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False Positive Reduction: An Algorithmic Approach

Item Type	event;event
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Download date	2026-06-10 12:53:54
Link to Item	https://hdl.handle.net/20.500.14394/25396

False Positive Reduction: An Algorithmic Approach

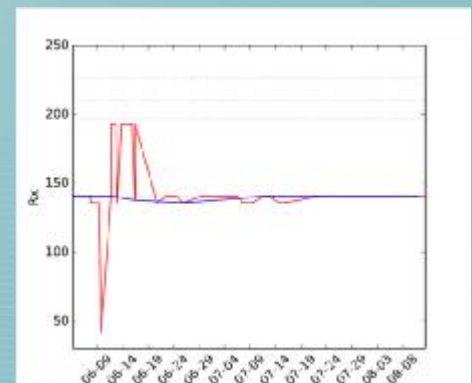
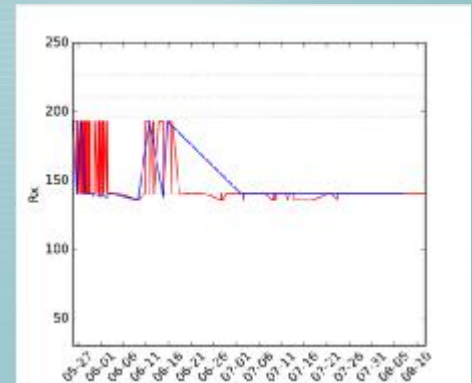
K. Nebiolo
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Kleinschmidt



What are false positives? Why do we care?

- Problems with telemetry data of all types (Beeman & Perry 2012)
 - Received signal may not correctly assigned
 - Not all records generated by receivers are from tagged fish
 - Not all tagged fish are recorded when present
- This introduces false positives into our data
 - Bias results in favor of presence and overestimate frequency of occurrence
 - Or overestimate residence time within critical infrastructure, which increases measures of delay



Current False Positive Reduction Methods

- Current false positive reduction methods rely simple metrics and subjective opinion
 - Power floors
 - Consecutive detections (2, 4, 6, etc...) (Beeman & Perry, 2012)
 - Logical errors in site progression
- Manual classifications are labor intensive
 - For very large studies with many releases and sites (whole river studies) classification can become cost prohibitive

Naive Bayes Classifier (Minsky 1961)

- Bayes rule (conditional probability) can estimate the probability that a record is either true or false positive given observed data
- *Prior*: marginal probability for a detection class (C)
- *Likelihood*: The conditional probability of an observable event (F_1, \dots, F_n) given each state of nature (C)
- *Posterior*: the probability of the class occurring given the observable event

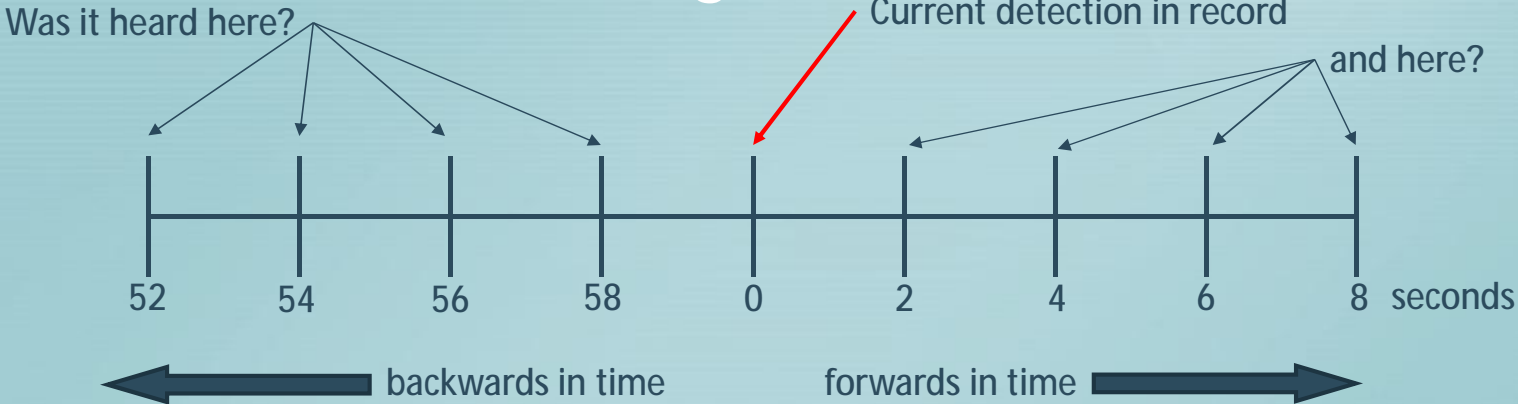
$$P(C|F_1, \dots, F_n) \propto P(C) * \prod_{i=1}^n P(F_i|C)$$

Diagram illustrating the Naive Bayes Classifier equation with labels and arrows:

- Posterior (points to $P(C|F_1, \dots, F_n)$)
- Prior (points to $P(C)$)
- Likelihood (points to $P(F_i|C)$)

- Training data set contains observations of feature variables ($F_1 \dots F_n$) and known detection classifications (C)
- Naive assumption

Predictors – Creating the Detection History



P	X	P	X	P	X	P	P	P
1	0	1	0	1	0	1	1	1

Implementation

- Algorithm split into two parts, *Training* and *Classification*
- Training:
 - Beacon tags placed at strategic locations throughout the study area - provide information on what known true positive detections look like
 - Miss coded and noise transmissions provide information on what false positive detections look like
 - Loop over all beacon tag and miss coded detections and derive metrics
 - (detection history, hit ratio, etc.)
 - Store to RDBMS in this case SQLite
- Classification:
 - Loop through records for known study tags,
 - Derive metrics
 - Calculate posterior for true and false positive – use MAP to classify
- Algorithm Accuracy assessed with k-fold cross validation (k = 10)
 - Sensitivity, Specificity, Positive Predictive Value (PPV) and Negative Predictive Value (NPV)

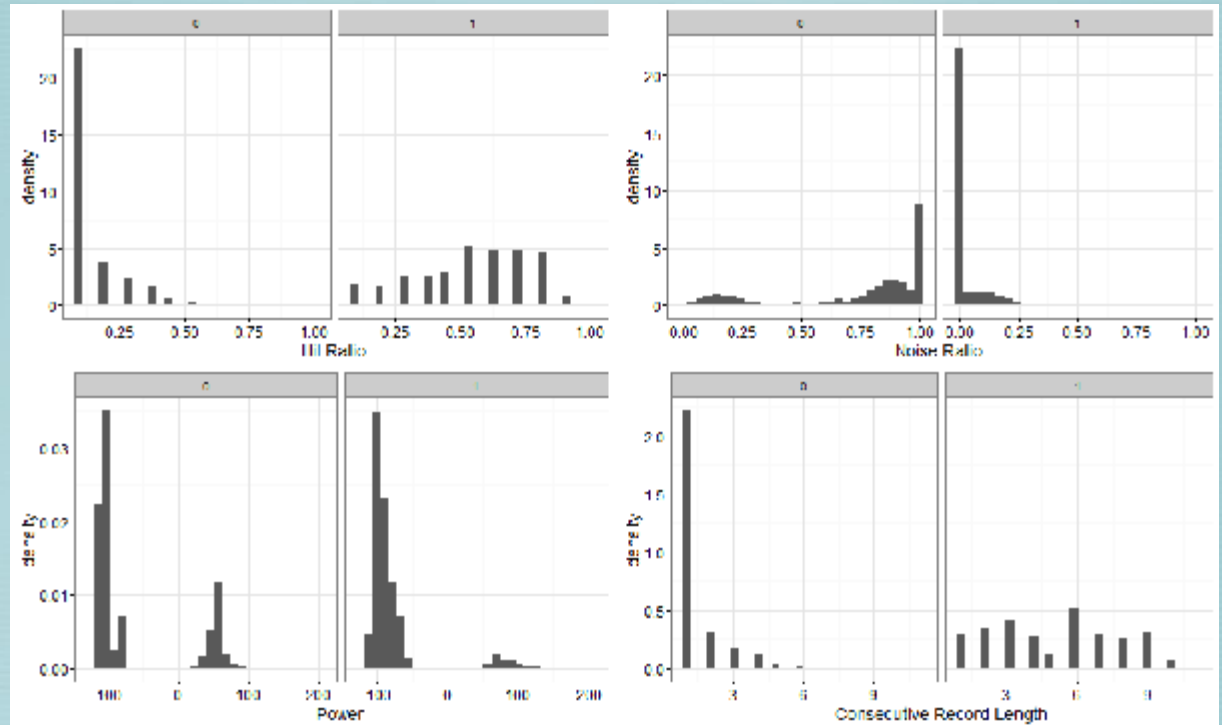
Beacon Tag Locations



Results – Orion Training

- In total – 2,644,990 beacon tag hits and 517,881 known false positives

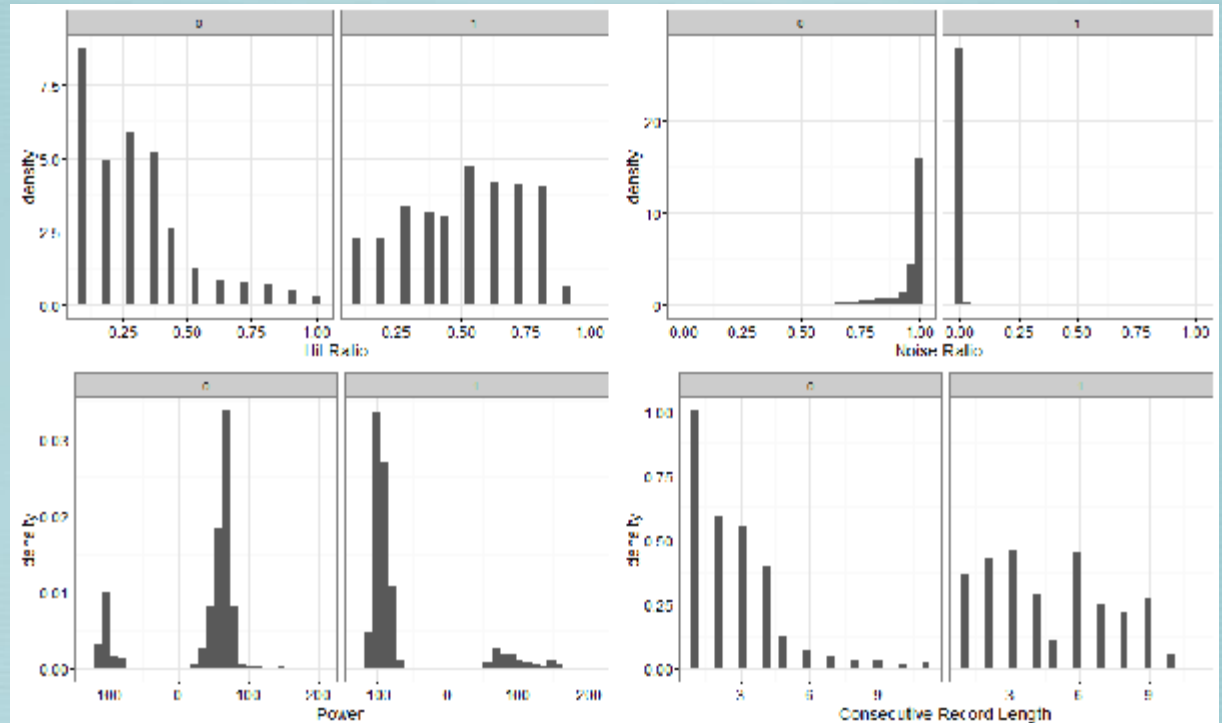
	Classified		
	False	True	
True Negative	479,349	38,532	NPV: 0.93
True Positive	39,745	2,605,245	PPV: 0.98
	Specificity: 0.92	Sensitivity: 0.99	



Results – Lotek Training

- In total – 2,215,818 beacon tag hits and 331,612 known false positives

	Classified		
	False	True	
True Negative	298,927	32,685	NPV: 0.90
True Positive	5,073	2,210,745	PPV: 0.99
	Specificity: 0.98	Sensitivity: 0.99	

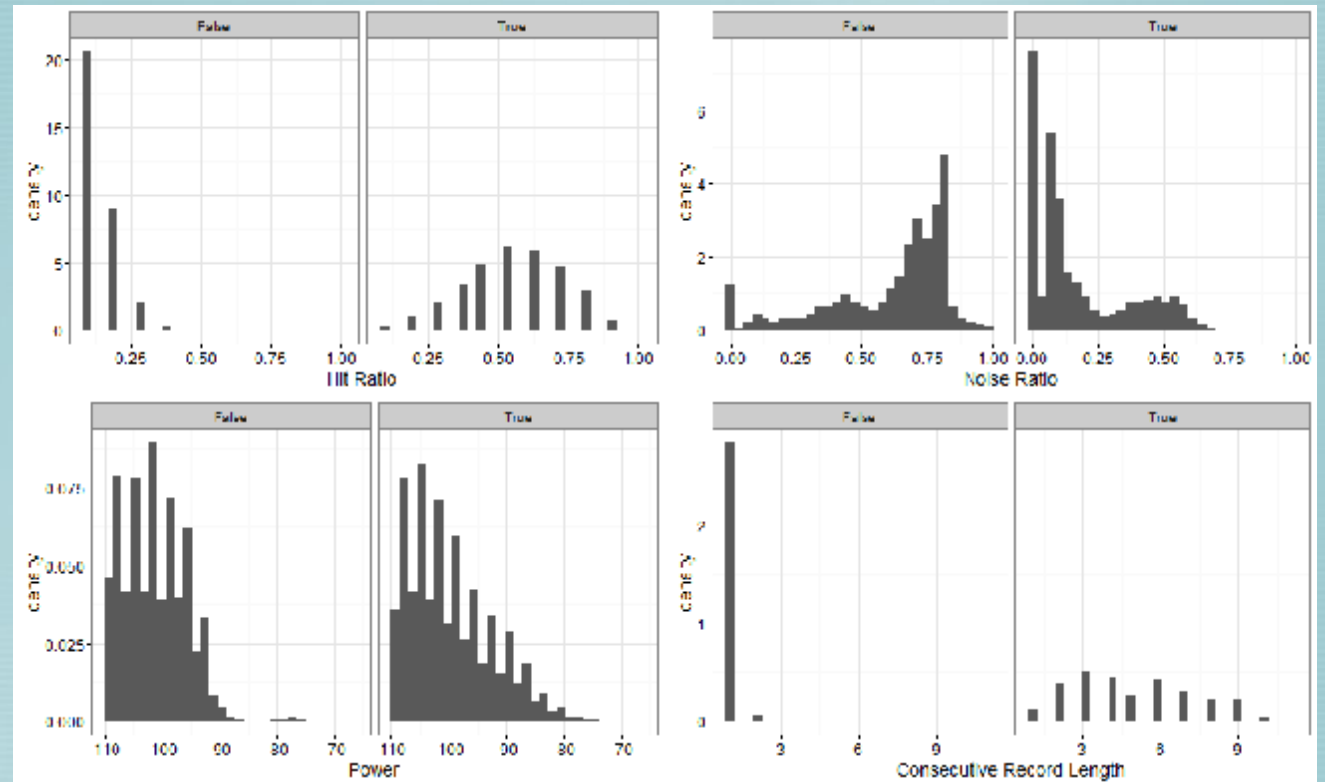


Results – Orion Classification

575,548 study tag detections

- 503,347 true
- 72,201 false positive

14% False Positive removal rate

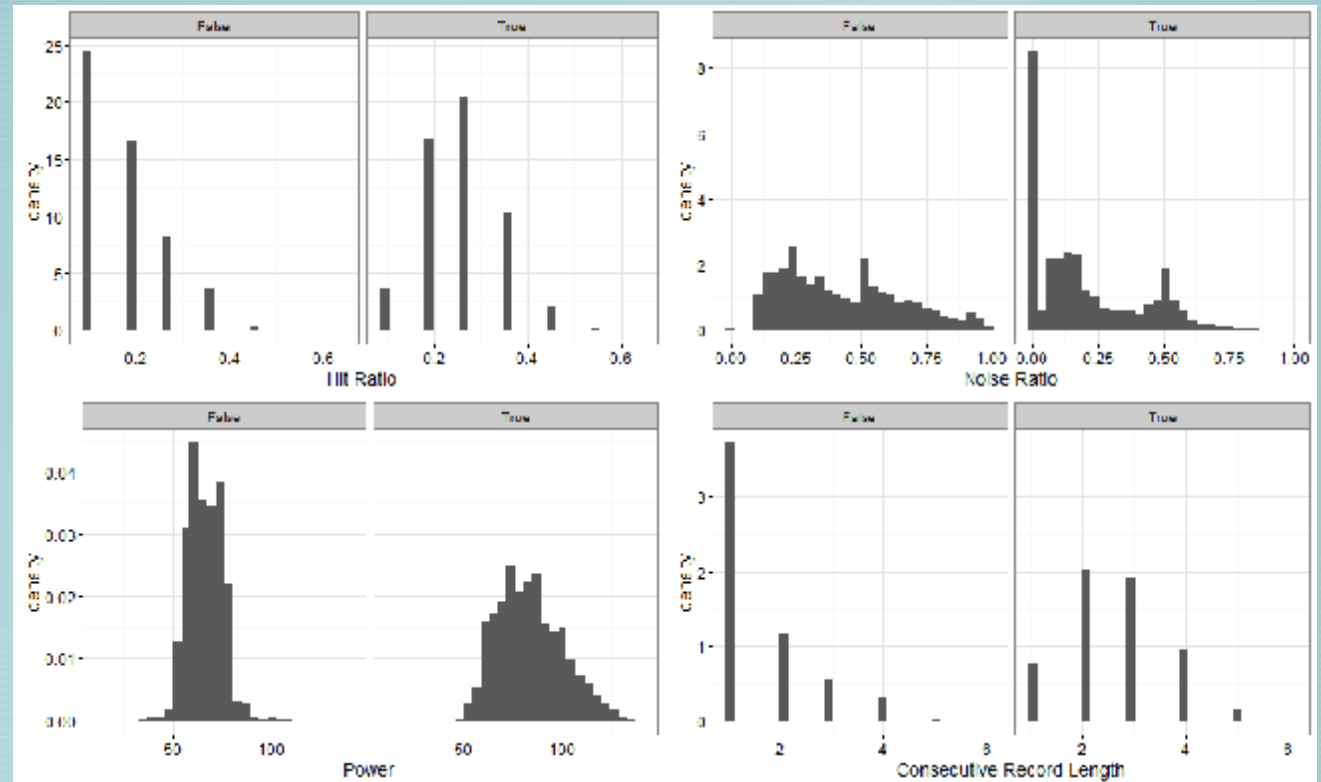


Results – Lotek Classification

131,088 study tag detections

- 106,693 true
- 24,395 false positive

23% False Positive removal rate



Conclusion

- Once the algorithm is up and running it takes minimal supervision
 - ~ 15 minutes every hour
 - Computationally, detection history creation most time consuming part
- Does a great job of removing garbage detections with minimal effort
- Does not do a good job at discriminating position when receiver detection zones overlap
- From raw data through statistical analysis with 300 tagged at 14 stations – 2 weeks

Works Cited

- Beeman, John W. and Russel W. Perry. "Telemetry Techniques: A User Guide for Fisheries Research; Chapter 9: Bias from False-Positive Detections and Strategies for their Removal in Studies Using Telemetry." American Fisheries Society, 2012. 505-517.
- Minsky, Marvin. "Steps toward artificial intelligence." *Proceedings of the IRE* 49.1 (1961): 8-30.

Thank you

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