AI for MCS Professionals

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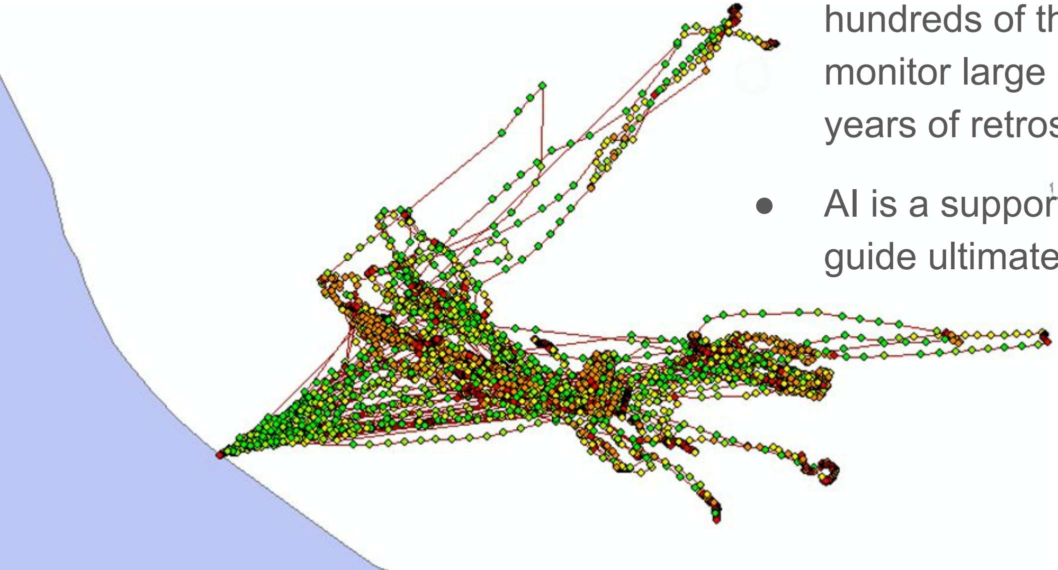
VULCAN

Overview

- Intro to AI
- Getting started
- Exploration of potential AI uses
    - Behavior Identification
    - Satellite Imagery
    - Vessel Characteristics/Type
    - Fleet Identification
    - Logbook Digitization
- Takeaways and additional discussion topics

What AI can do for you

- AI is a group of processes to apply algorithms to data in order to find or match patterns - replicate the judgement of an analyst
- Strength is **scale**: simultaneously scan through the tracks of hundreds of thousands of vessels for behaviors of interest, monitor large swaths of ocean for dark vessels, process years of retrospective analysis, and more
- AI is a support for, not a replacement of, analyst expertise to guide ultimate decisionmaking



Useful terms

Artificial Intelligence (AI): A large family of algorithms used to find and make judgements based on patterns in data.

Computer Vision: Algorithms within AI designed to apply to image data. Facial recognition is an example of computer vision.

Time series analysis: Algorithms within AI designed to apply to data with a time dimension. Many forms of behavior identification are examples of this.

Natural Language Processing: Algorithms within AI designed to apply to text. For example, “reading” a news article to automatically identify the subject and tone would be accomplished with natural language processing.

Labeled data: “Correct” examples of the task an AI algorithm should accomplish, usually provided by human analysts. Not all AI requires this, but examples discussed in this presentation would.

Where to start

- Think in terms of “What do I have” and “What do I want to know” (“data” and “question”)
- These fundamentally inform each other
- Example 1: If I want to know every vessel who is visiting a particular area and what I have is AIS, my ability to answer that question is limited. Imagery or other non-voluntary sources should be explored.
- Example 2: I am interested in the behavior/pattern of life of a particular type of or group of vessels - here imagery isn’t going to work, because it’s very challenging to infer behavior from infrequent data. AIS, VMS, or similar are good here.

Rule of thumb: If an analyst could answer your question with the data you have given years or a lot of resources, it’s a good candidate for AI-based analysis.

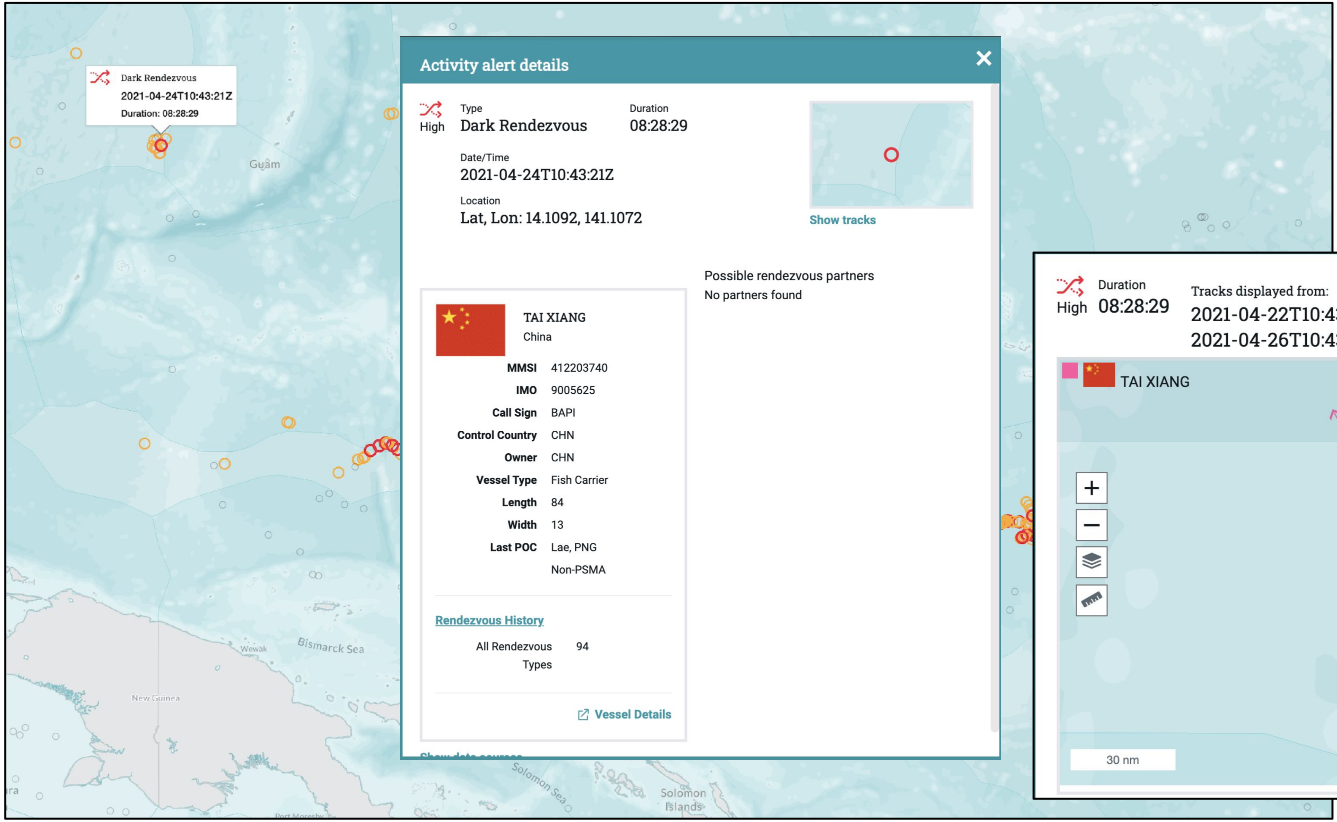
AI-friendly questions

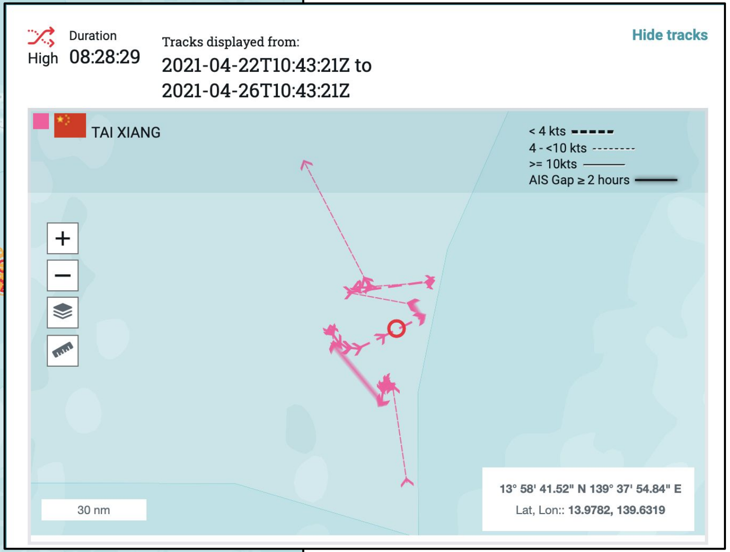
- More structure to your question = better results

When is a vessel doing something illegal?	VS	When is a vessel fishing using a particular gear type?
When is a vessel doing something suspicious?	VS	When is a vessel fishing near a restricted area?

Behavior Identification: Dark Rendezvous

Identification via AI of vessel rendezvous when only one vessel appears on AIS.
Currently in Skylight.

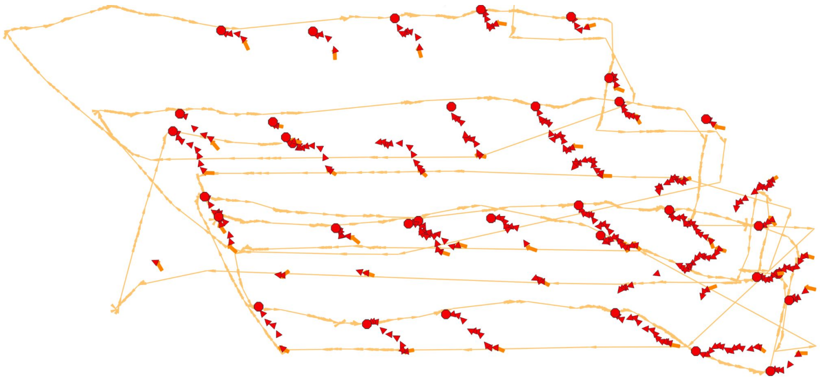




Behavior Identification: Marked Fishing Gear

- Identify AIS transponders attached to fishing gear distinctly from transponders on vessels
- Identify if attached to gear by metadata and recent behavior
- Filter out two-sided rendezvous and (in the future) identify contribution to fishing effort

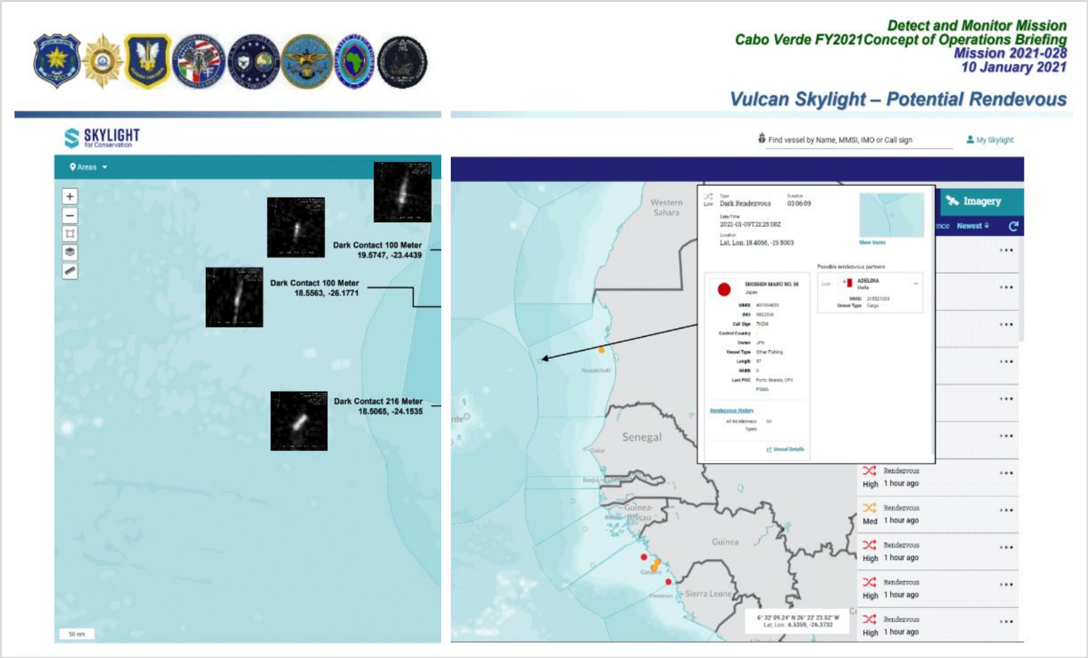
Currently in Skylight.



CASE STUDY: SKYLIGHT USE IN CABO VERDE

Guiding air patrol towards suspicious maneuvers and loitering
// Dec – Apr 2021

- Skylight collected satellite radar (SAR) and gave the Cabo Verde Coast Guard and US Navy access to Skylight during the anti-narcotics and -IUUF operation
- When preparing weekly pre-flight briefs, the agencies first checked Skylight for dark rendezvous events and dark detections because of their low density
- Those events were double checked on SeaVision and then made into 'contacts of interest' for the flight.

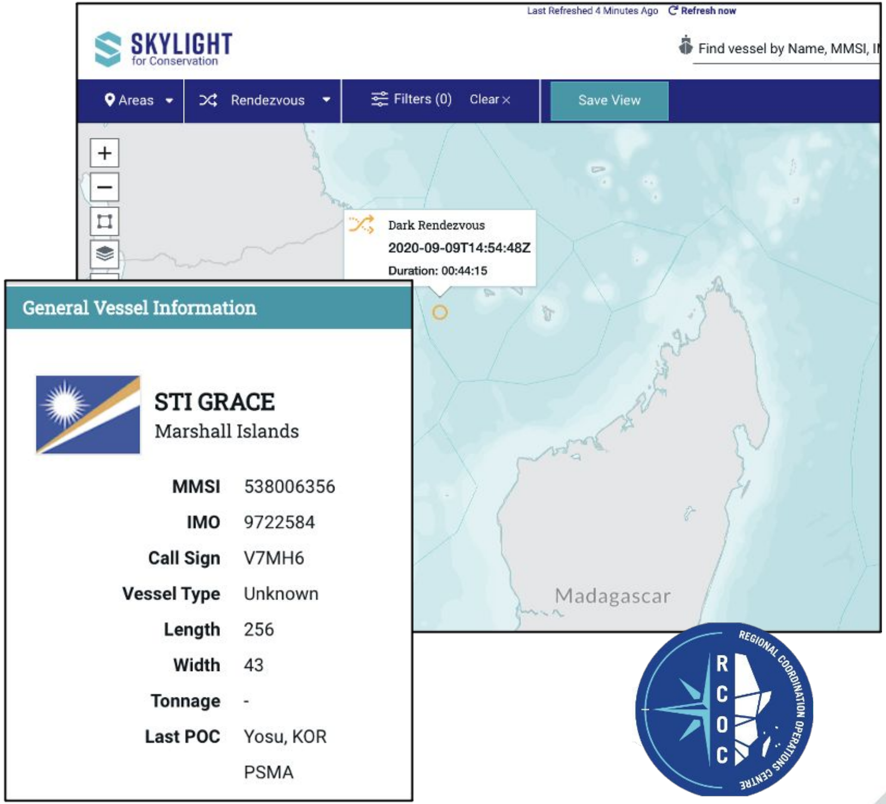


US Navy Africa: "[Dark Rendezvous] events have helped detect subtle changes in the environment, pattern-of-life, and focus… I may know that a contact was idle because I have a view set up in for less than 5 knots, but I don't necessarily have the indication like what the AI pulls out for me… I've found fishing vessels slowing down and picking up their lines, three reefers that were loitering in the area potentially transshipping.. the activity is not always illegal but it interesting and I can make them contacts of interest for the flight."

CASE STUDY: WESTERN INDIAN OCEAN

Detecting large vessels suddenly loitering
// Sept 2020 - Ongoing

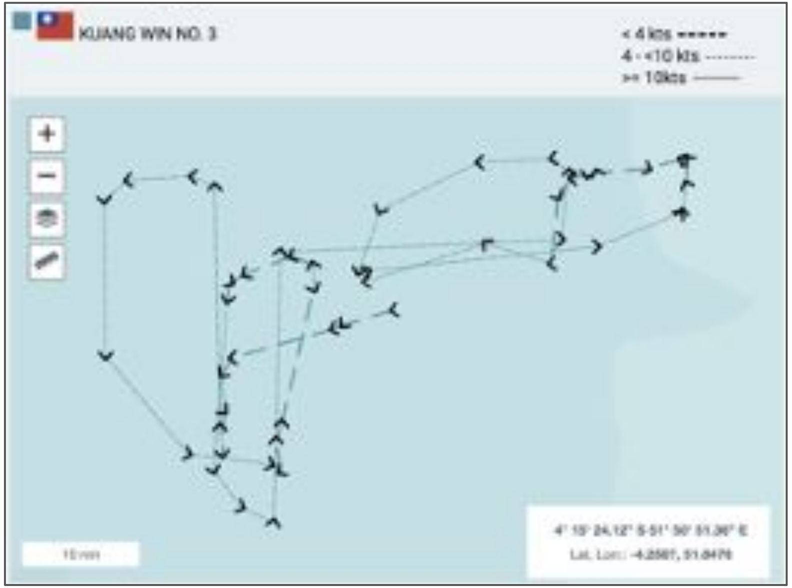
- The Regional Coordination and Operations Centre (Indian Ocean) uses Skylight alerts every day to detect suspicious movements in a region over 7 million km2.
- Dark Rendezvous alerts can identify vessels like *M/V STI Grace* unexpectedly loitering on their way to port.
- RCOC informed Kenyan authorities to inspect the vessel and the captain managed to prove that he had paused in the area not to clean bilge, but to take instructions from the vessels owner to enter a different port due to piracy concerns.
- RCOC thought the knowledge of these decisions was beneficial to their maritime domain awareness of the area and the deterrence effect was positive: “They know we are watching.”

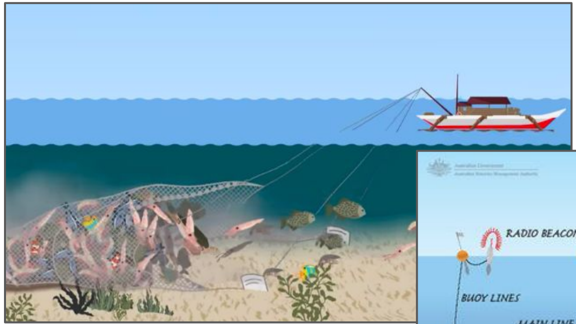


Behavior Identification: Fishing

Using AIS or VMS track data to automatically identify fishing activity, and determine what gear type is in use.

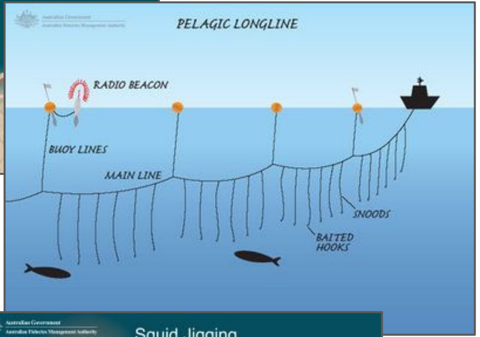
In active development for Skylight.

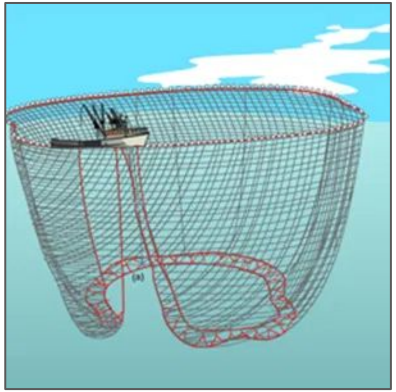




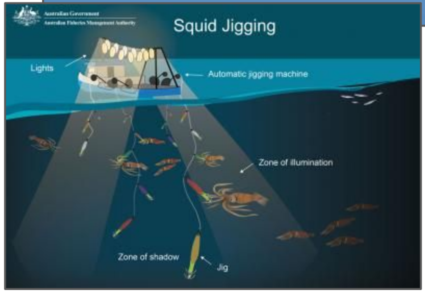
Trawling

Longlining





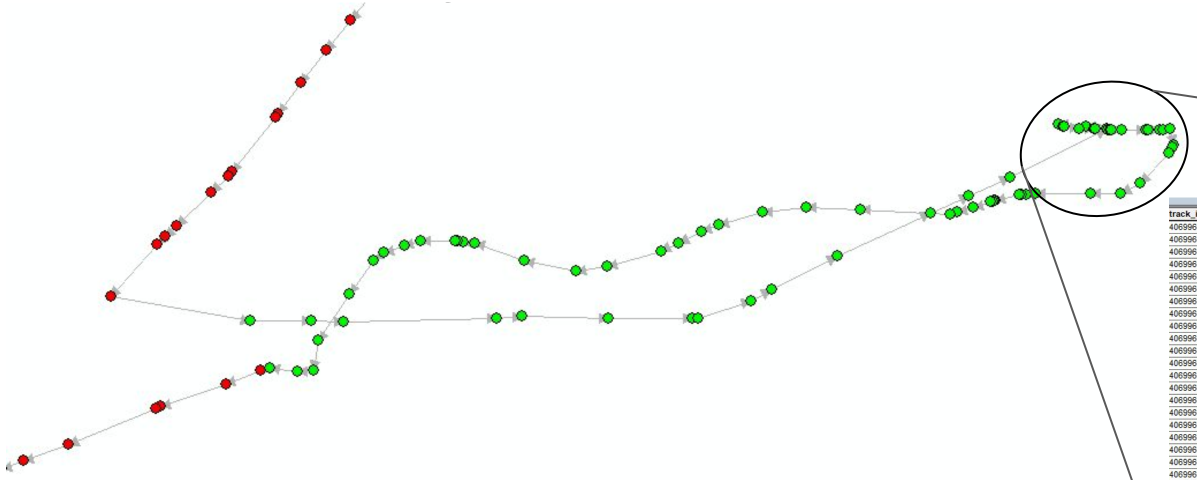
Purse Seining



Squid Jigging

Behavior Identification: Data Considerations

- Model learns from labeled examples to look for more examples
- This is an example track section of a longliner setting and recovering a line
- Green is AIS position points labeled as fishing behavior, red is transiting
- Data for models are just **numbers**; critical to ask how you are representing



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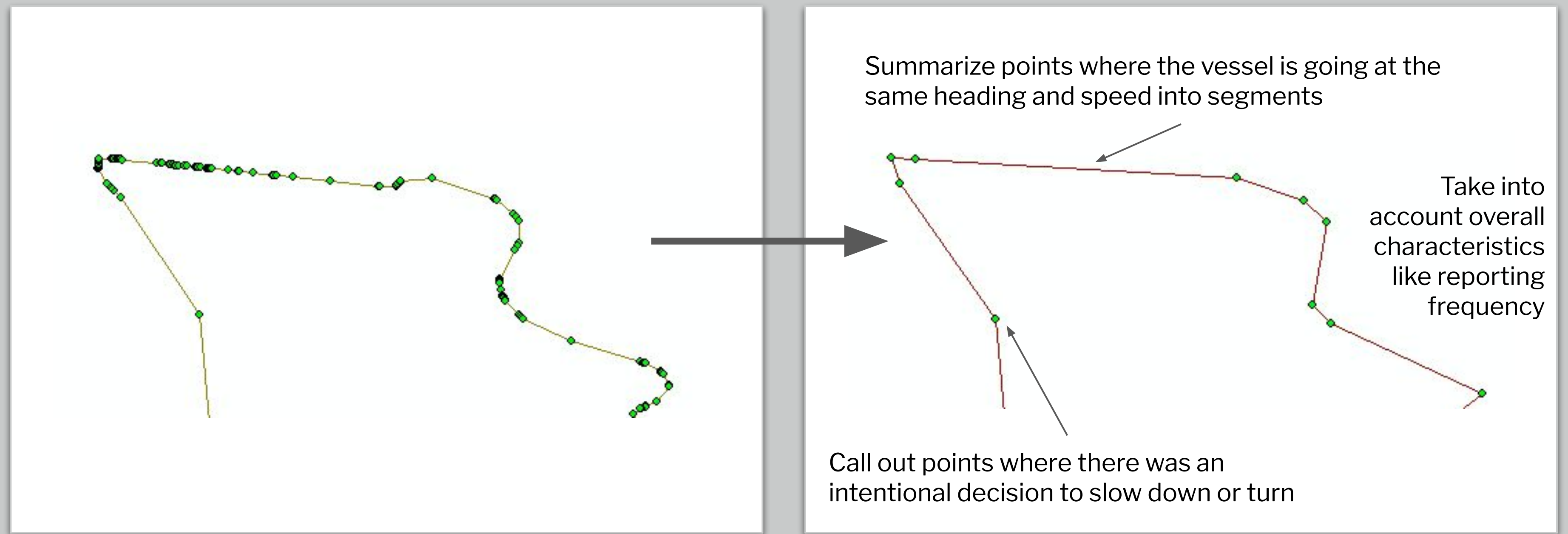
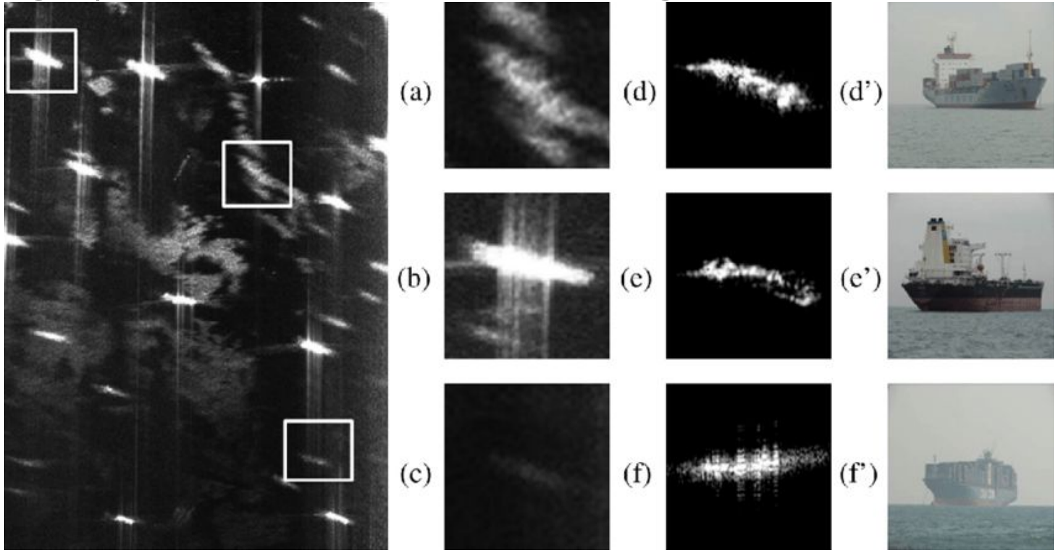
Behavior Identification: Structuring Data

Example of converting raw AIS into an approximation of operator decisions - significant benefits for behavior identification. Just one example of helpful structure



Vessel Detection

- Computer vision - application of AI to image processing
- Vessel detection to entire scenes is labor-intensive
- AI can be used to ID vessels in electro-optical imagery (left), synthetic aperture radar imagery (right), and other remote sensing modalities



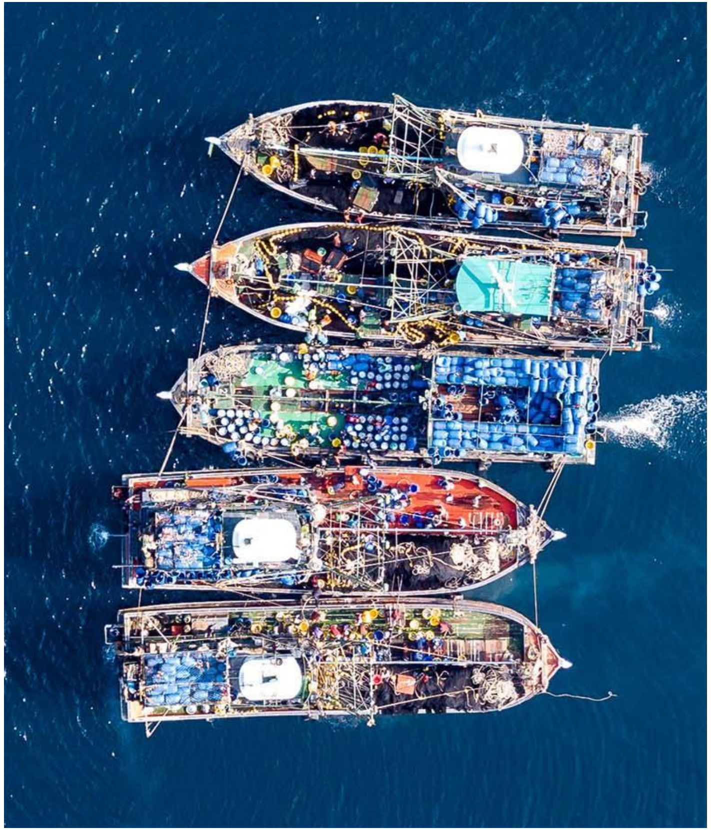
Hierarchical ship detection and recognition with high-resolution polarimetric synthetic aperture radar imagery, Lang et. al

Vessel Type Classification

- Documented cases of deception in self-reported vessel type (“pleasure” instead of “fishing” common substitution)
- Often indicative of IUU fishing
- Assignment of probable type of vessel through behavior, freeing from reliance on self-reported information

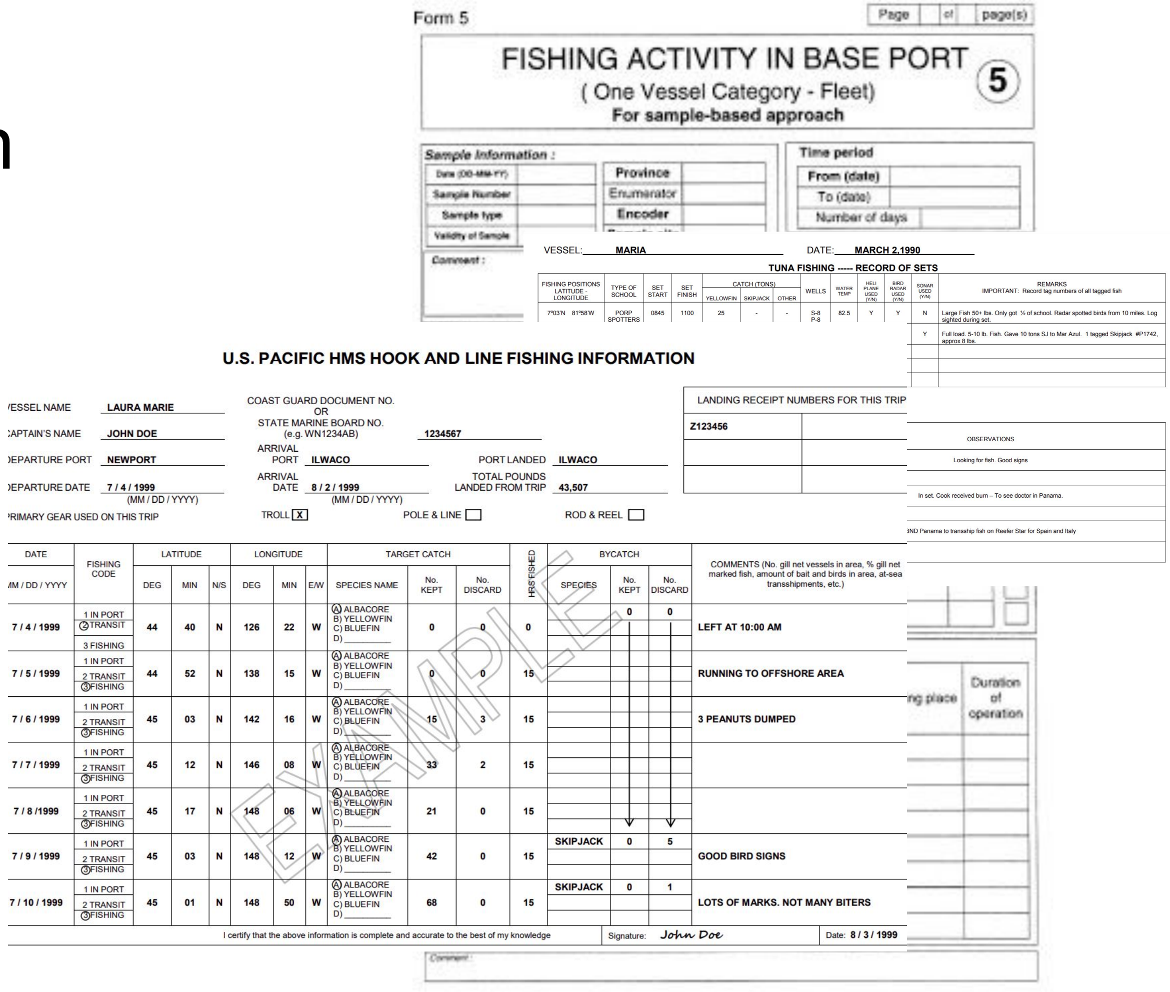
Fleet Identification

- Automatic association of affiliated or similar vessels
- Enables more effective supply chain analysis and estimation
- Possible data sources can include
  - Naming conventions
  - Behavior - association with/resupply by common vessels
  - Ownership information, if known
  - Pattern of life from port visits



Logbook digitization

- Logbook examination critical tool for investigation, particularly looking for IUU fishing
- Paper documents labor-intensive to search through
- Combination of computer vision and natural language processing
- Enables identification of suspicious patterns


Form 5

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FISHING ACTIVITY IN BASE PORT 5

(One Vessel Category - Fleet)

For sample-based approach

Sample Information :

Date (DD-MM-YY)

Sample Number

Sample type

Validity of Sample

Province

Enumerator

Encoder

Time period

From (date)

To (date)

Number of days

Comment :

VESSEL: MARIA DATE: MARCH 2,1990

TUNA FISHING ----- RECORD OF SETS

FISHING POSITIONS LATITUDE - LONGITUDE	TYPE OF SCHOOL	SET START	SET FINISH	CATCH (TONS) YELLOWFIN	SKIPJACK	OTHER	WELLS	WATER TEMP	HELI PLANE USED (Y/N)	BIRD RADAR USED (Y/N)	SONAR USED (Y/N)	REMARKS IMPORTANT: Record tag numbers of all tagged fish
7°03'N 81°58'W	PORP SPOTTERS	0845	1100	25	-	-	S-8 P-8	82.5	Y	Y	N	Large Fish 50+ lbs. Only got ½ of school. Radar spotted birds from 10 miles. Log sighted during set.
											Y	Full load. 5-10 lb. Fish. Gave 10 tons SJ to Mar Azul. 1 tagged Skipjack #P1742, approx 8 lbs.

OBSERVATIONS

Looking for fish. Good signs

In set. Cook received burn – To see doctor in Panama.

END Panama to transship fish on Reefer Star for Spain and Italy

U.S. PACIFIC HMS HOOK AND LINE FISHING INFORMATION

VESSEL NAME: LAURA MARIE

CAPTAIN'S NAME: JOHN DOE

DEPARTURE PORT: NEWPORT

DEPARTURE DATE: 7 / 4 / 1999 (MM / DD / YYYY)

PRIMARY GEAR USED ON THIS TRIP: TROLL [X] POLE & LINE [ ] ROD & REEL [ ]

COAST GUARD DOCUMENT NO. OR STATE MARINE BOARD NO. (e.g. WN1234AB): 1234567

ARRIVAL PORT: ILWACO

ARRIVAL DATE: 8 / 2 / 1999 (MM / DD / YYYY)

PORT LANDED: ILWACO

TOTAL POUNDS LANDED FROM TRIP: 43,507

LANDING RECEIPT NUMBERS FOR THIS TRIP: Z123456

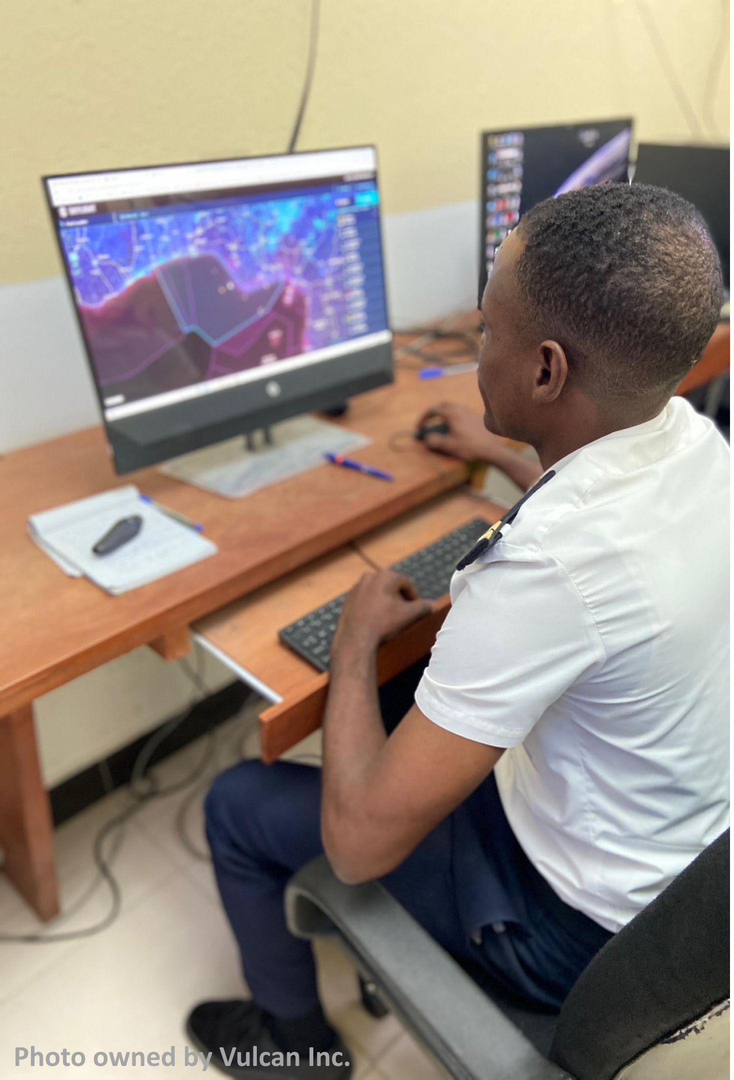
DATE MM / DD / YYYY	FISHING CODE	LATITUDE DEG	MIN	N/S	LONGITUDE DEG	MIN	E/W	TARGET CATCH SPECIES NAME	No. KEPT	No. DISCARD	HRS FISHED	BYCATCH SPECIES	No. KEPT	No. DISCARD	COMMENTS (No. gill net vessels in area, % gill net marked fish, amount of bait and birds in area, at-sea transshipments, etc.)
7 / 4 / 1999	1 IN PORT 2 TRANSIT 3 FISHING	44	40	N	126	22	W	A) ALBACORE B) YELLOWFIN C) BLUEFIN D)	0	0	0		0	0	LEFT AT 10:00 AM
7 / 5 / 1999	1 IN PORT 2 TRANSIT 3 FISHING	44	52	N	138	15	W	A) ALBACORE B) YELLOWFIN C) BLUEFIN D)	0	0	15				RUNNING TO OFFSHORE AREA
7 / 6 / 1999	1 IN PORT 2 TRANSIT 3 FISHING	45	03	N	142	16	W	A) ALBACORE B) YELLOWFIN C) BLUEFIN D)	15	3	15				3 PEANUTS DUMPED
7 / 7 / 1999	1 IN PORT 2 TRANSIT 3 FISHING	45	12	N	146	08	W	A) ALBACORE B) YELLOWFIN C) BLUEFIN D)	33	2	15				
7 / 8 /1999	1 IN PORT 2 TRANSIT 3 FISHING	45	17	N	148	06	W	A) ALBACORE B) YELLOWFIN C) BLUEFIN D)	21	0	15				
7 / 9 / 1999	1 IN PORT 2 TRANSIT 3 FISHING	45	03	N	148	12	W	A) ALBACORE B) YELLOWFIN C) BLUEFIN D)	42	0	15	SKIPJACK	0	5	GOOD BIRD SIGNS
7 / 10 / 1999	1 IN PORT 2 TRANSIT 3 FISHING	45	01	N	148	50	W	A) ALBACORE B) YELLOWFIN C) BLUEFIN D)	68	0	15	SKIPJACK	0	1	LOTS OF MARKS. NOT MANY BITERS

EXAMPLE

I certify that the above information is complete and accurate to the best of my knowledge Signature: John Doe Date: 8 / 3 / 1999

Duration of operation

Comment :



Takeaways

- AI's strength is scale
- AI is an augmentation to, not a replacement of, analyst expertise
- Many possible questions addressable with AI tools
- Carefully consider data representation
- AI does better with a more defined and well-represented problem.

Thank you for your interest!

Contact: rosehe@vulcan.com

Discussion questions/additional topics

1. How might AI-generated analysis fit into current analyst workflow?
2. What problems do you have that AI might be applied to solving?
3. Do you have access to any unique data sources not mentioned here that might be good candidates for AI?
4. Could labeled data be curated from activities currently undertaken by analysts or regulatory enforcement activities? For example, fisheries observer data?
5. How would you validate or act on AI-generated analysis?
6. What are concerns you have about using AI?

Thank You