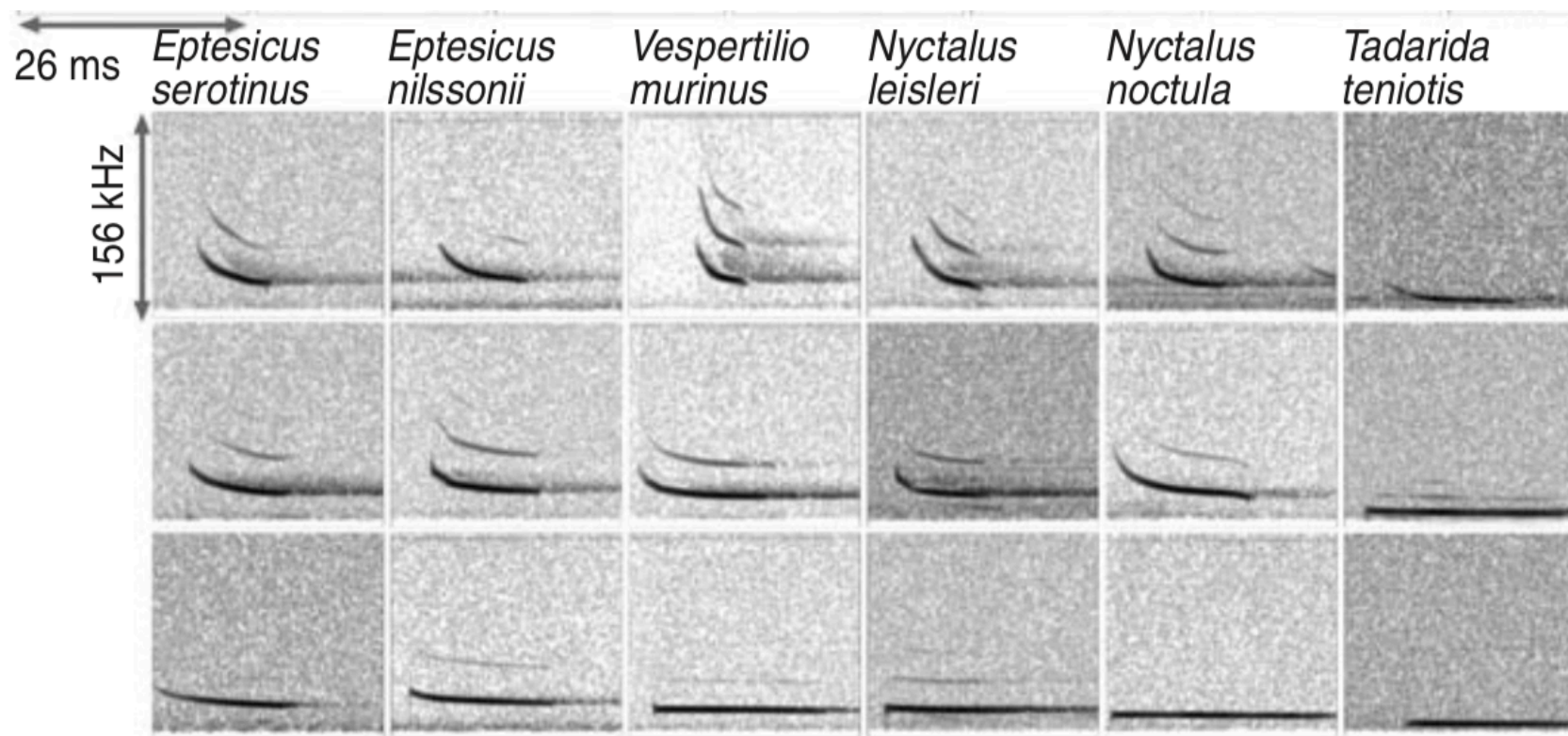
FLEDERMAUS

KI-ERGEBNISSE

IDENTIFIKATION VON ARTEN

► Intra- und Interspezifische Variabilität

Obrist, M. K., Boesch, R., & Flückiger, P. F. (**2004**). Variability in echolocation call design of 26 Swiss bat species: consequences, limits and options for automated field identification with a synergetic pattern recognition approach.



IDENTIFIKATION VON ARTEN

Assigned to species	Myotis bechsteinii	Myotis blythii	Myotis brandtii	Myotis capaccinii	Myotis daubentonii	Myotis emarginatus	Myotis myotis	Myotis mystacinus	Myotis nattereri	Barbastella barbastellus	Plecotus auritus	Plecotus austriacus	Hypsugo savii	Pipistrellus kuhlii	Pipistrellus nathusii	Pipistrellus pipistrellus	Pipistrellus pygmaeus	Miniopterus schreibersii	Eptesicus serotinus	Eptesicus nilssonii	Vespertilio murinus	Nyctalus leisleri	Nyctalus noctula	Tadarida teniotis	Rhinolophus hipposideros	Rhinolophus ferrumequinum	correct classifications
From species	Myotis bechsteinii	Myotis blythii	Myotis brandtii	Myotis capaccinii	Myotis daubentonii	Myotis emarginatus	Myotis myotis	Myotis mystacinus	Myotis nattereri	Barbastella barbastellus	Plecotus auritus	Plecotus austriacus	Hypsugo savii	Pipistrellus kuhlii	Pipistrellus nathusii	Pipistrellus pipistrellus	Pipistrellus pygmaeus	Miniopterus schreibersii	Eptesicus serotinus	Eptesicus nilssonii	Vespertilio murinus	Nyctalus leisleri	Nyctalus noctula	Tadarida teniotis	Rhinolophus hipposideros	Rhinolophus ferrumequinum	correct classifications
Myotis bechsteinii	31%	13%	14%	2%	6%	2%	2%	28%	1%																	31%	
M. blythii	7%	64%	2%		2%	4%	1%	16%	4%		1%															64%	
M. brandtii	19%	1%	28%	4%	9%	1%	7%	28%	0%					1%	1%											28%	
M. capaccinii	1%		4%	68%	5%	5%	1%	5%						8%	4%											68%	
M. daubentonii	3%		2%	14%	60%	0%	7%	10%		1%	2%			0%												60%	
M.emarginatus	1%	2%	1%	7%		86%		4%						0%												86%	
M. myotis	1%	6%	3%	1%	6%		73%	2%	3%		0%	1%										4%				73%	
M. mystacinus	17%	10%	5%	3%	19%	7%	3%	36%							0%											36%	
M. nattereri	0%	12%	2%				4%	1%	82%																	82%	
average Myotis																										59%	
Barbastella barbastellus										87%	1%	6%	3%	2%								1%				87%	
Plecotus auritus	0%	1%						0%	1%	6%	85%	6%									0%	1%				85%	
P. austriacus							0%			5%	6%	89%														89%	
Hypsugo savii				2%						6%			90%	1%								1%				90%	
Pipistrellus kuhlii				9%	0%									0%	81%	10%										81%	
P. nathusii				3%				0%						18%	80%											80%	
P. pipistrellus				1%											0%	95%		4%								95%	
P. pygmaeus																	94%	6%								94%	
Miniopterus schreibersii																4%	6%	89%								89%	
Eptesicus serotinus							1%												69%	5%	10%	10%	5%			69%	
E. nilssonii							1%												5%	90%	1%	2%	1%			90%	
Vespertilio murinus							1%			1%		0%							10%		72%	6%	10%			72%	
Nyctalus leisleri				3%			3%			1%									41%		21%	27%	3%			27%	
N. noctula							0%					1%							13%	1%	6%	5%	75%			75%	
Tadarida teniotis											0%											2%	97%			97%	
Rhinolophus hipposideros																								100%		100%	
R. ferrumequinum																	0%								100%	100%	
average non-Myotis																										84%	
Total average																										75%	

AUTOMATISCHE RUFBESTIMMUNG

- ▶ Manuelle versus automatische Artbestimmung
 - ▶ Jennings et al. (**2008**). Human vs. machine: identification of bat species from their echolocation calls by humans and by artificial neural networks.
 - ▶ Fritsch, G., & Bruckner, A. (2014). Operator bias in software-aided bat call identification.





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Table 1. Summary classification rates of bat recordings, assessed by using sensitivity (recordings correctly classified) and positive predictive power (PPP; predictions that were actually recordings of that species) for humans and artificial neural networks (ANNs).

Taxon	N*	Humans			ANNs	
		Number of confusion species	Median percent sensitivity	Median percent PPP	Percent sensitivity	Percent PPP
<i>Pipistrellus pipistrellus</i>	3	1	100 (100–100)	100 (100–100)	100	100
<i>Pipistrellus pygmaeus</i>	2	2	100 (100–100)	100 (100–100)	100	100
<i>Pipistrellus</i> (to genus)	5	—	100 (100–100)	100 (100–100)	100	100
<i>Nyctalus leisleri</i>	3	5	33 (0–67)	67 (0–100)	33	100
<i>Nyctalus noctula</i>	3	2	100 (100–100)	75 (75–100)	100	86
<i>Nyctalus</i> (to genus)	6	—	67 (67–83)	100 (80–100)	75	100
<i>Eptesicus serotinus</i>	4	7	50 (50–75)	67 (53–75)	88†	78†

Note: Values in parentheses are interquartile ranges.
*The number of recordings in the data set.
†The classification rate of the ANNs was above the interquartile range of that of the human participants.



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 - ▶ Fritsch, G., & Bruckner, A. (2014). Operator bias in software-aided bat call identification.
- ▶ Software für automatische Artbestimmung
 - ▶ Russo, D., & Voigt, C. C. (2016). The use of automated identification of bat echolocation calls in acoustic monitoring: A cautionary note for a sound analysis.
 - ▶ Rydell et al. (2017). Testing the performances of automated identification of bat echolocation calls: A request for prudence.
 - ▶ Brabant et al. (2018). Comparing the results of four widely used automated bat identification software programs to identify nine bat species in coastal Western Europe.



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 - ▶ Fritsch, G., & Bruckner, A. (2014). Operator bias in software-aided bat call identification.

- ▶ Software für automatische Artbestimmung

Species	Software A					Software B			Software C			Software D				
	Right species group (%)	Wrong species group (%)	Right species (%)	Wrong species (%)	NoID (%)	Right species (%)	Wrong species (%)	NoID (%)	Right species (%)	Wrong species (%)	NoID (%)	Right species group (%)	Wrong species group (%)	Right species (%)	Wrong species (%)	NoID (%)
Total (n=148)	88.0	12.0	77.3	22.7	0.0	31.3	66.7	2.0	71.3	10.7	18.0	85.3	14.7	65.3	34.7	0.0

- ▶ Brabant et al. (2018). Comparing the results of four widely used automated bat identification software programs to identify nine bat species in coastal Western Europe.

AUTOMATISCHE RUFBESTIMMUNG: SONAGRAMM-KI

► Open-source Bild-KI (Runkel 2021)

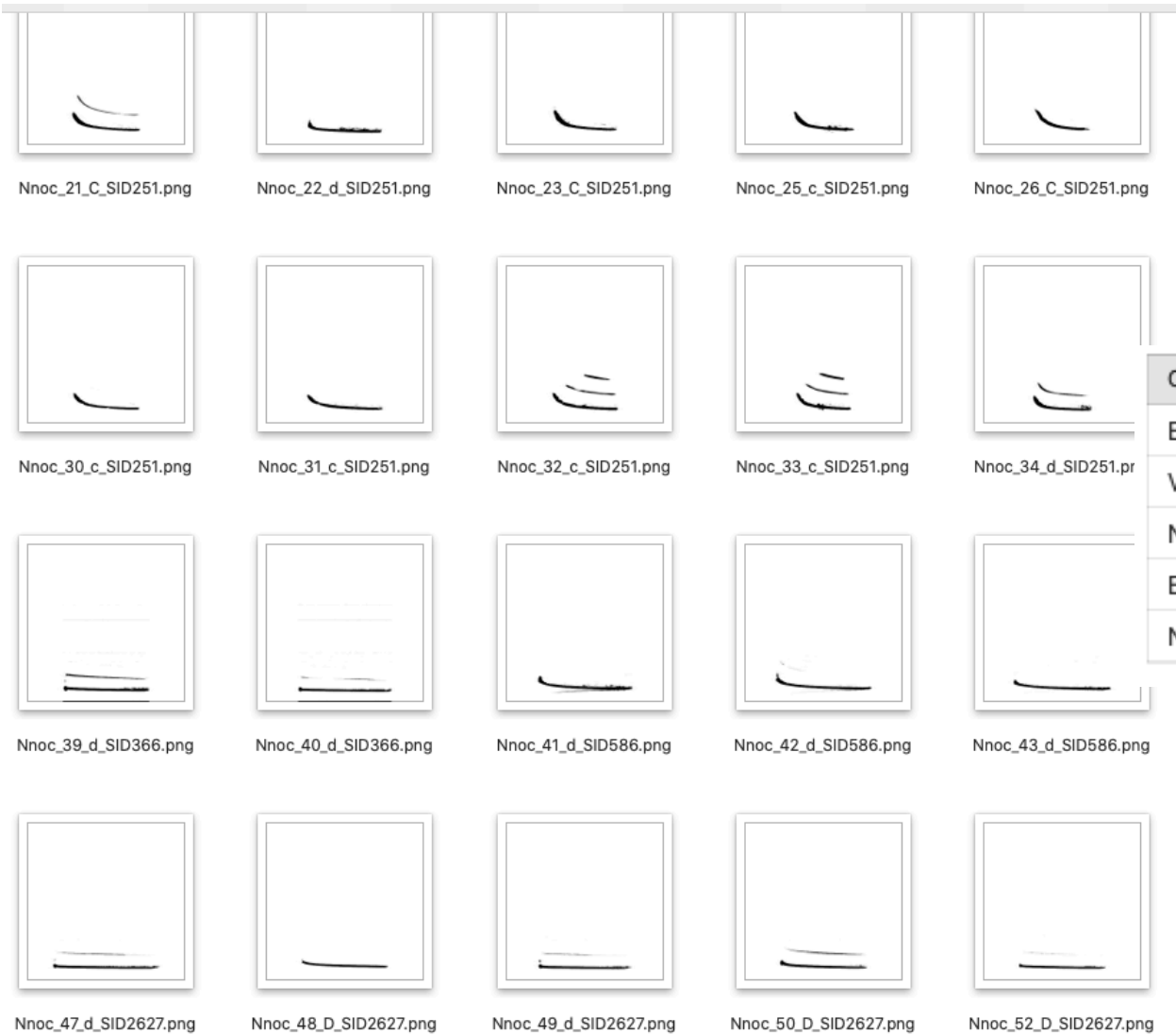
Class	Item Count	Precision	Recall
Enil	12	88 %	58 %
Vmur	14	73 %	57 %
Nlei	8	67 %	50 %
Eser	7	60 %	86 %
Nnoc	9	53 %	89 %

<https://github.com/vrunkel/CoreMLBats-model-calls>

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AUTOMATISCHE RUFBESTIMMUNG: SONAGRAMM-KI

- Schwab et al. (2022): Automated bat call classification using deep convolutional neural networks. Bioacoustics. 10.1080/09524622.2022.2050816

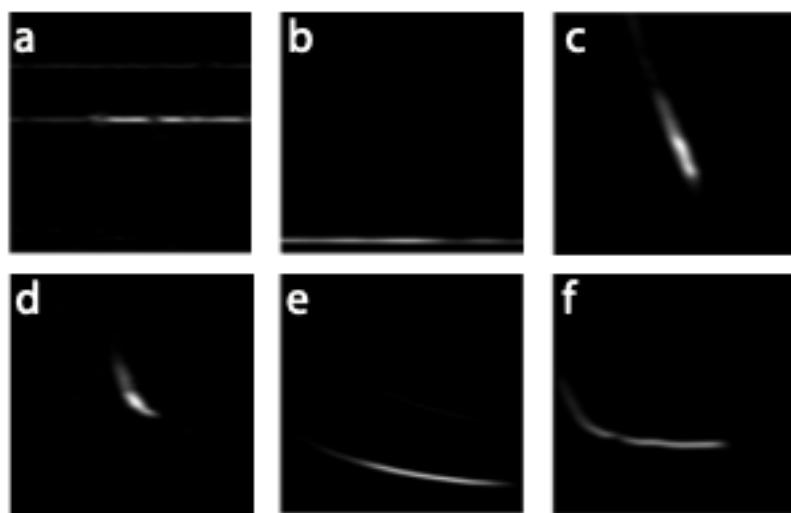


Table 2. Classification accuracy of the network architectures for the 18 included species on the test set (four different CNN topologies).

Species	CNN Type			
	CNN6	CNN10	CNNIncept	CNNResNet
Barbastella barbastellus	93.41	95.36	99.85	100.0
Eptesicus nilssonii	79.97	82.84	92.93	96.21
Eptesicus serotinus	64.59	67.77	77.38	93.14
Myotis bechsteinii	89.91	92.84	97.94	100.0
Myotis brandtii/Myotis mystacinus	88.61	91.89	96.64	96.19
Myotis dasycneme	11.47	22.48	57.98	93.21
Myotis daubentonii	69.25	76.80	75.93	97.73
Myotis emarginatus	94.94	97.92	99.94	98.29
Myotis myotis	89.58	92.92	97.92	99.57
Myotis nattereri	94.78	97.82	99.91	98.11
Nyctalus leisleri	74.79	80.74	90.02	94.62
Nyctalus noctula	94.85	97.97	99.95	97.93
Pipistrellus kuhlii	78.76	80.41	92.20	92.97
Pipistrellus nathusii	79.61	82.69	92.59	88.90
Pipistrellus pipistrellus	88.95	92.01	97.66	98.54
Pipistrellus pygmaeus	94.91	97.92	99.97	98.10
Plecotus austriacus/auritus	85.25	90.00	96.30	97.83
Vespertilio murinus	79.21	82.70	92.73	93.31
Mean Accuracy	80.71	84.62	92.10	96.13

A photograph of a bat in flight against a dark background. A heatmap overlay is visible, showing three vertical yellow-orange lines and several blue and yellow speckled areas, likely representing echolocation or sensor data. The bat is positioned in the upper left quadrant, with its wings spread.

FLEDERMAUS

KONTROLLE DER KI

UNABHÄNGIGE VALIDIERUNG

- ▶ Vergleich bestehender und neuer Systeme
 - ▶ unabhängig
 - ▶ neutrale Einordnung von Ergebnissen
- ▶ Validierungs-Datensatz
 - ▶ gesicherte Habitataufnahmen
 - ▶ möglichst gute Abdeckung der Variabilität
 - ▶ seit 2024 erster öffentlicher Datensatz verfügbar:
<https://batident.eu/downloads/ValidationSet.zip>



BEWERTUNG VON QUALITÄT

- ▶ Genauigkeit / Fehler
 - ▶ je Gruppe, Gattung und Art
 - ▶ Falsch-positive / falsch-negative
- ▶ Einzelaufnahmen
- ▶ Große Datensätze
 - ▶ Geschwindigkeit / Aufwand

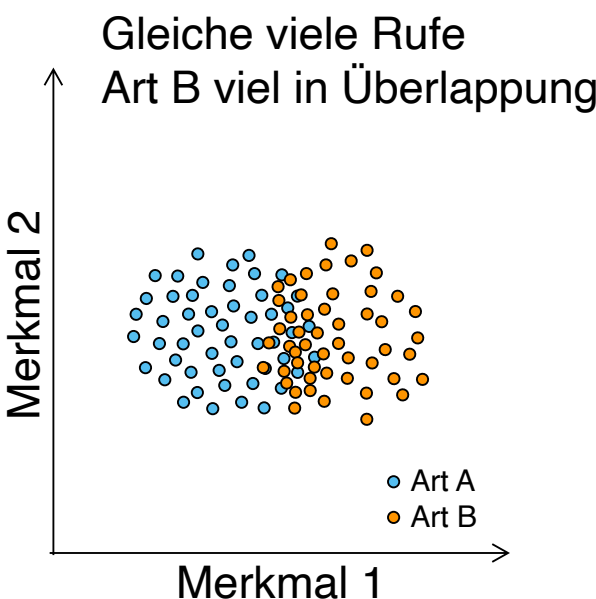
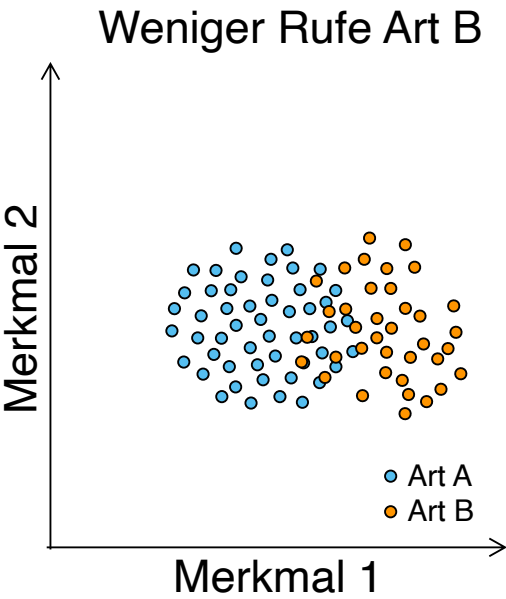
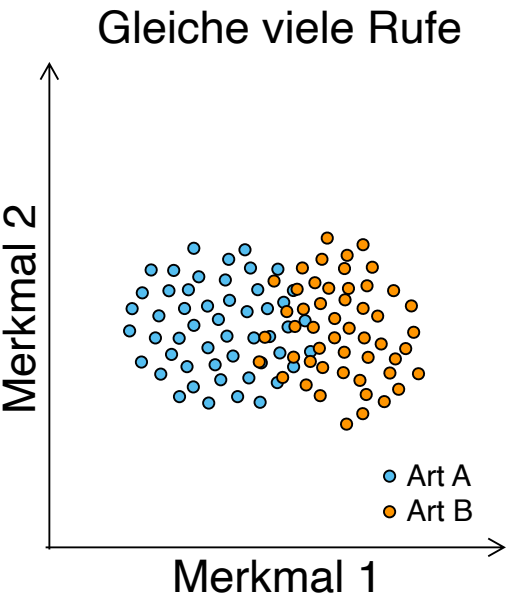
Gute Informationen zur Bewertung (ecoObs 2009):

<https://ecoobs.de/herunterladen/leitfaden-die-automatische-rufanalyse-mit-dem-batcorder-system/?tmstv=1758868547>



FEHLERQUELLEN

► Rufspektrum nicht adäquat abgedeckt



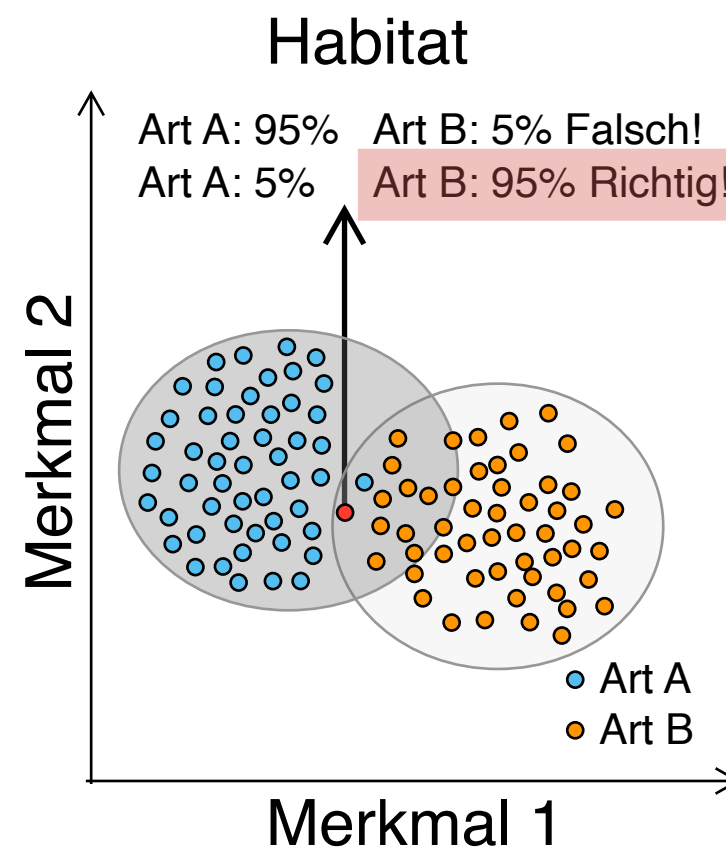
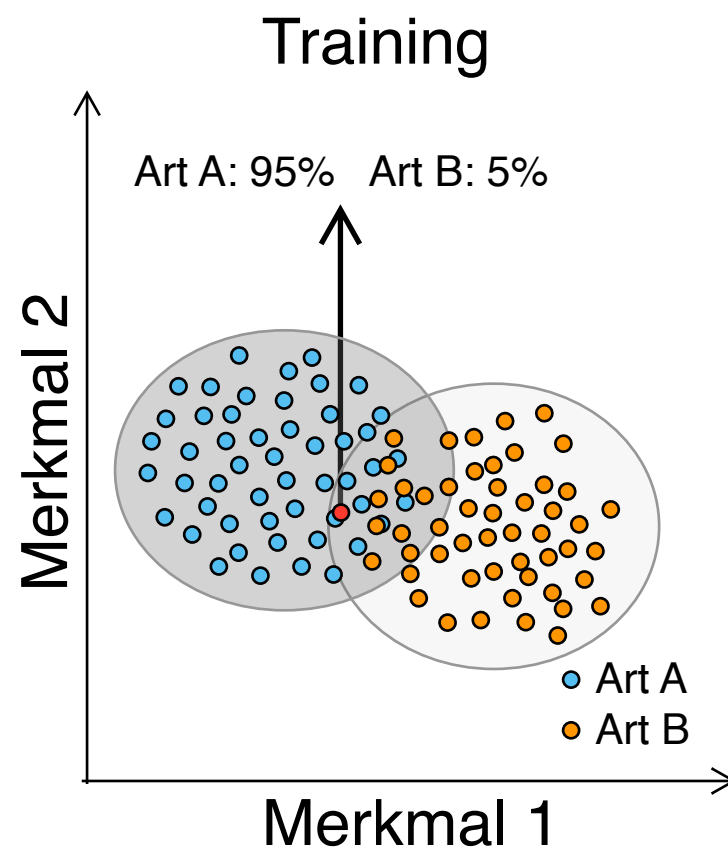
Vorhersage Wahr	Art A	Art B	falsch-negativ Sensitivität	n
Art A	450	50	10%	500
Art B	50	450	10%	500
falsch-positiv Wirksamkeit	10%	10%		

Vorhersage Wahr	Art A	Art B	falsch-negativ Sensitivität	n
Art A	450	50	10%	500
Art B	20	180	10%	200
falsch-positiv Wirksamkeit	4,26%	21,74%		

Vorhersage Wahr	Art A	Art B	falsch-negativ Sensitivität	n
Art A	450	50	10%	500
Art B	150	350	30%	500
falsch-positiv Wirksamkeit	25%	12,50%		

WAHRSCHEINLICHKEIT ALS MAßZAHL?

- ▶ Training-/Habitat: Unterschiedliche Ruftypen
 - ▶ Standorte unterscheiden sich
 - ▶ Geografische Variabilität



FEHLER ERKENNEN

- ▶ Fehler einfach erkennen, wenn
 - ▶ schlechte Aufnahmequalität
 - ▶ Art nicht am Standort / Region nachgewiesen
- ▶ Fehler nur als Profi erkennen, wenn
 - ▶ seltene, aber dennoch charakteristische Rufe
- ▶ Fehler selbst als Profi nicht erkennen, wenn
 - ▶ Rufe untypisch und selten
 - ▶ Rufe beinahe 100% überlappend mit anderer Art



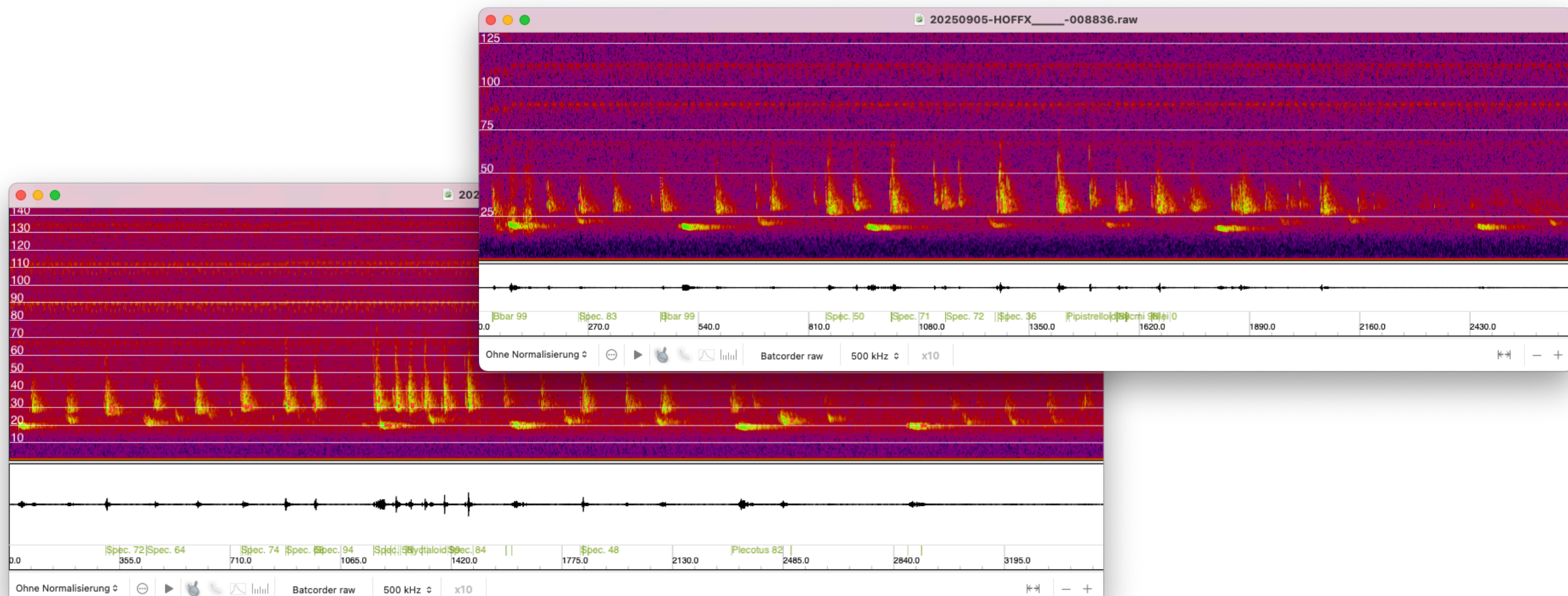
FLEDERMAUS

TÄGLICHE PRAXIS

GROßE DATENMENGEN – AUTOMATISCHE ERFASSUNG

► Monitoring

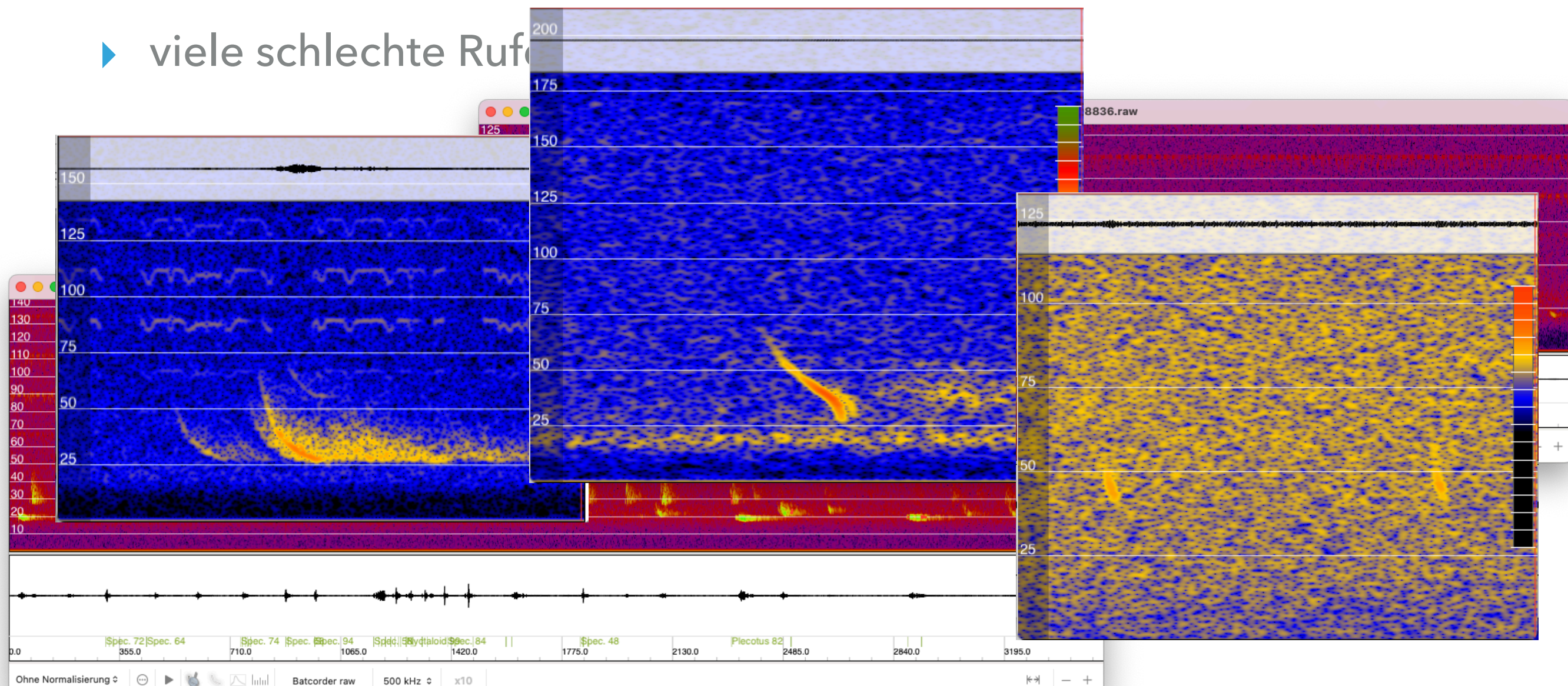
- mehrere 100.000 Aufnahmen
- viele schlechte Rufe in starker Überzahl



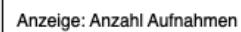
GROßE DATENMENGEN – AUTOMATISCHE ERFASSUNG

► Monitoring

- mehrere 100.000 Aufnahmen
- viele schlechte Rufe

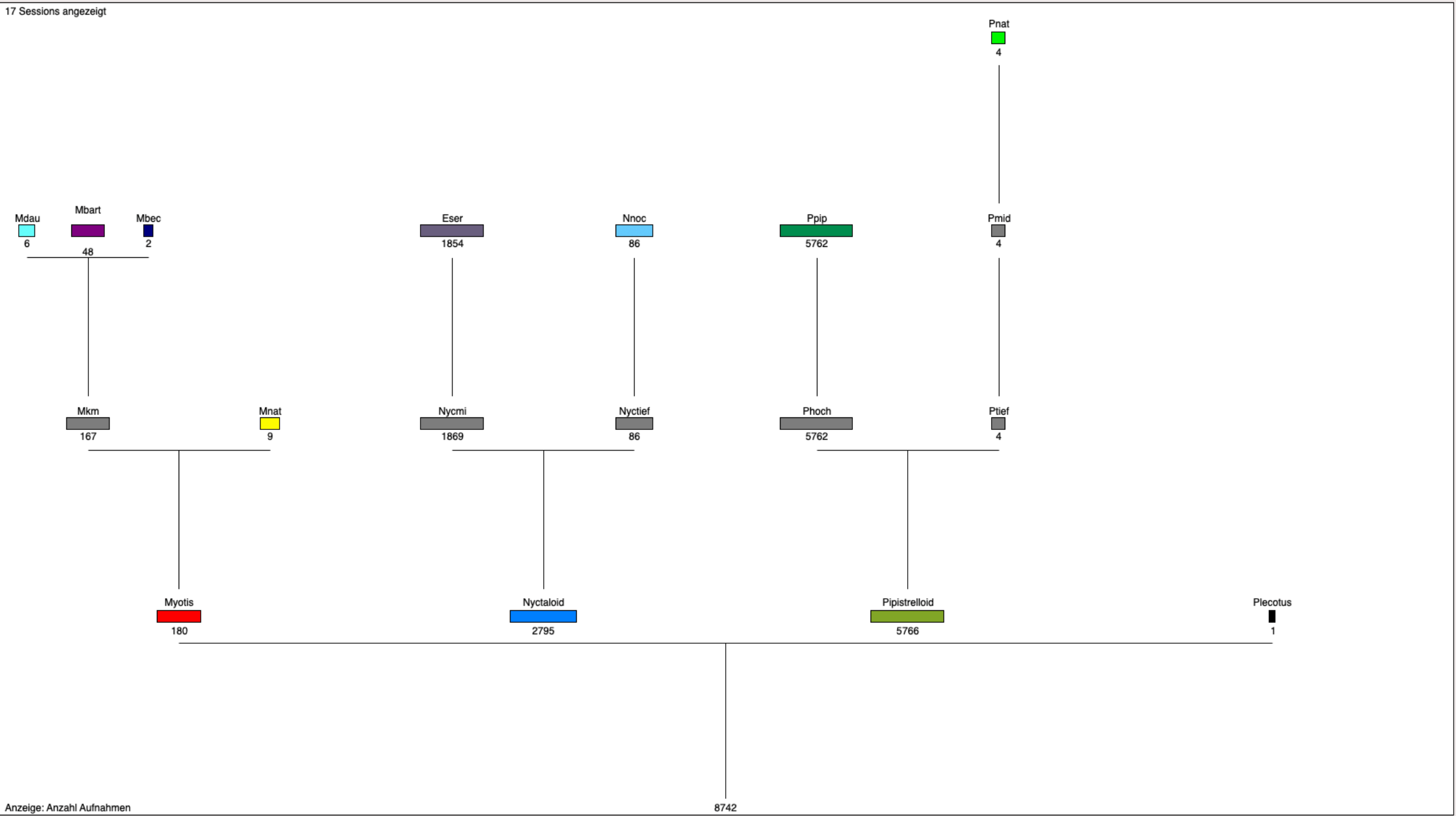


17 Sessions angezeigt





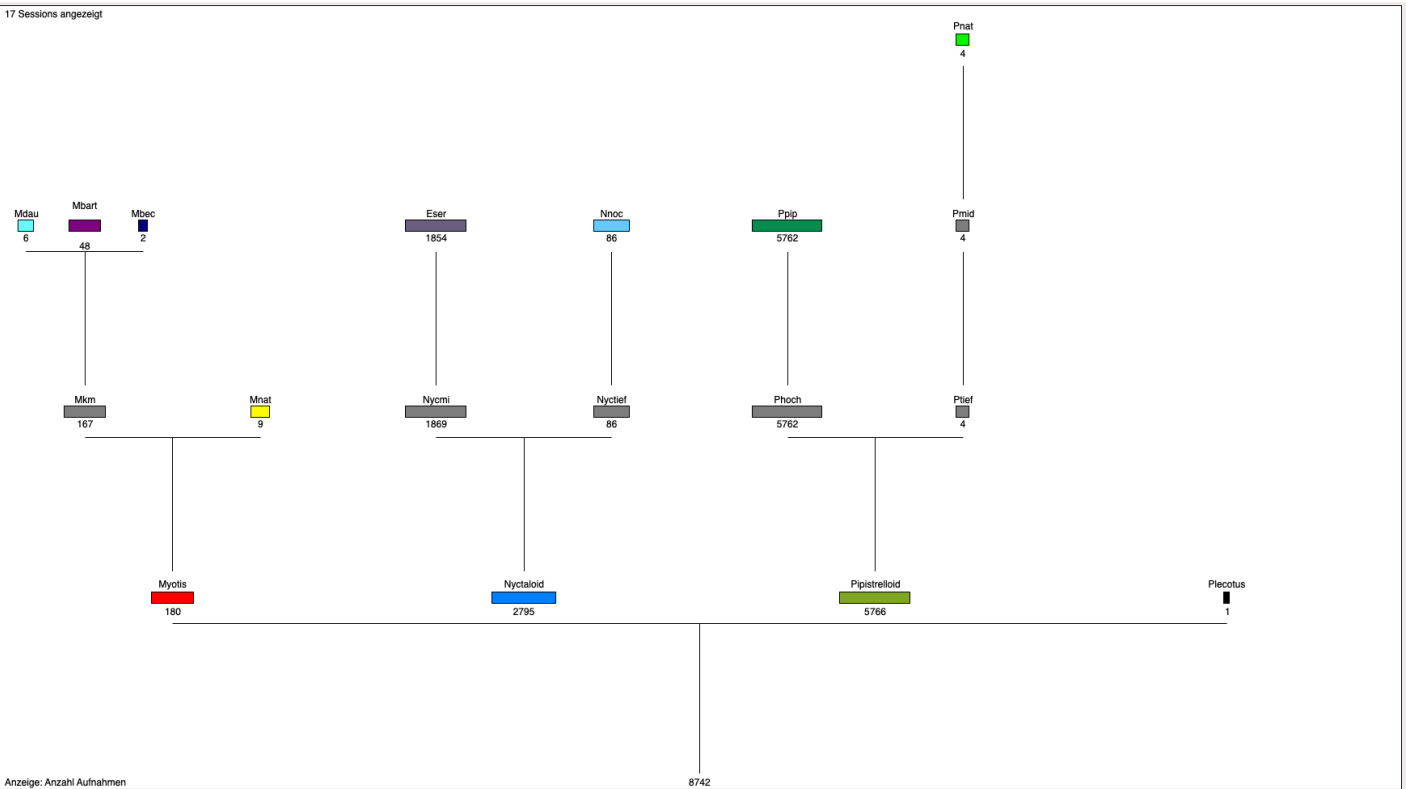
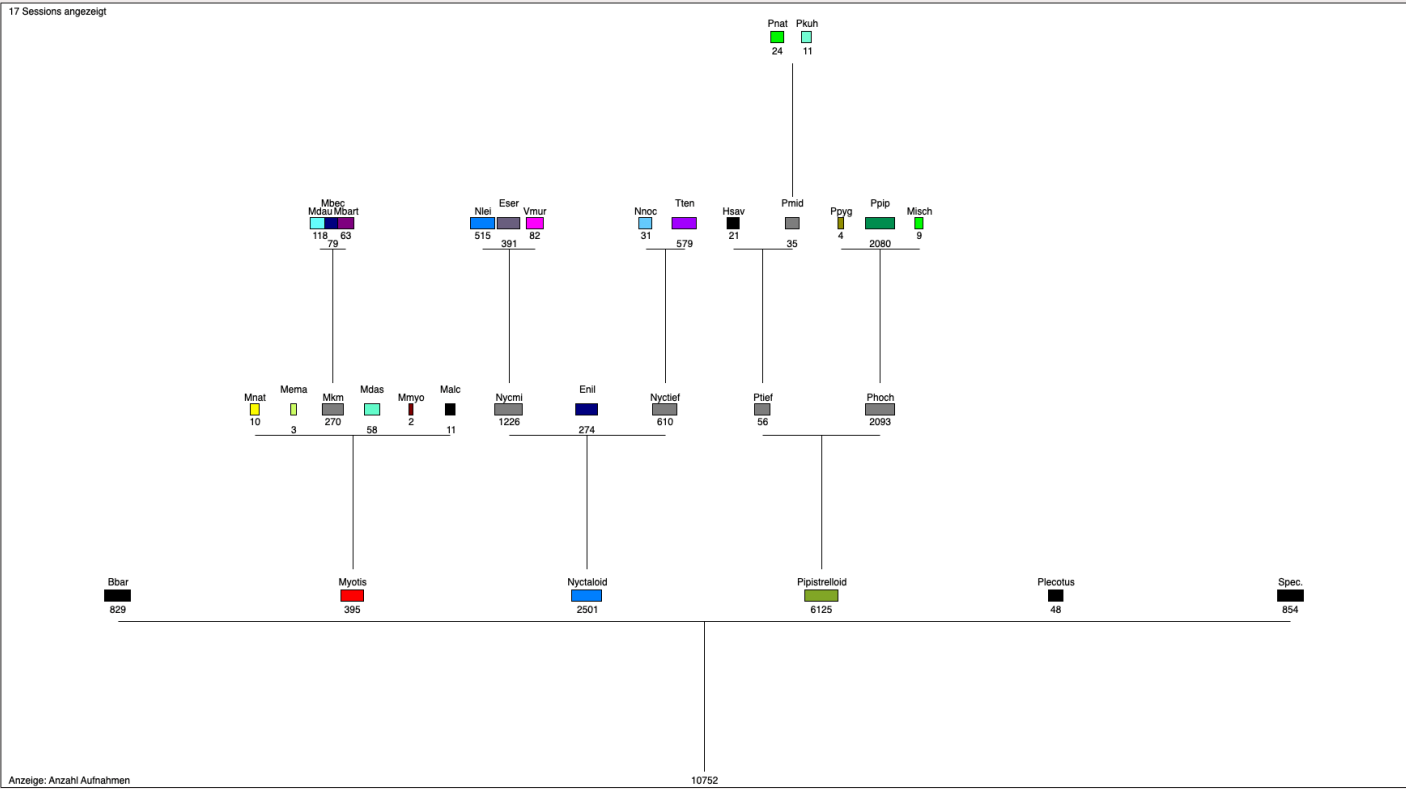
GROÙE DATENMENGEN – AUTOMATISCHE ERFASSUNG





GROßE DATENMANGEN AUTOMATISCHE RUFBESTIMMUNG

- ▶ Monitoring
- ▶ mehrere 10
- ▶ viele schlech



GROßE DATENMENGEN – MANUELLE KONTROLLE

- ▶ Manuelle Kontrollen sind nötig
 - ▶ Prüfung seltener Arten
 - ▶ Korrektur - Reduktion auf Gattung / Rufgruppe
- ▶ Problem: eigene Kenntnisse
 - ▶ Was man nicht kennt, kann man nicht kontrollieren
 - ▶ Im Zweifel: Vorsichtige Zurückhaltung
 - ▶ Falsche Arten sind Fehler, richtige Gattungen sind keine Fehler

IST DIE KI „GUT“ GENUG?

- ▶ Machine learning - wirklich bessere Ergebnisse?!
 - ▶ Variabilität und Überlappung bleiben das Problem
 - ▶ aber: Fehler objektiv, daher immer gleich
- ▶ Kombination von Verfahren
 - ▶ diverse automatische Algorithmen
 - ▶ ergänzt durch „schnelle“ manuelle Kontrolle
- ▶ Welches Ziel?
 - ▶ Jede Aufnahme Artgenau bestimmen ODER
 - ▶ Daten hinreichend sicher bestimmen für Modellierungen

DISKUSSION

WEITERE FRAGEN

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DANKE FÜR IHRE AUFMERKSAMKEIT

FOLIEN VERFÜGBAR UNTER

[HTTPS://VOLKERRUNKEL.DE/PROJECT-3.HTML](https://volkerrunkel.de/project-3.html)

