



NOAA
FISHERIES

2023 Western Groundfish Conference

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Fourier transform near infrared spectroscopy of otoliths coupled with machine learning to improve fish age predictions

Irina M. Benson¹, Thomas E. Helser¹, and Beverly K. Barnett²

¹National Marine Fisheries Service, Alaska Fisheries Science Center, Seattle, WA, USA,

²National Marine Fisheries Service, Southeast Fisheries Science Center, Panama City Facility, Panama City, FL, USA

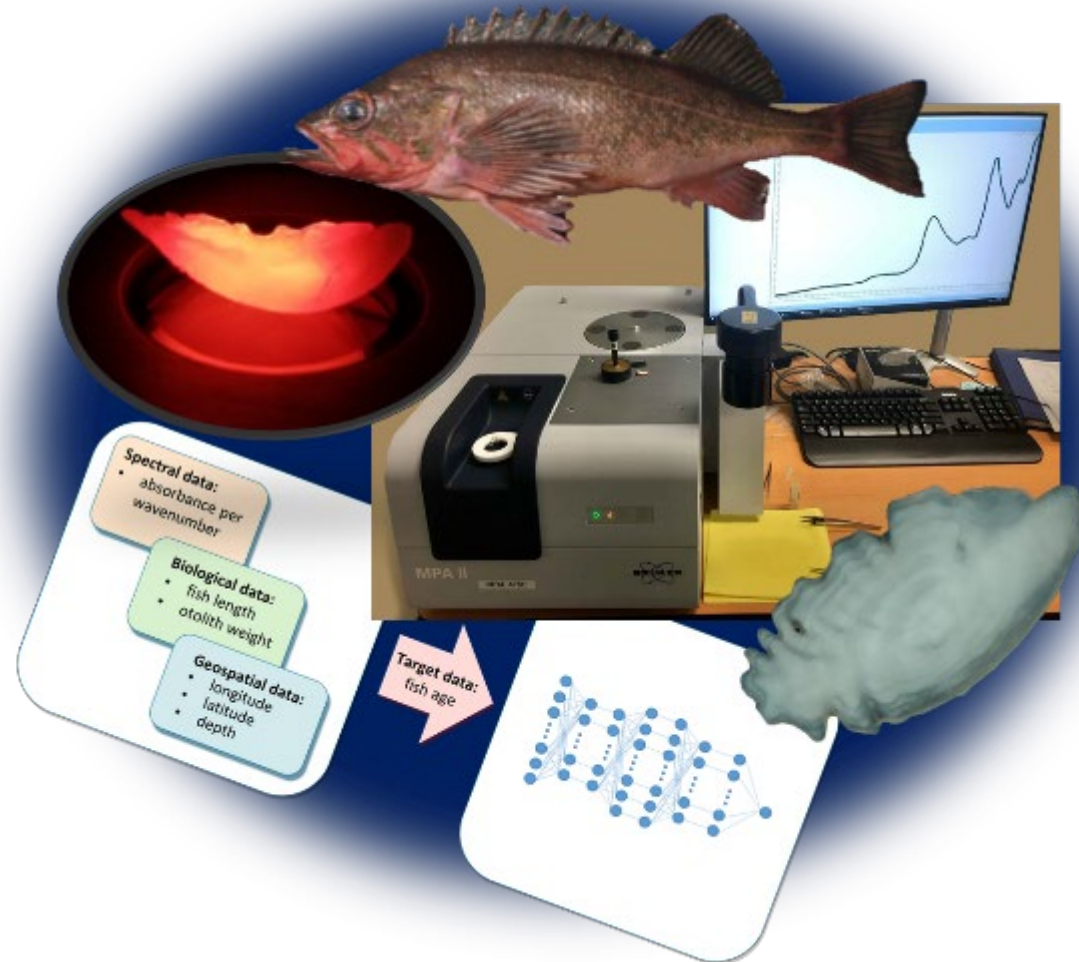
Study Objective and Presentation Outline

Study objective:

Explore advanced technologies using FT-NIR spectroscopy of fish otoliths coupled with deep machine learning models to estimate fish age more rapidly and with greater efficiency than traditional approaches.

Presentation outline:

- Fish ageing methods
 - Traditional microscopic method
 - FT-NIR spectroscopy method
- Deep learning approach
- Results
- Conclusions



Traditional Ageing Method



Otoliths:

- Small calcified structures in the inner ear of fish.
- Continue to grow throughout the life of a fish.
- Composed of alternating protein-rich and mineral-rich bands.
- Lay down an annulus (year mark) once per year.

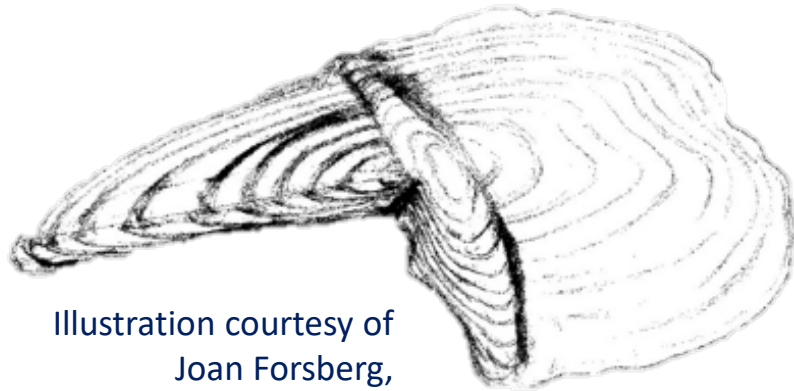
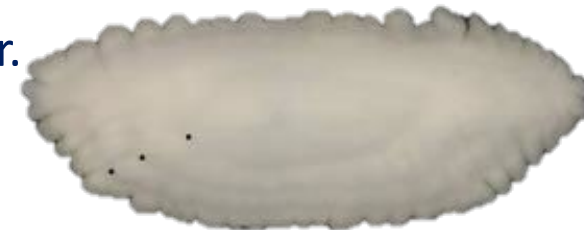
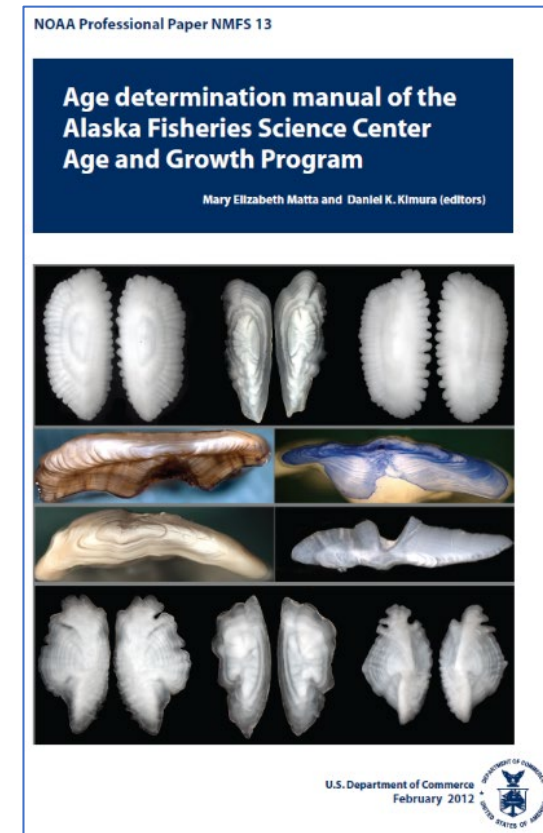


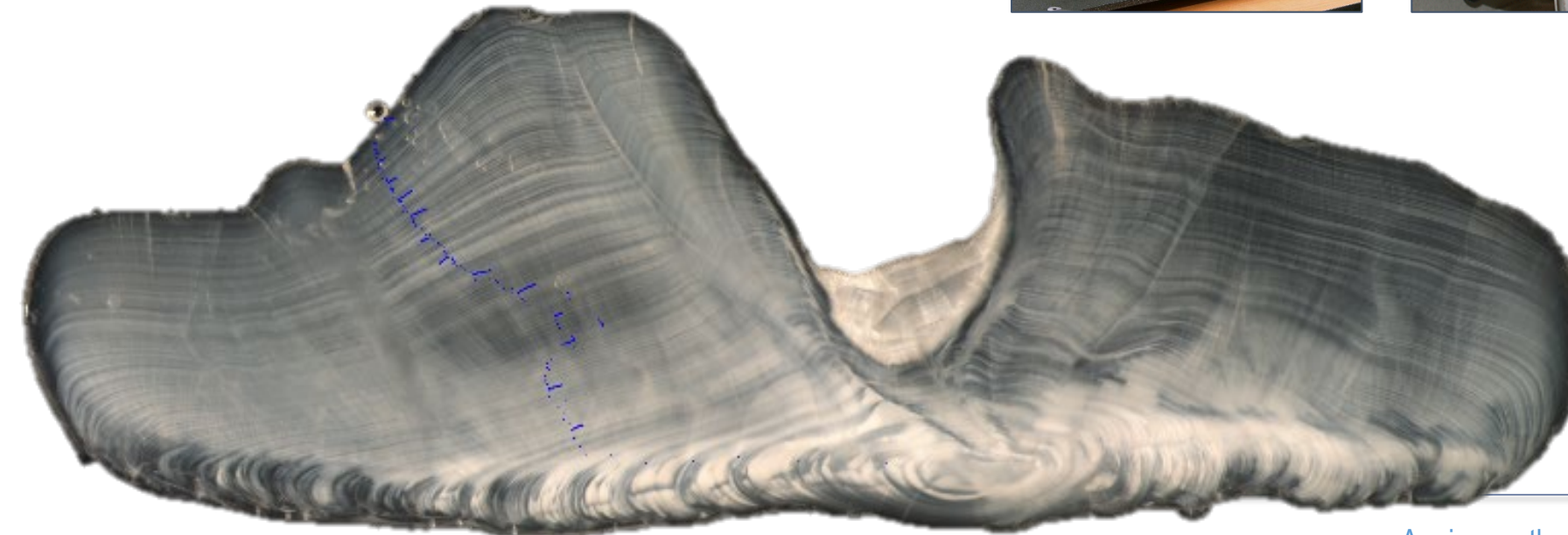
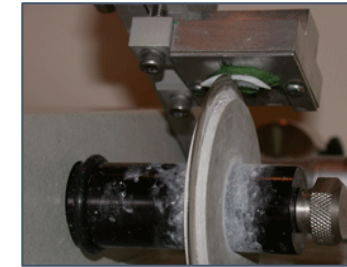
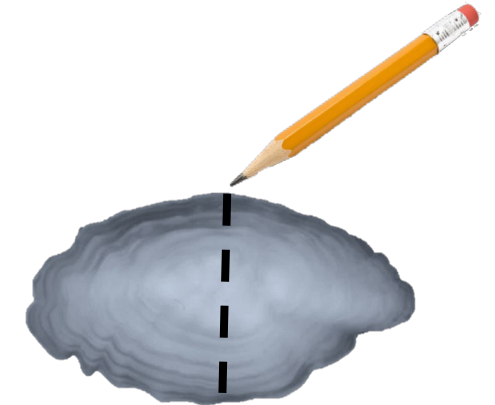
Illustration courtesy of
Joan Forsberg,
International Pacific
Halibut Commission



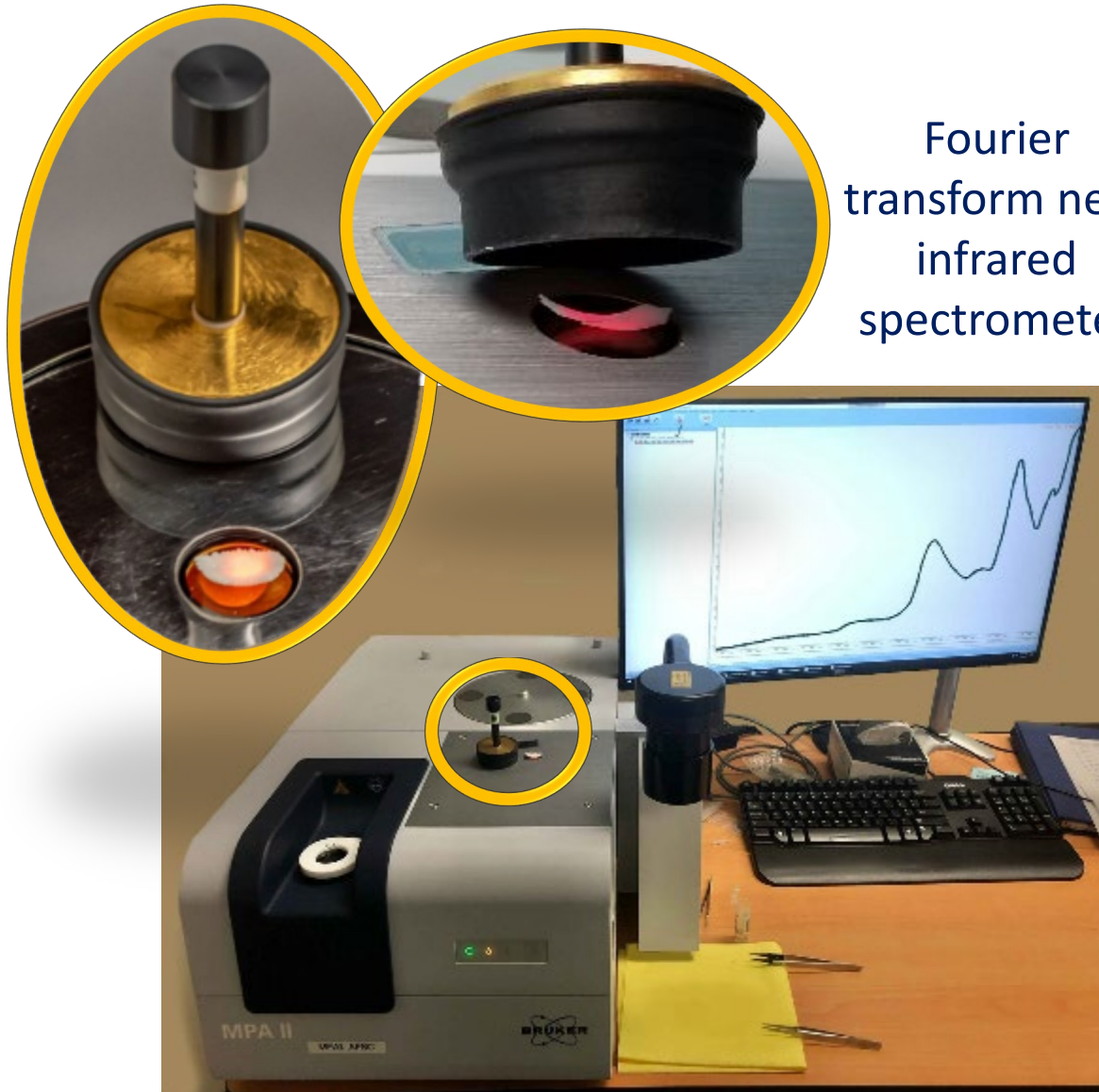
Traditional Ageing Method

Fish age determination:

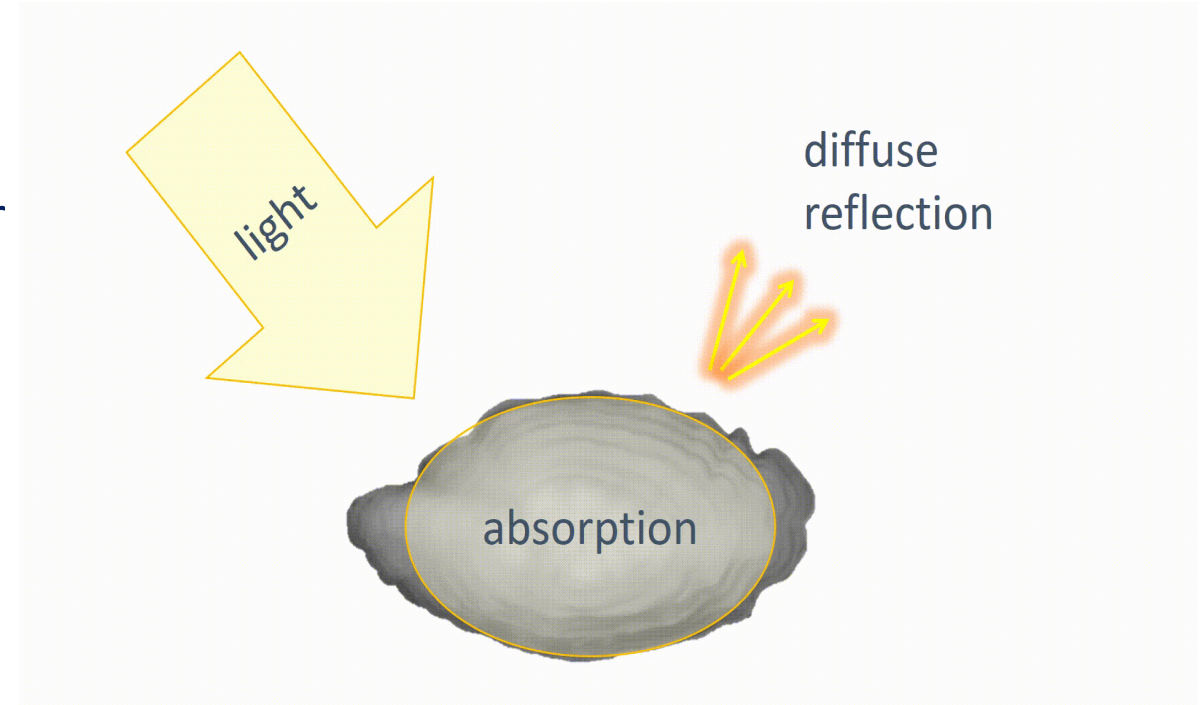
- Counting visible annual growth rings under a microscope.
- Labor-intensive particularly for long-lived species (3-10 minutes per age).
- Can be subject to poor repeatability.



Diffuse Reflectance Spectroscopy



Fourier
transform near
infrared
spectrometer

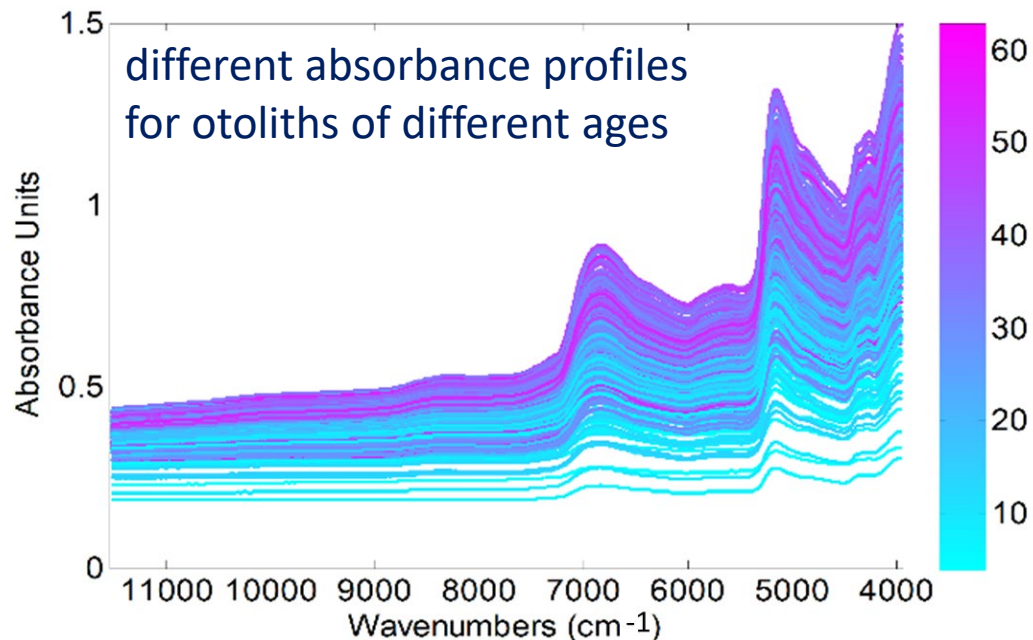


Greater efficiency to derive machine-based ages from FT-NIR spectroscopy:

- Each scan takes about one minute.
- No otolith cutting required.

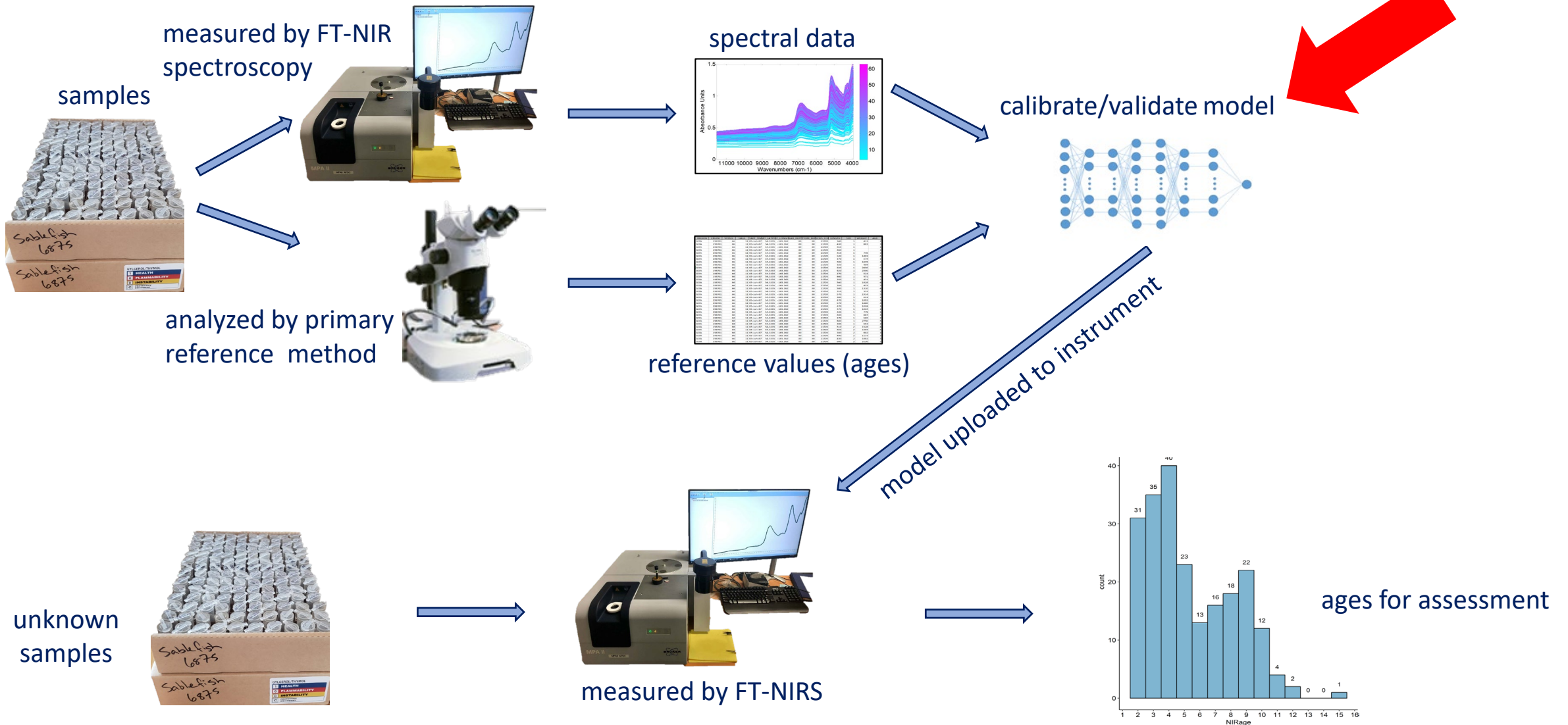
Fundamental Principles of FT-NIR Spectroscopy

- Spectra in the NIR region result from energy absorption by organic molecules.
- NIR region absorption bands include overtones and combinations of overtones originating from fundamental bond vibrations (stretching or bending).



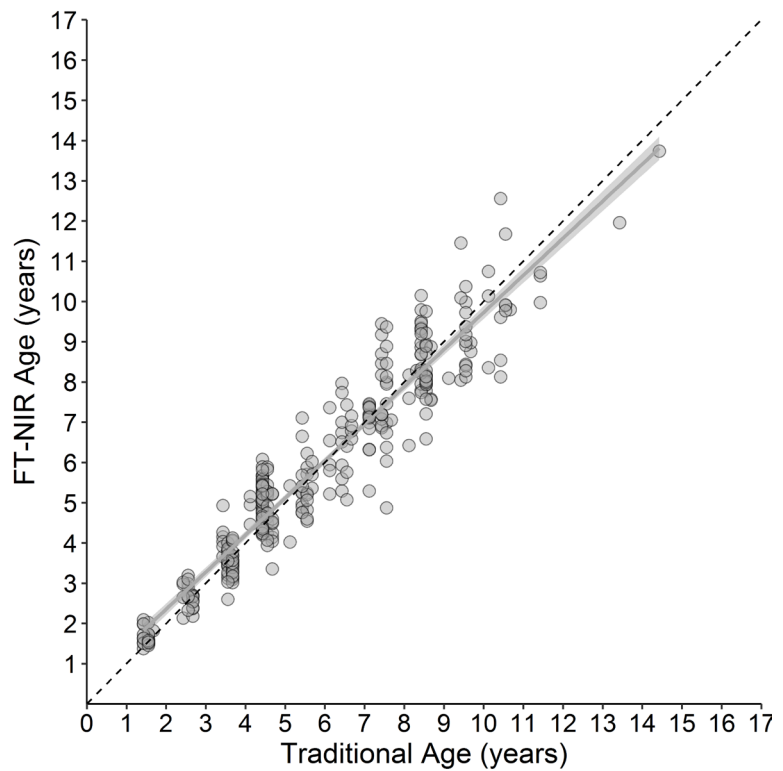
- Due to the overtone and combination modes, FT-NIR spectra are complex (consist of many overlapping peaks).
- Multivariate calibration is needed to find relationships between spectral measurements and reference measurements.

Predicting Fish Age from Otolith Spectra




General Chemometrics Approach

- Partial least-squares regression (PLS) predicts target feature using small set of intermediate linear latent variables.
- PLS exhibits good results for fish ageing.
- Rely on users having advanced skills to deal with non-selectivity and non-linearity problems.



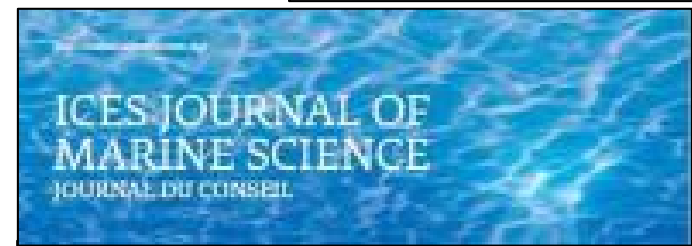
Canadian Journal of
**Fisheries and
Aquatic Sciences**

A transformative approach to ageing fish otoliths using Fourier transform near infrared spectroscopy: a case study of eastern Bering Sea walleye pollock (*Gadus chalcogrammus*)



ECOSPHERE
AN ESA OPEN ACCESS JOURNAL


Ageing fish at the molecular level using Fourier transform near infrared spectroscopy (FT-NIRS): A case study of Pacific cod



**ICES JOURNAL OF
MARINE SCIENCE**
JOURNAL DU CONSEIL

Age estimation of red snapper (*Lutjanus campechanus*) using FT-NIR spectroscopy: Towards a feasibility for fisheries management

ICES CIEM OXFORD UNIVERSITY PRESS



MARINE & FRESHWATER RESEARCH

Rapid age estimation of longnose skate (*Raja rhina*) vertebrae using near infrared spectroscopy

Calibration Problems

Non-linearity:

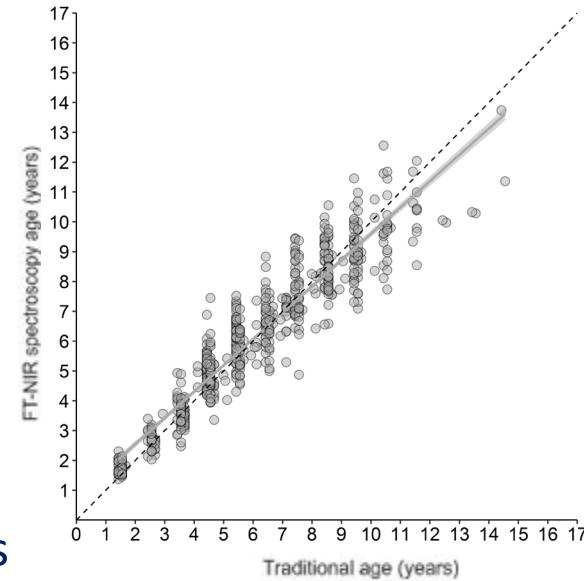
- Differences in sample absorbance variations and light scattering.

Non-selectivity:

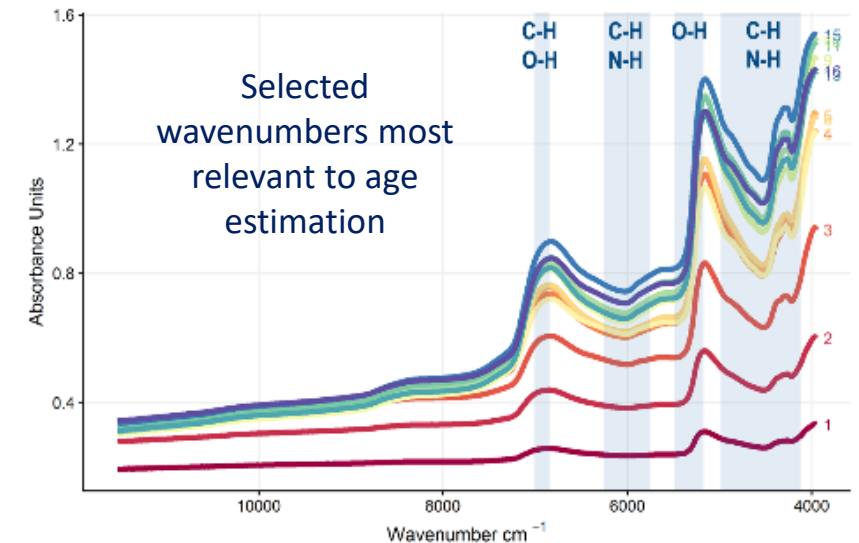
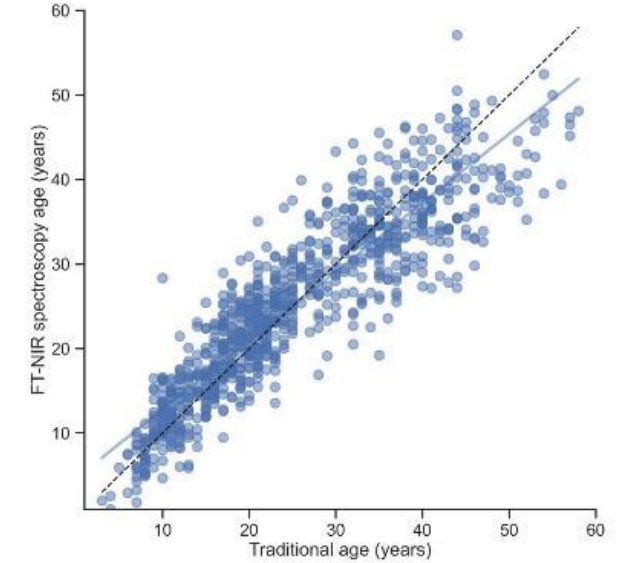
- Each spectrum contains thousands of wavenumbers that are highly correlated.
- Difficulty to find exact wavenumbers for the chemical constituents in the sample.

Existing chemometric techniques:

- Often effective dealing with these issues.
- Introduce many adjustable parameters.
- Increase difficulty of analysis and may not lead to an optimal model.

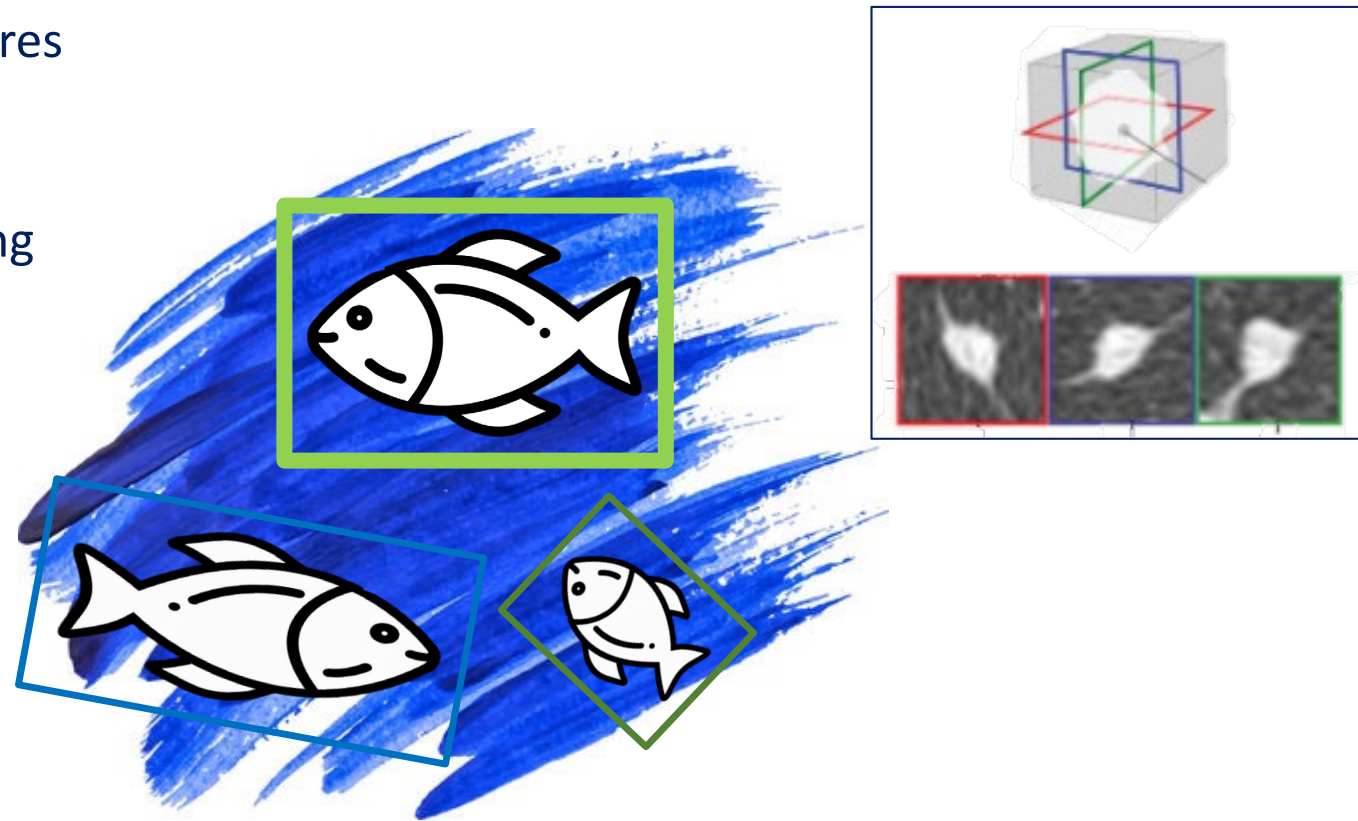
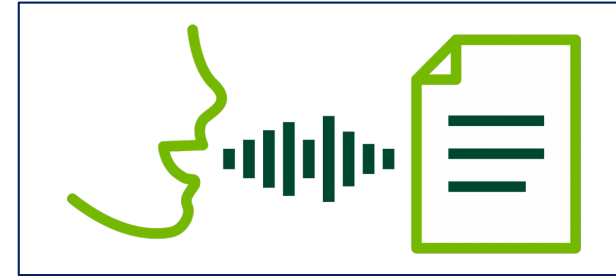


PLS regression

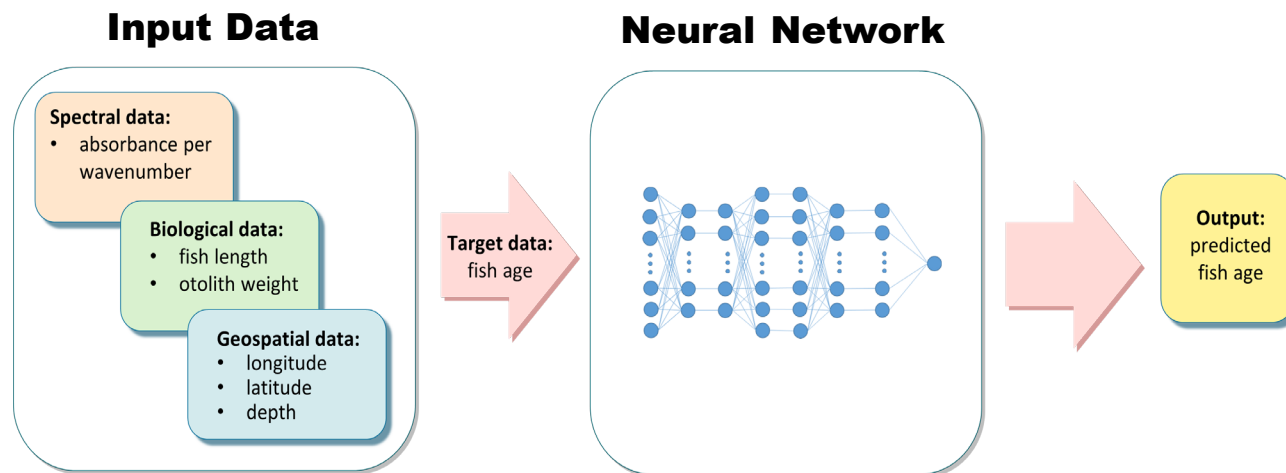


Deep Learning

- Recent developments of deep learning in speech recognition, object detection, and image processing.
- Can automatically learn features in data.
- Efficient way to process and extract features of high-dimensional data (automated wavenumber selection).
- Neural networks (NN) used for overcoming the effects of non-linearity.



First Neural Network



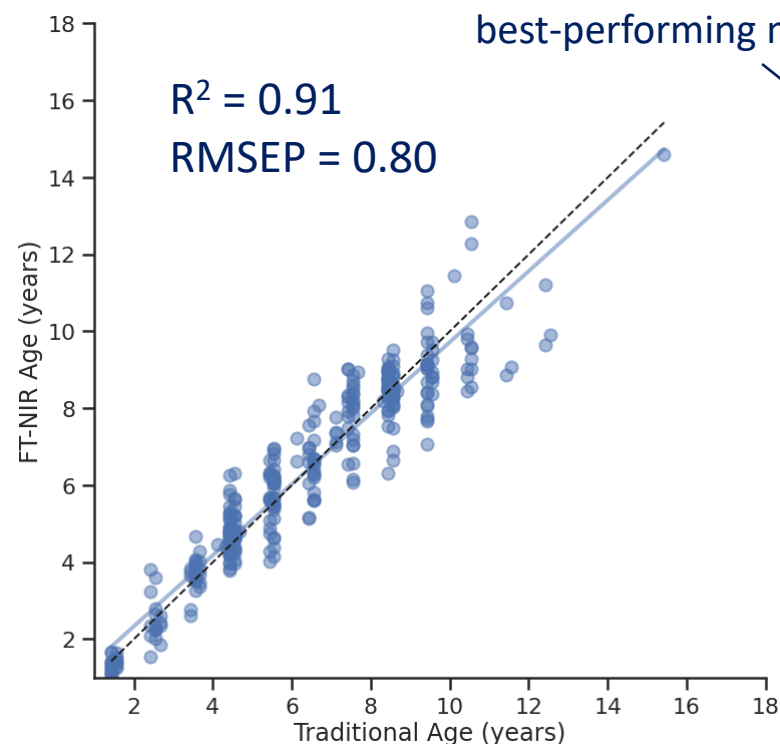
Bering sea survey pollock
2016-2017
n=3,363



ARTICLE

A transformative approach to ageing fish otoliths using Fourier transform near infrared spectroscopy: a case study of eastern Bering Sea walleye pollock (*Gadus chalcogrammus*)
Thomas E. Helser, Irina Benson, Jason Erickson, Jordan Healy, Craig Kestelle, and Jonathan A. Short

published PLSR model

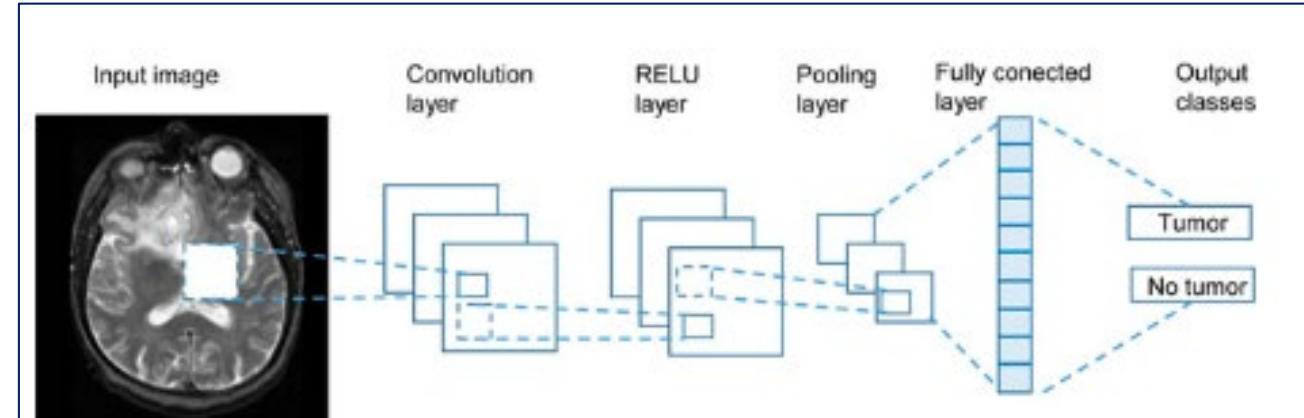


best-performing model

Model	Spectral Data	R ²	RMSEP	% RMSEP Improvement
PLS Regression (Helser et al., 2019)	initial collection (smaller data set, no ancillary data)	0.89	0.96	
AI Platform1 (Hyperband tuner)	unprocessed spectral data / all specimens	0.91	0.80	-17%
AI Platform2 (Bayesian optimization tuner)	unprocessed spectral data / all specimens	0.90	0.84	-13%
AI Platform3 (Hyperband tuner)	1 st derivative / excluded spectral data outliers	0.88	0.94	-2%
AI Platform4 (Bayesian optimization tuner)	1 st derivative / excluded spectral data outliers	0.90	0.87	-9%
Basic Random Forest Regression1	unprocessed spectral data / all specimens	0.88	0.92	-4%
Basic Random Forest Regression2	1 st derivative / excluded spectral data outliers	0.86	1.02	+6%

Convolutional Neural Network

- Convolutional neural networks (CNN) are based on the study of the brain's visual cortex and have been applied for RGB (2D) and hyperspectral (3D) image recognition since the 1980s.
- CNN algorithms were found to be useful for spectral data (spectra can be represented as 1D image data).
- CNN is more robust to overfitting because it relies on the spatial relationship in the spectral data and has fewer parameters than traditional neural networks.



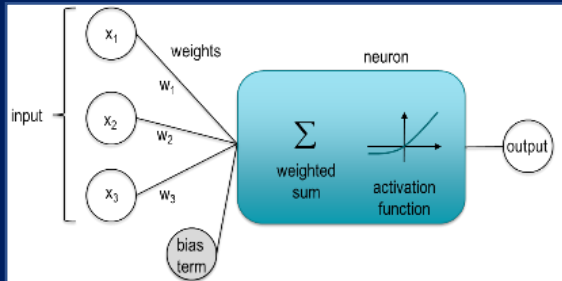
Modern practical convolutional neural networks for multivariate regression: applications to NIR calibration

Chenhao Cui and Tom Fearn

*Department of Statistical Science,
University College London, London, WC1E 6BT, U.K.*

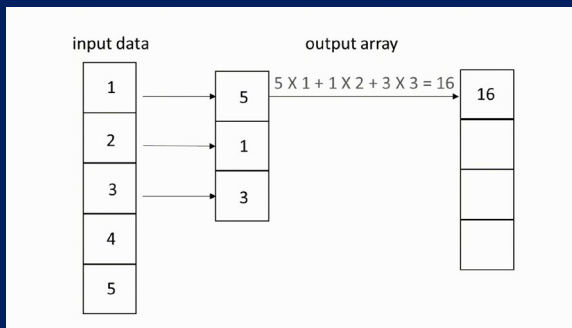
The Proposed Multi-Input Neural Network

Most fundamental unit used to build a neural network is perceptron.

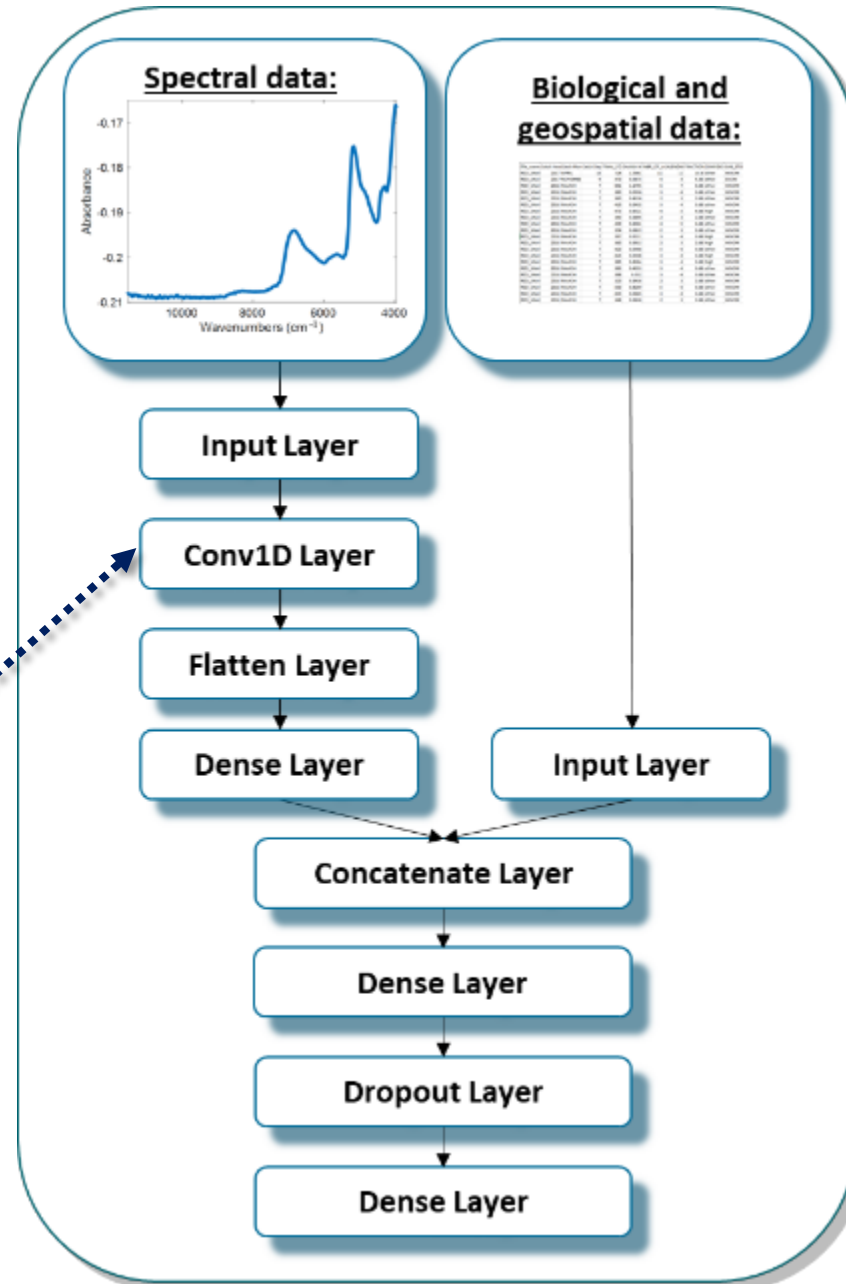


Simple computational unit that have weighted input signals and produce an output signal using an activation function.

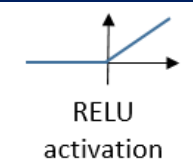
Convolutional layer consists of a kernel that slides along our data and applies its weights to the data values.



Convolutional kernels can lower data complexity and capture features (i.e. identify important spectral regions).



Activation function governs the threshold at which neuron is activated.



Non-linear activation functions introduce non-linear properties into network.

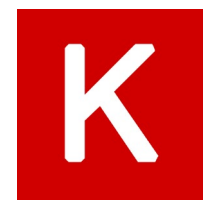
Runtime



IDE



Libraries



SHAP

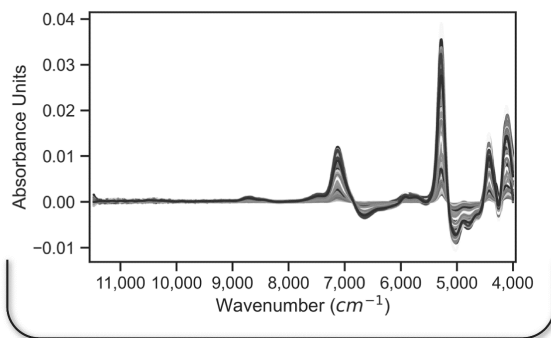
Case Study: shorter-lived species



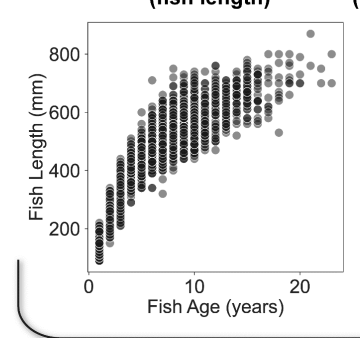
Walleye pollock
(*Gadus chalcogrammus*)

- Shorter lived species (over 20 years old)
- Commercially important species in eastern Bering Sea and Gulf of Alaska

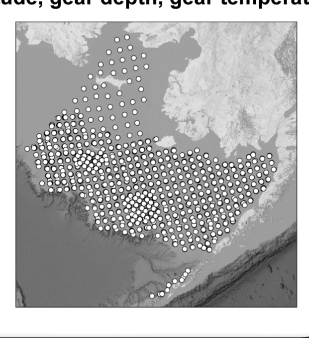
Spectral Data



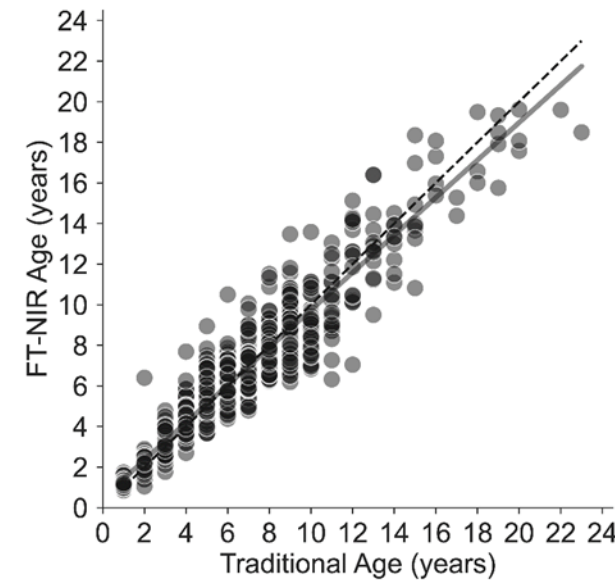
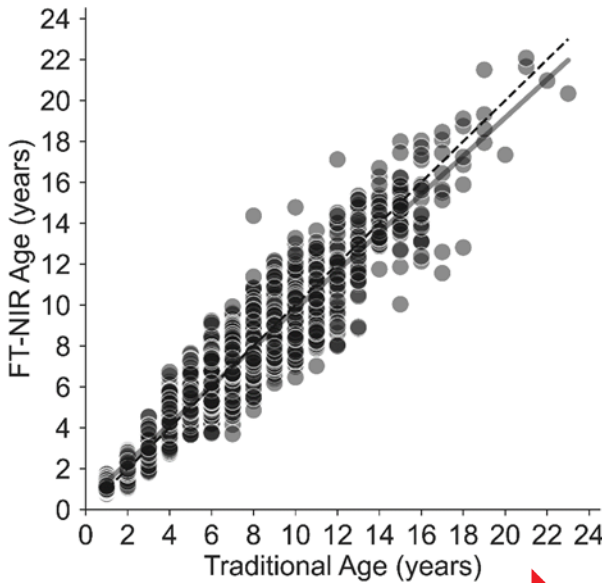
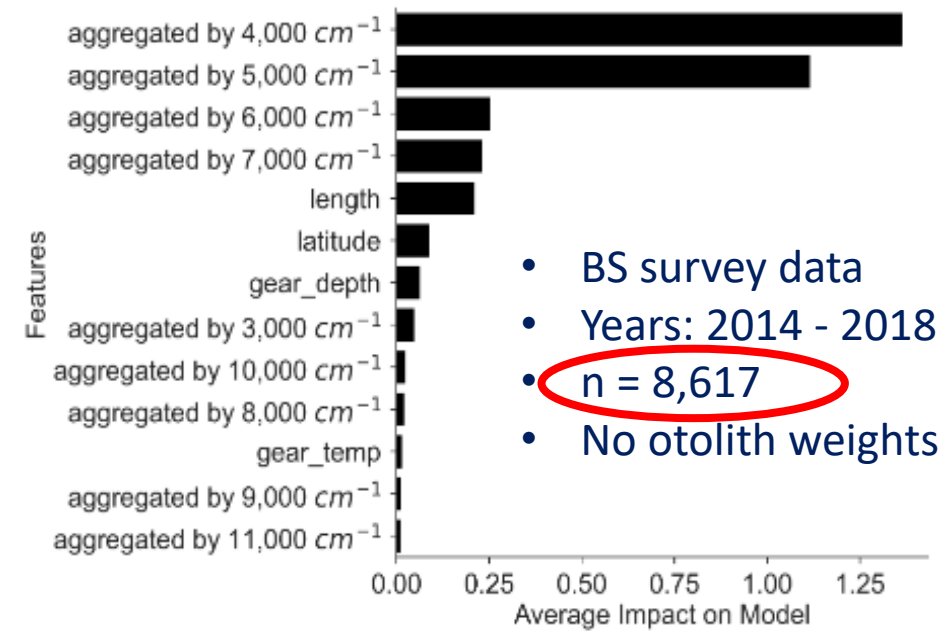
Biological Data
(fish length)



Geospatial Data
(latitude, gear depth, gear temperature)



Relative feature importance



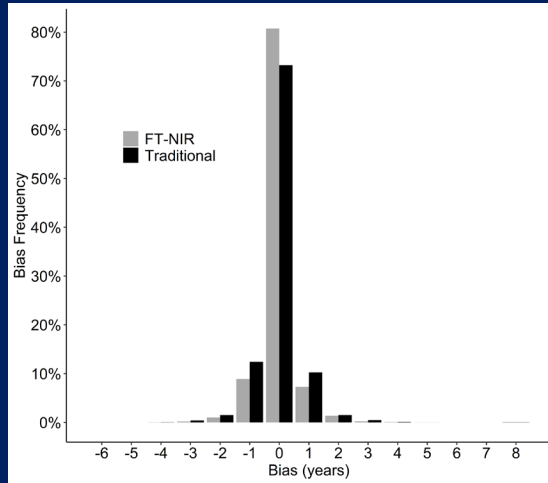
Model	Number of otoliths			R ²		RMSE	
	Train	Test	Outliers*	Train	Test	Train	Test
NN				0.93	0.92	0.83	0.91
PLS with all spectral wavenumbers	6866	1751	12	0.89	0.87	0.99	1.14
PLS with selected spectral wavenumbers				0.90	0.87	0.97	1.12



Model Performance

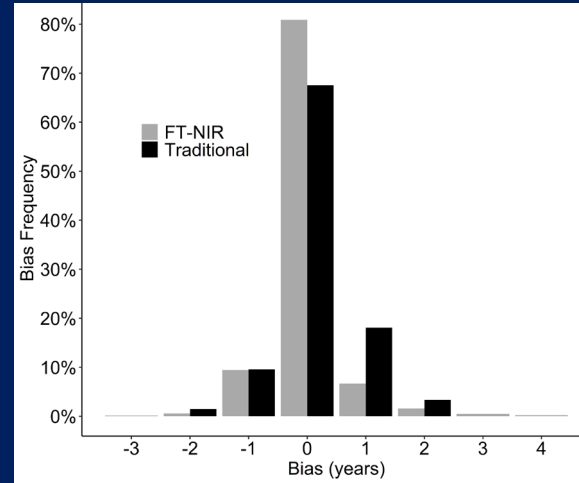
2014-2018
test set

n=1751



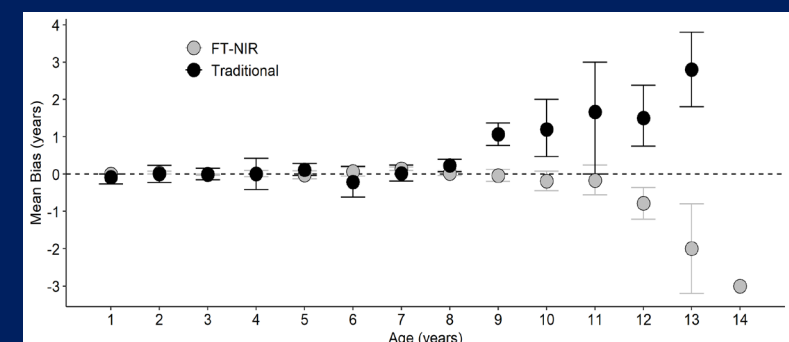
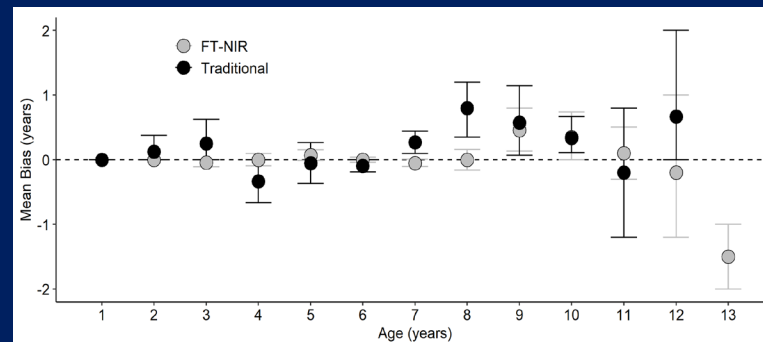
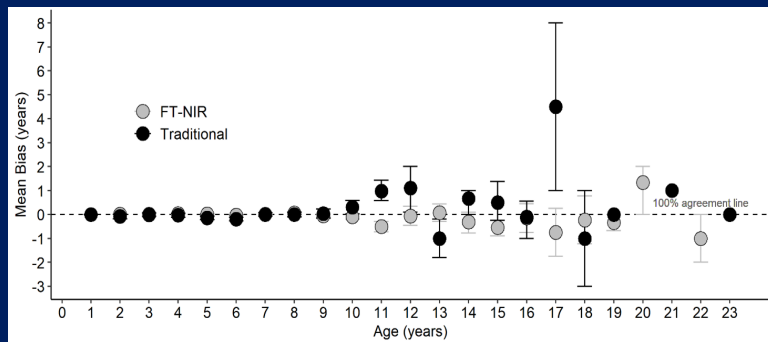
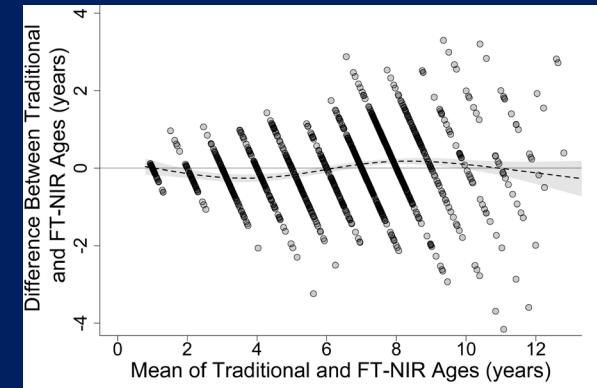
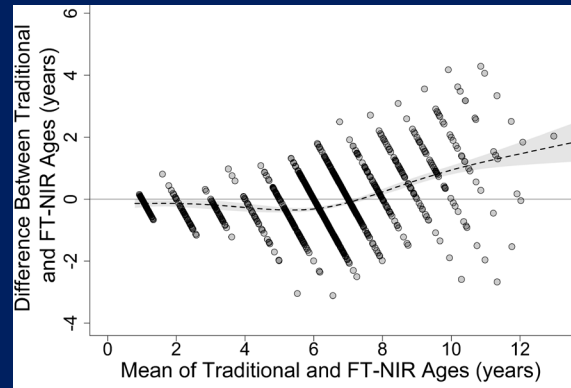
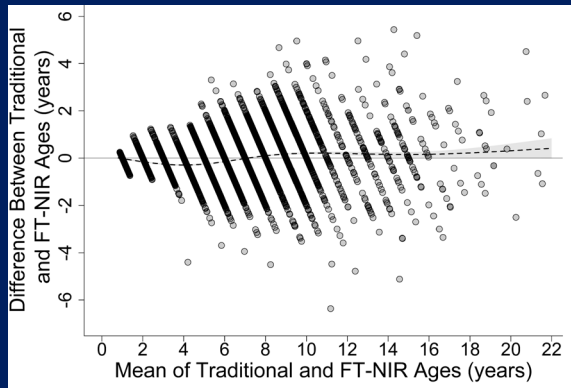
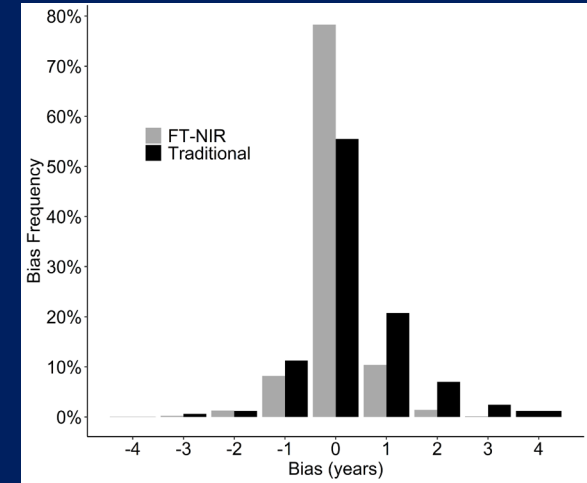
2019

n=1379



2021

n=1340



Model Uncertainty

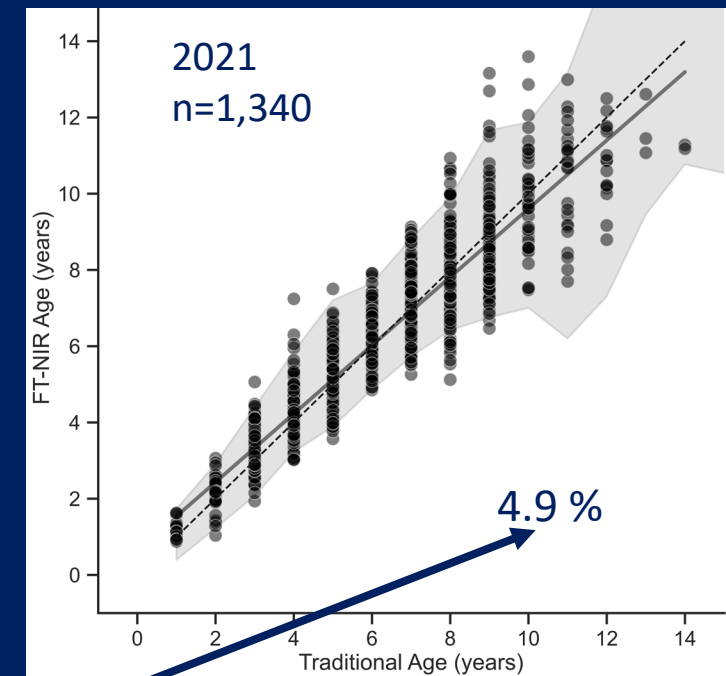
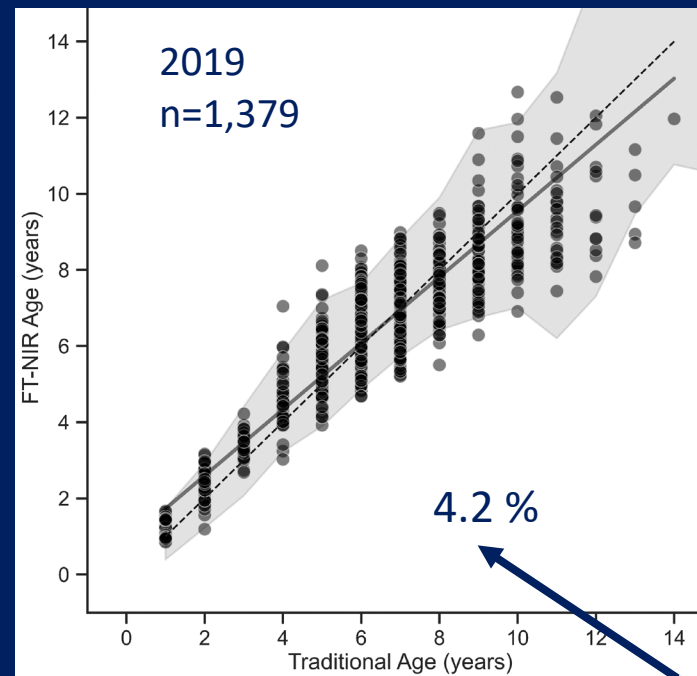
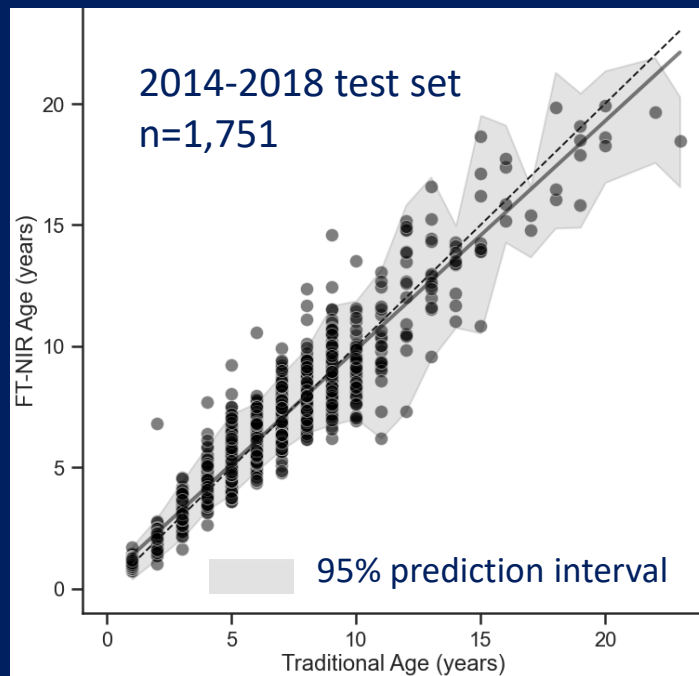


Dropout as a Bayesian Approximation:
Representing Model Uncertainty in Deep Learning

Yarin Gal
Zoubin Ghahramani
University of Cambridge

2016

- Established connection between dropout networks and approximate Bayesian inference.
- Monte Carlo Dropout is a good measure of the model's uncertainty.

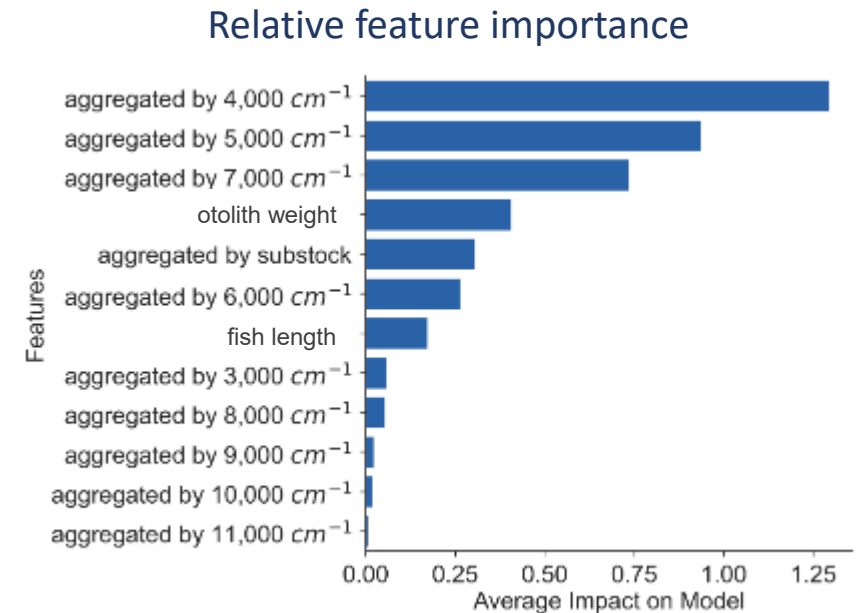
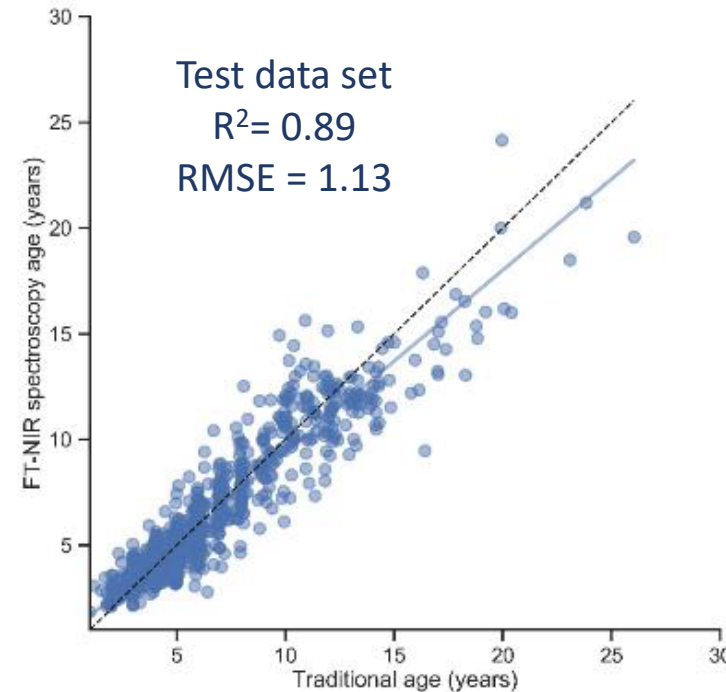
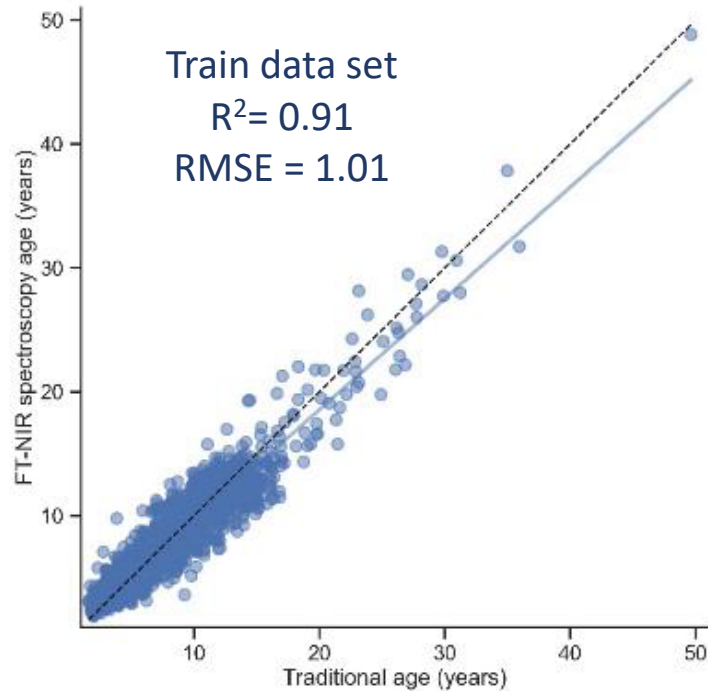
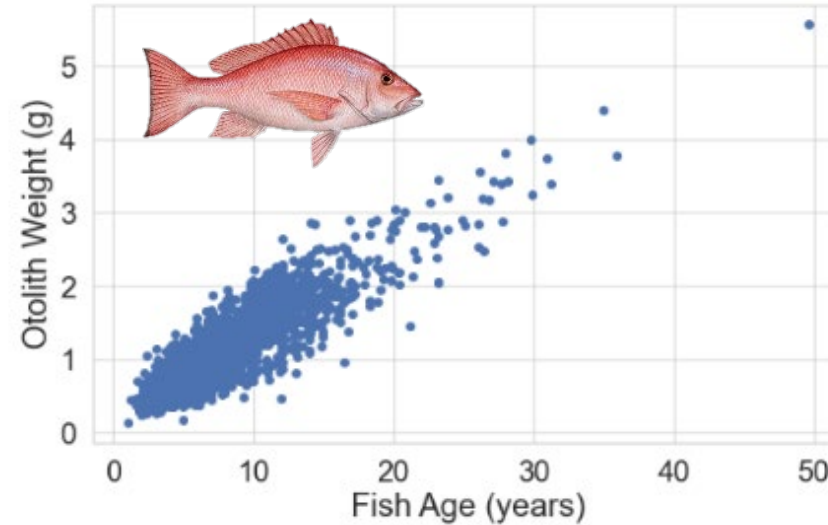


probability of the prediction sample set not being contained within the interval

Case Study: long-lived species

Red Snapper
(*Lutjanus campechanus*)

- Long-lived reef fish (50+ years)
- Ecologically and economically important
- Estimated to be recovering in US Gulf of Mexico waters

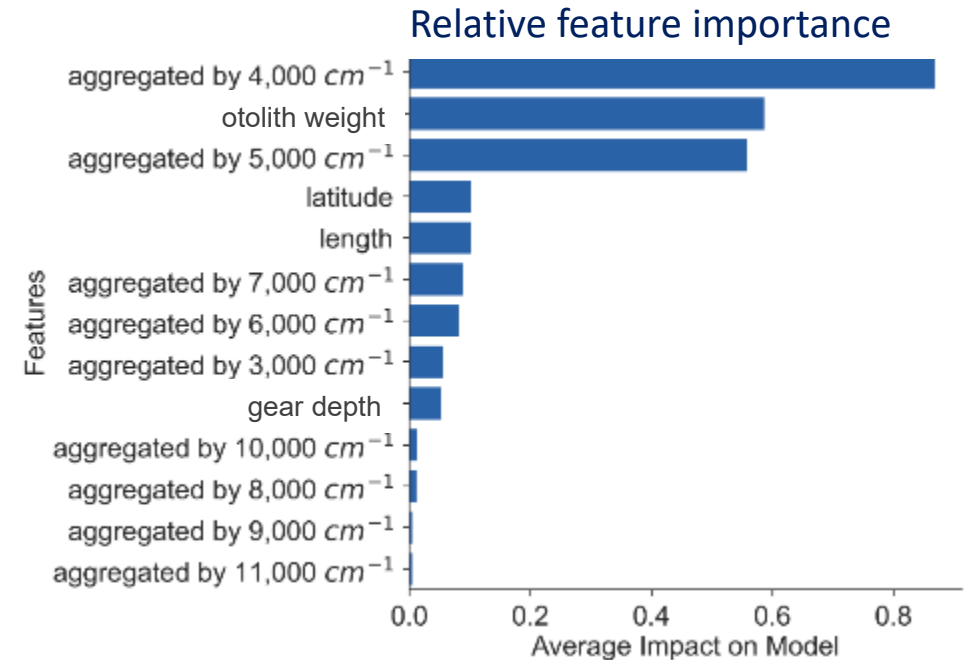
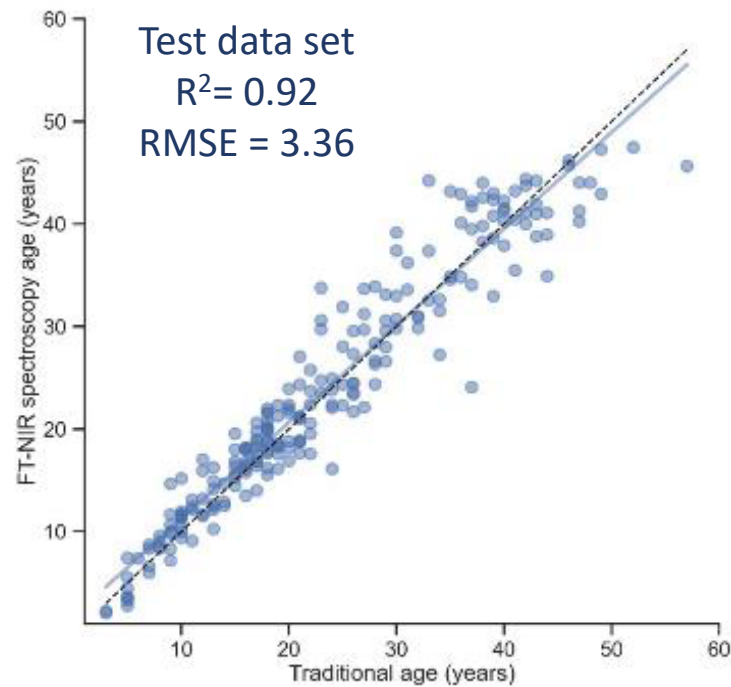
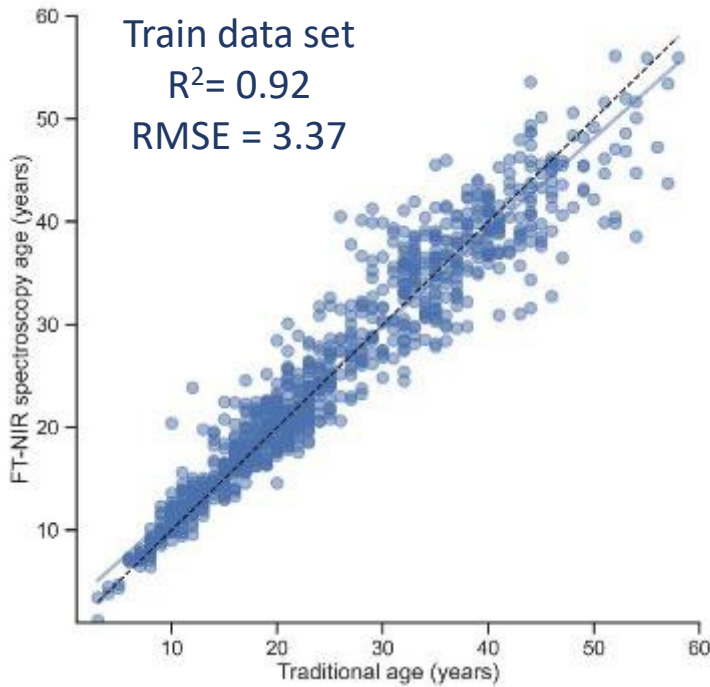
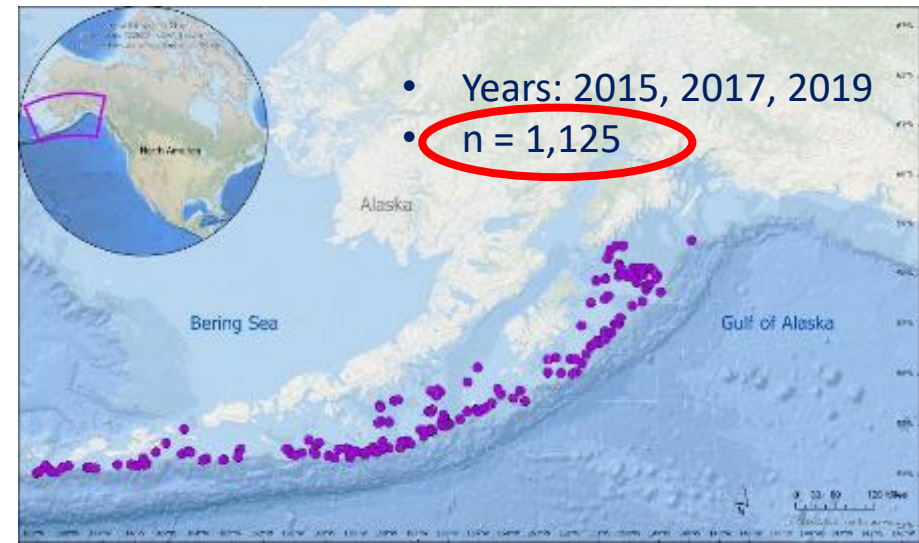
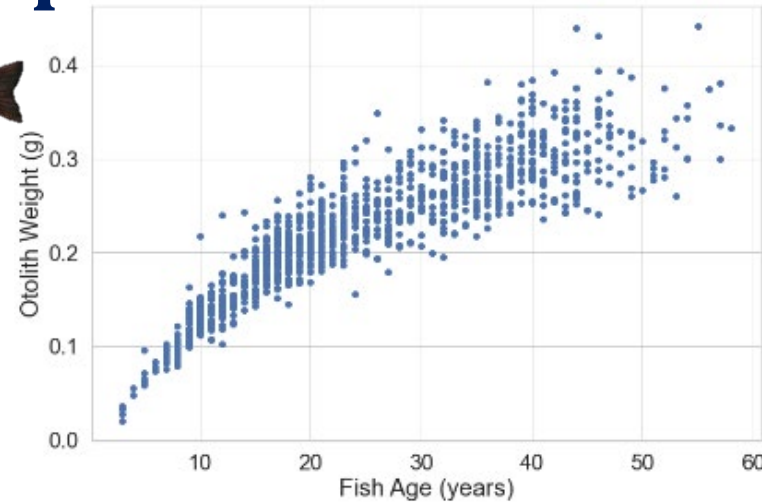


Case Study: long-lived species

Northern Rockfish
(*Sebastes polyspinus*)



- Long-lived rockfish (80+ years).
- Commercially important rockfish in the Gulf of Alaska and the Aleutian Islands fisheries management areas.



Conclusions

- Deep learning models are capable of accepting and learning information from multiple feature types, extracting important spectral features automatically, and handling non-linearity in data better than traditional chemometrics approach.
- FT-NIR spectroscopy of otoliths coupled with deep machine learning can predict fish ages more rapidly, with greater efficiency, and with comparable precision to traditional microscopic ageing method.

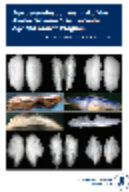


- Working with UW Information Processing Lab (Prof. Hwang) to develop more sophisticated model. Collecting otolith images and otolith weights for walleye pollock (AFSC) and red snapper (SEFSC).
- Evaluating FT-NIR age data performance in stock assessments.
- Evaluating trade offs between traditional ageing (double reads, outliers, issues specimens, model updating) and FT-NIR efficiency gains.
- Establishing decision rules for model updating – important for future predictions.

Acknowledgements



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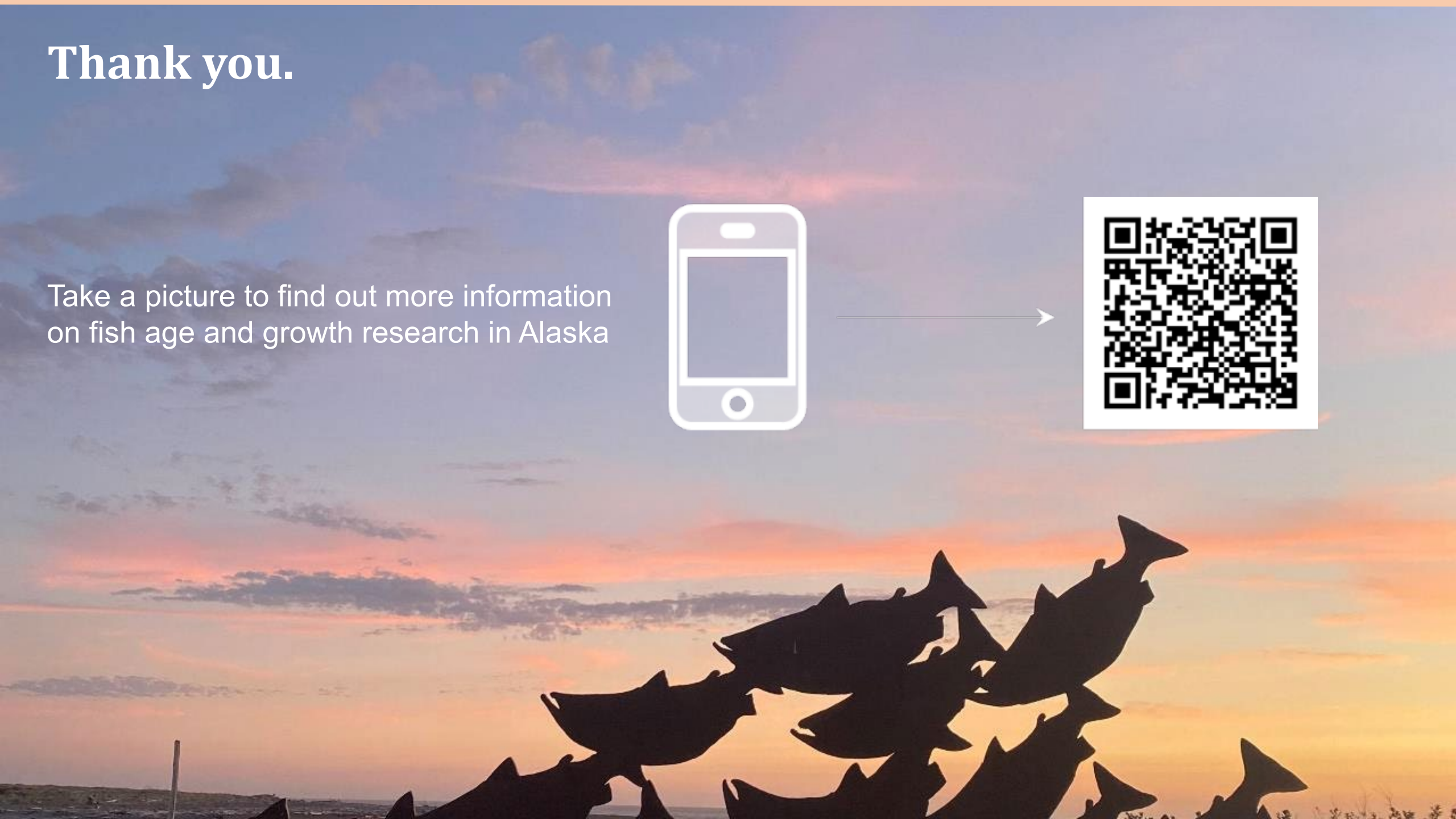
We thank the National Marine Fisheries Service Science Board for providing support for the NIR spectroscopy scientific endeavor.

We express sincere appreciation to everyone at NOAA AFSC whose contributions made this research successful:

- The Age and Growth Program staff who scanned and aged otoliths.
- Brenna Groom manages the spectroscopy lab and is always ready to answer any questions about collected spectra.
- Jon Short manages data and creates tools to improve data export efficiencies.
- Ajith Abraham (AFSC) and Giovanni Marchetti (Google) introduced us to the deep machine learning possibilities.
- Jason Erickson (Bruker) provides application support.

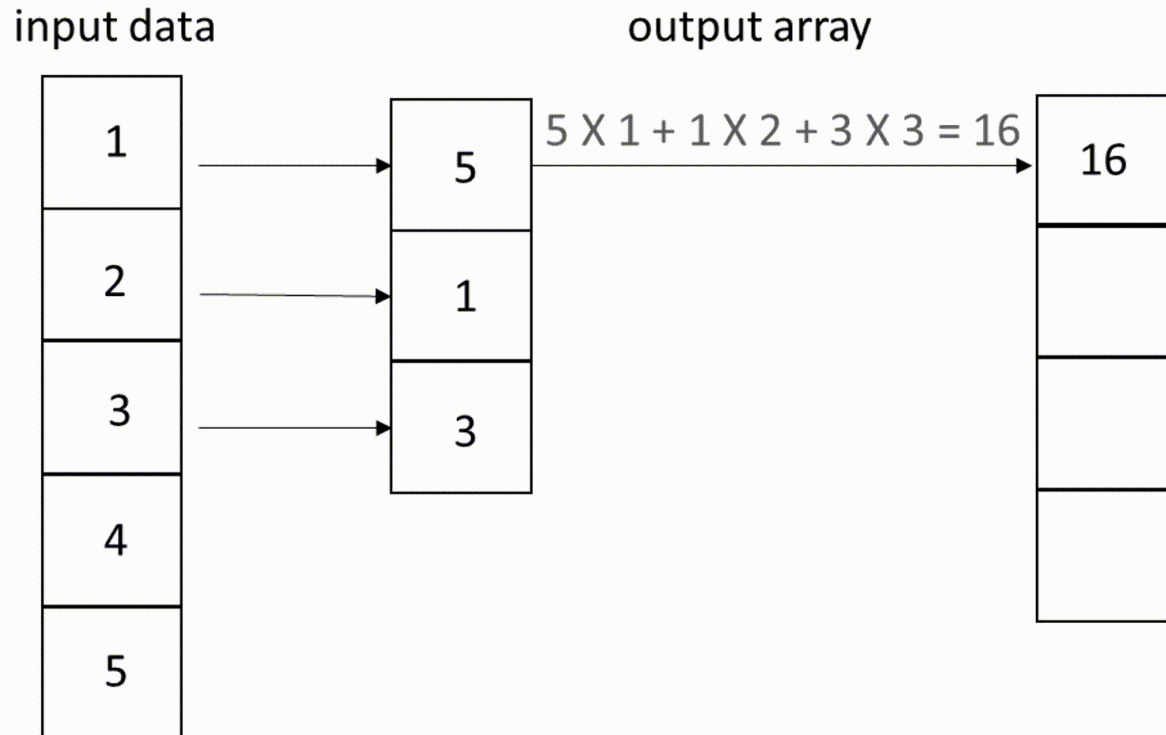
Thank you.

Take a picture to find out more information
on fish age and growth research in Alaska



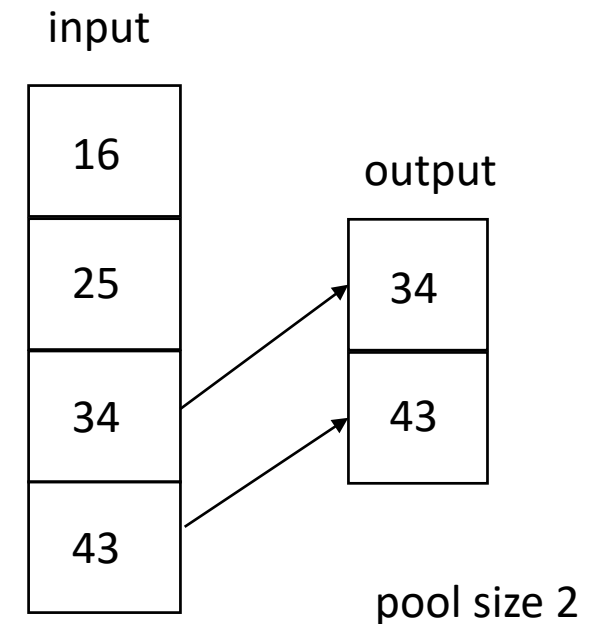
CNN Building Blocks

Convolutional layer consists of a kernel that slides along our data and applies its weights to the data values.



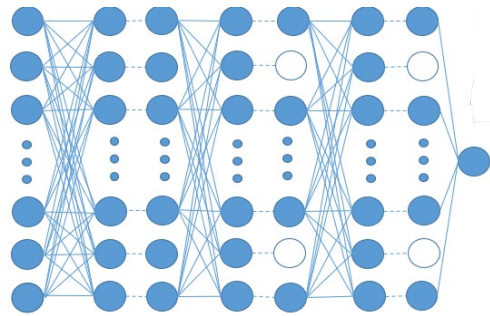
Deep learning networks have multiple kernels and will produce multiple output arrays.

Pooling layer reduces the amount of parameters and computation in the network.



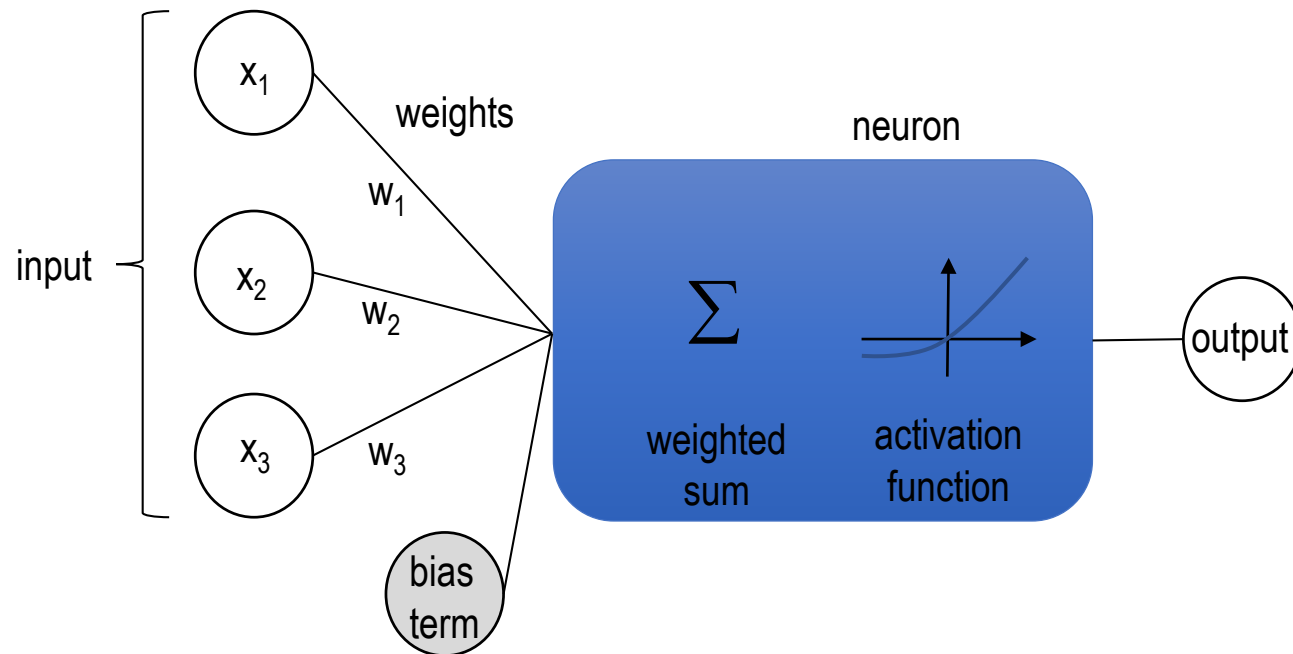
Maximum pooling reduces the spatial size of a layer keeping just the maximum values.

Core Processing Unit of NN

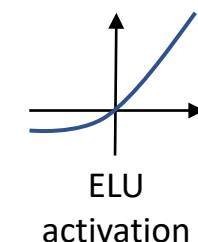
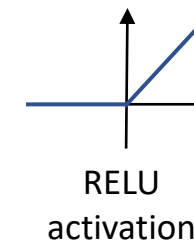


Perceptron:

- Most fundamental unit used to build a neural network.
- Resembles a neuron in the human brain.
- Simple computational unit that have weighted input signals and produce an output signal using an activation function.

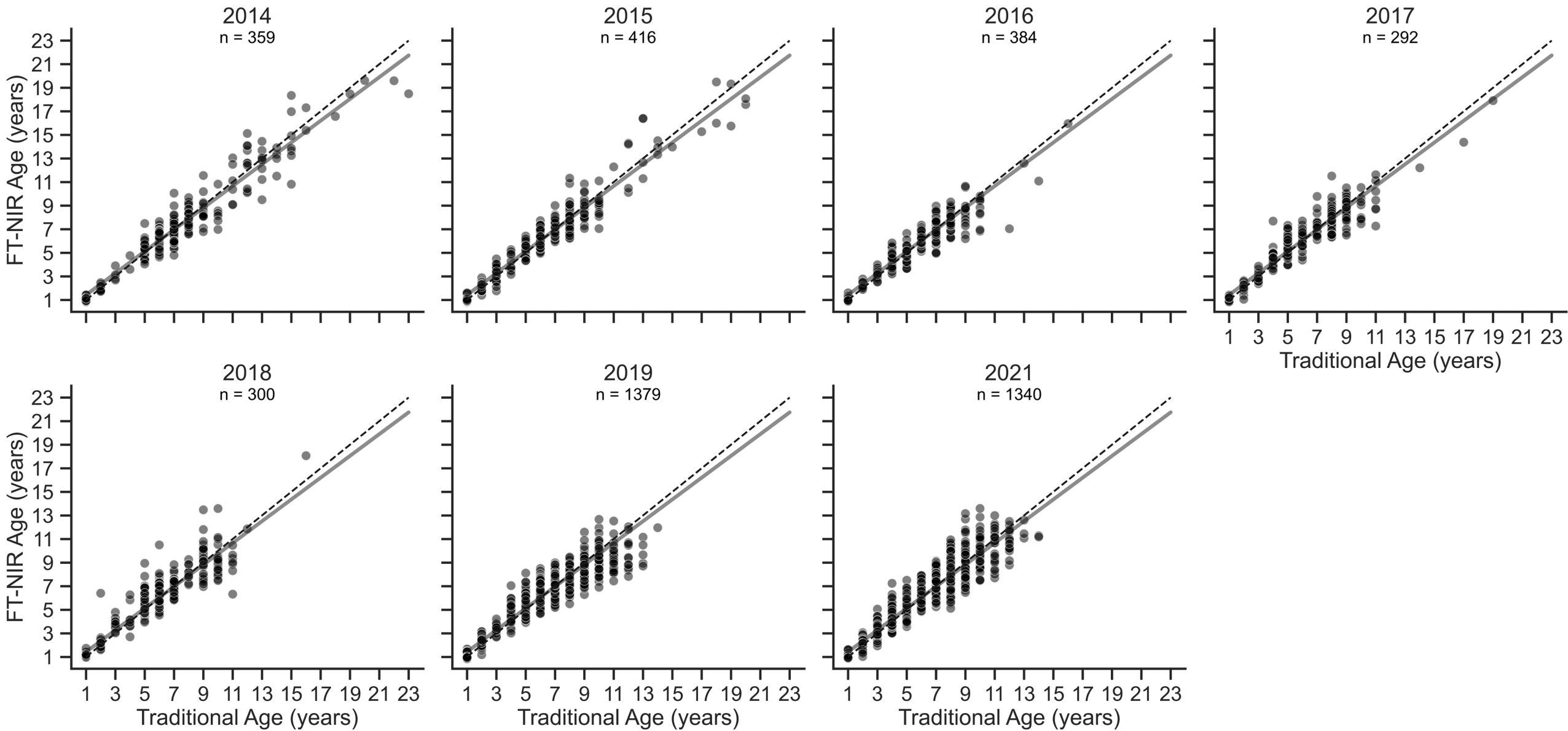


Activation function governs the threshold at which neuron is activated.



Non-linear activation functions introduce non-linear properties into network.

Model 1.2 test data set predictions plus 2019 and 2021



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NOAA Fisheries

- Alaska Fisheries Science Center, Age and Growth Program
- Southeast Fisheries Science Center, Panama City Facility



Alaska Fisheries Science Center
Age and Growth Program



Southeast Fisheries Science Center
Panama City Facility