Artificial Intelligence
A Primer and Potential Applications to Land Reclamation

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Partner
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ar·ti·fi·cial in·tel·li·gence

/ˌärdəˈfiSHəl inˈteləjəns/

noun

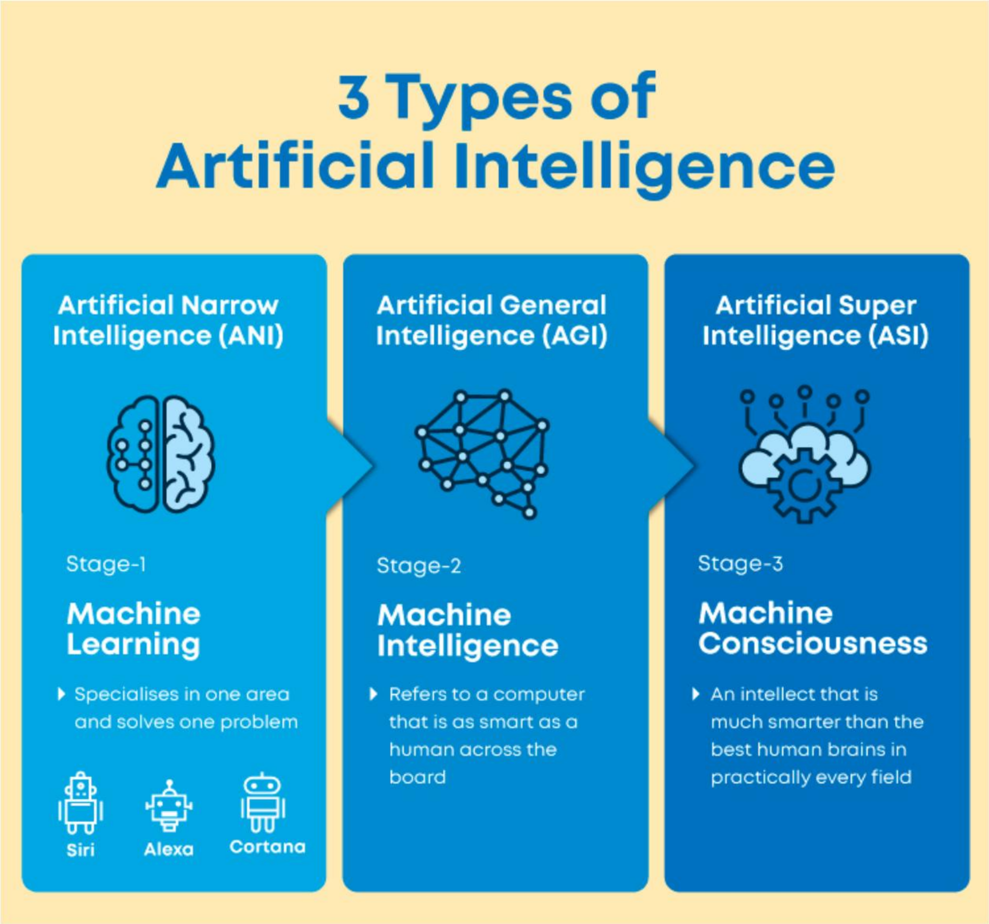
the theory and development of computer systems able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages.

machine learning

noun

the use and development of computer systems that are able to learn and adapt without following explicit instructions, by using algorithms and statistical models to analyze and draw inferences from patterns in data.

"the application of machine learning to biological databases has increased"


3 Types of
Artificial Intelligence
Artificial Narrow Intelligence (ANI)
Stage-1
Machine Learning
Specialises in one area and solves one problem
Siri
Alexa
Cortana
Artificial General Intelligence (AGI)
Stage-2
Machine Intelligence
Refers to a computer that is as smart as a human across the board
Artificial Super Intelligence (ASI)
Stage-3
Machine Consciousness
An intellect that is much smarter than the best human brains in practically every field

Key AI breakthroughs from 1950 to today and beyond

1950 Alan Turing published “Computing Machinery and Intelligence,” introducing the Turing test and opening the doors to what would be known as AI.

1951 Marvin Minsky and Dean Edmonds developed the first artificial neural network (ANN) called SNARC using 3,000 vacuum tubes to simulate a network of 40 neurons.

1952 Arthur Samuel developed Samuel Checkers-Playing Program, the world's first program to play games that was self-learning.

1956 John McCarthy, Marvin Minsky, Nathaniel Rochester and Claude Shannon coined the term artificial intelligence in a proposal for a workshop widely recognized as a founding event in the AI field.

1958 Frank Rosenblatt developed the perceptron, an early ANN that could learn from data and became the foundation for modern neural networks.

John McCarthy developed the programming language Lisp, which was quickly adopted by the AI industry and gained enormous popularity among developers.

1959 Arthur Samuel coined the term machine learning in a seminal paper explaining that the computer could be programmed to outplay its programmer.

Oliver Selfridge published “Pandemonium: A Paradigm for Learning,” a landmark contribution to machine learning that described a model that could adaptively improve itself to find patterns in events.

1964 Daniel Bobrow developed STUDENT, an early natural language processing (NLP) program designed to solve algebra word problems, while he was a doctoral candidate at MIT.

1965 Edward Feigenbaum, Bruce G. Buchanan, Joshua Lederberg and Carl Djerassi developed the first expert system, Dendral, which assisted organic chemists in identifying unknown organic molecules.

1966 Joseph Weizenbaum created Eliza, one of the more celebrated computer programs of all time, capable of engaging in conversations with humans and making them believe the software had humanlike emotions.

Stanford Research Institute developed Shakey, the world's first mobile intelligent robot that combined AI, computer vision, navigation and NLP. It's the grandfather of self-driving cars and drones.

1968 Terry Winograd created SHRDLU, the first multimodal AI that could manipulate and reason out a world of blocks according to instructions from a user.

1969 Arthur Bryson and Yu-Chi Ho described a backpropagation learning algorithm to enable multilayer ANNs, an advancement over the perceptron and a foundation for deep learning.

Marvin Minsky and Seymour Papert published the book Perceptrons, which described the limitations of simple neural networks and caused neural network research to decline and symbolic AI research to thrive.

1973 James Lighthill released the report "Artificial Intelligence: A General Survey," which caused the British government to significantly reduce support for AI research.

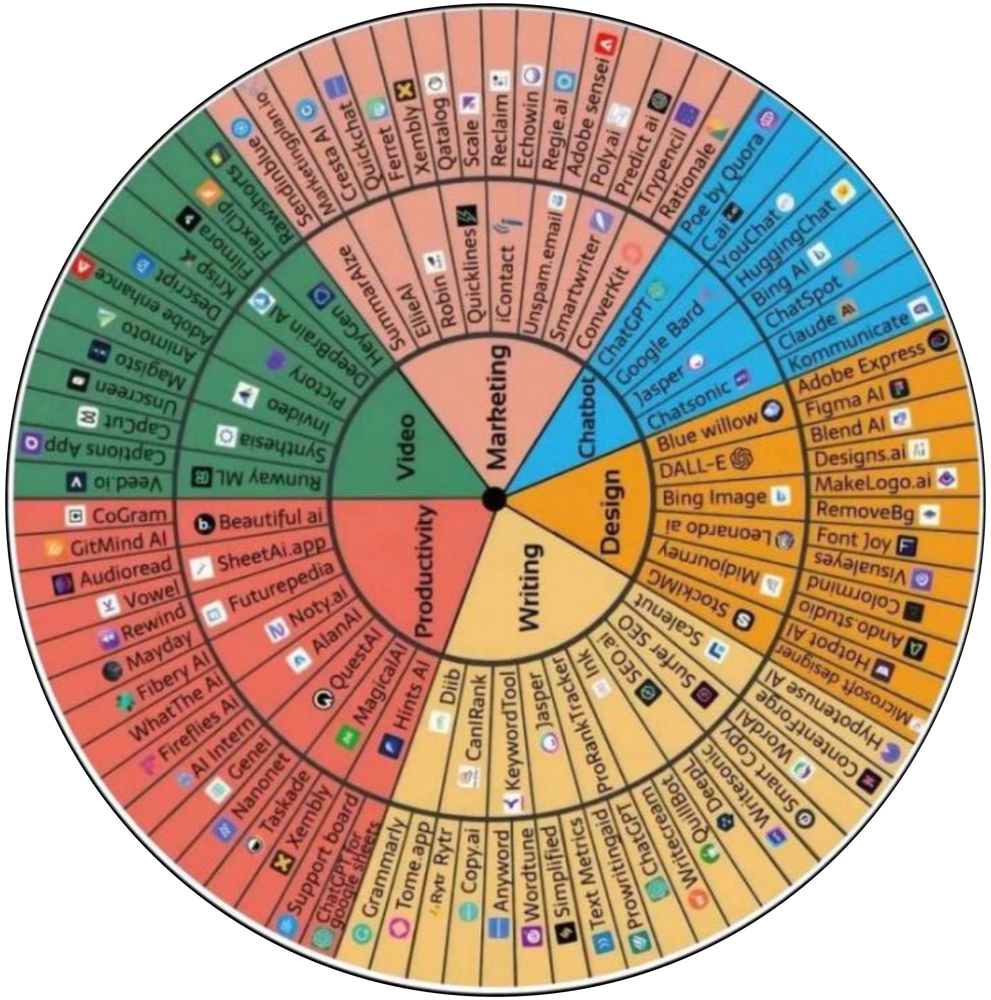
1980 Symbolics Lisp machines were commercialized, signaling an AI renaissance. Years later, the Lisp machine market collapsed.

1981 Danny Hillis designed parallel computers for AI and other computational tasks, an architecture similar to modern GPUs.

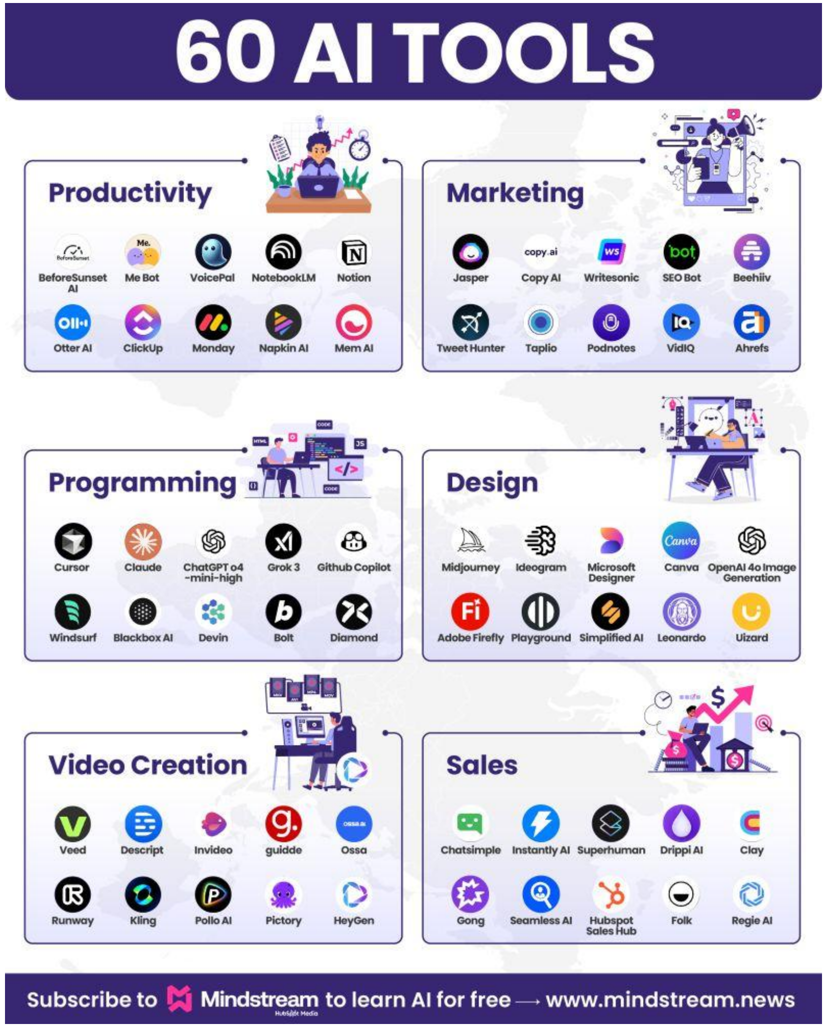
1984 Marvin Minsky and Roger Schank coined the term AI winter at a meeting of the Association for the Advancement of Artificial Intelligence, warning the business community that AI hype would lead to disappointment and the collapse of the industry, which happened three years later.

1985 Judea Pearl introduced Bayesian networks causal analysis, which provides statistical techniques for representing uncertainty in computers.

1988 Peter Brown et al. published "A Statistical Approach to Language Translation," paving the way for one of the more widely studied machine translation methods.



Marketing
SummarAIze
EllieAI
Robin
Quicklines
iContact
Unspam.email
Smartwriter
ConverKit
Sendinblue
Marketingblue.io
Cresta AI
Quickchat
Ferret
Xembly
Qatalog
Scale
Reclaim
Echowin
Regie.ai
Adobe sensei
Poly.ai
Predict ai
Trypencil
Rationale
Chatbot
ChatGPT
Google Bard
Jasper
Chatsonic
Poe by Quora
C.ai
YouChat
HuggingChat
Bing AI
ChatSpot
Claude
Kommunicate
Design
Blue willow
DALL-E
Bing Image
Leonardo ai
Midjourney
Stockimg
Adobe Express
Figma AI
Blend AI
Designs.ai
MakeLogo.ai
RemoveBg
Font Joy
Visualeyes
Colormind
Ando.studio
Hotpot AI
Microsoft designer
Writing
Scalenut
Surfer SEO
SEO.ai
Ink
ProRankTracker
Jasper
KeywordTool
CanIRank
Diib
Hypotenuse AI
Contentforge
WordAI
Smart Copy
Writesonic
Deepl
QuillBot
Writecream
ChatGPT
Prowritingaid
Text Metrics
Simplified
Wordtune
Anyword
Copy.ai
Rytr
Tome.app
Grammarly
Productivity
Beautiful ai
SheetAi.app
Futurepedia
Noty.ai
AlanAI
QuestAI
MagicalAI
Hints AI
CoGram
GitMind AI
Audioread
Vowel
Rewind
Mayday
Fibery AI
WhatThe AI
Fireflies AI
AI Intern
Genei
Nanonet
Taskade
Xembly
Support board
ChatGPT for google sheets
Video
Runway ML
Synthesia
Invideo
Pictory
DeepBrain AI
HeyGen
Veed.io
Captions App
CapCut
Unscreen
Magisto
Animoto
Adobe enhance
Descript
Krisp
Filmora
FlexClip
Rawshorts



60 AI TOOLS
Productivity
BeforeSunset AI
Me Bot
VoicePal
NotebookLM
Notion
Otter AI
ClickUp
Monday
Napkin AI
Mem AI
Marketing
Jasper
Copy AI
Writesonic
SEO Bot
Beehiiv
Tweet Hunter
Taplio
Podnotes
VidIQ
Ahrefs
Programming
Cursor
Claude
ChatGPT o4 -mini-high
Grok 3
Github Copilot
Windsurf
Blackbox AI
Devin
Bolt
Diamond
Design
Midjourney
Ideogram
Microsoft Designer
Canva
OpenAI 4o Image Generation
Adobe Firefly
Playground
Simplified AI
Leonardo
Uizard
Video Creation
Veed
Descript
Invideo
guidde
Ossa
Runway
Kling
Pollo AI
Pictory
HeyGen
Sales
Chatsimple
Instantly AI
Superhuman
Drippi AI
Clay
Gong
Seamless AI
Hubspot Sales Hub
Folk
Regie AI
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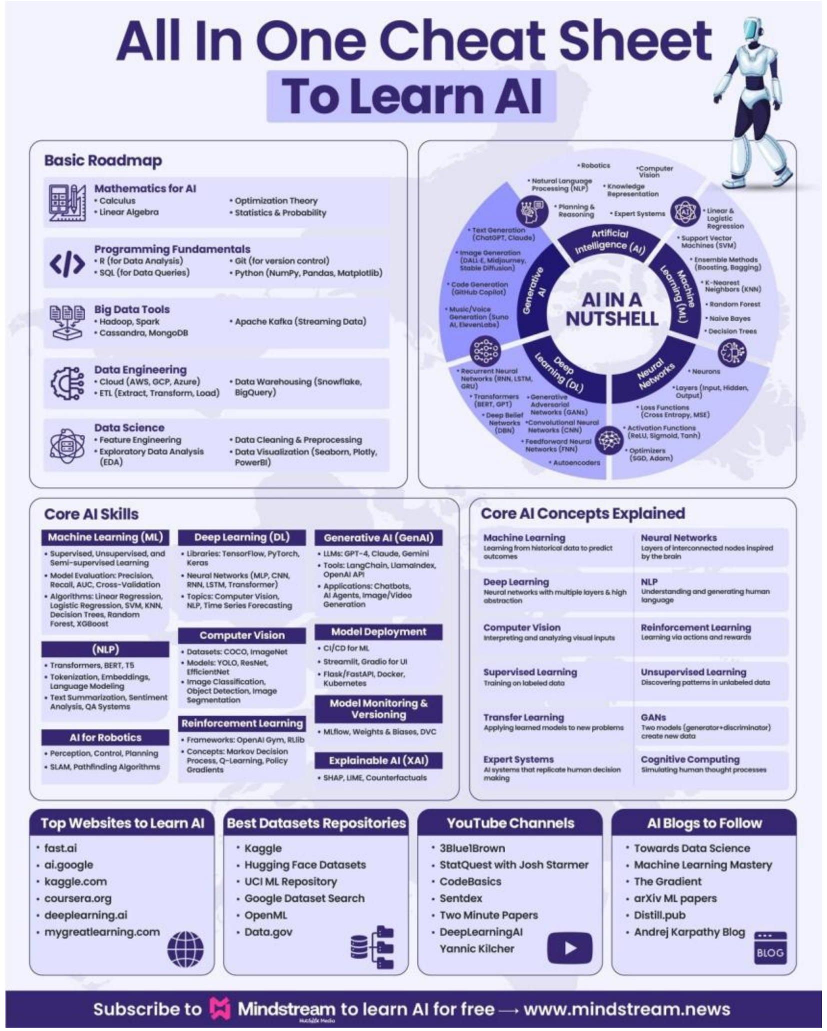
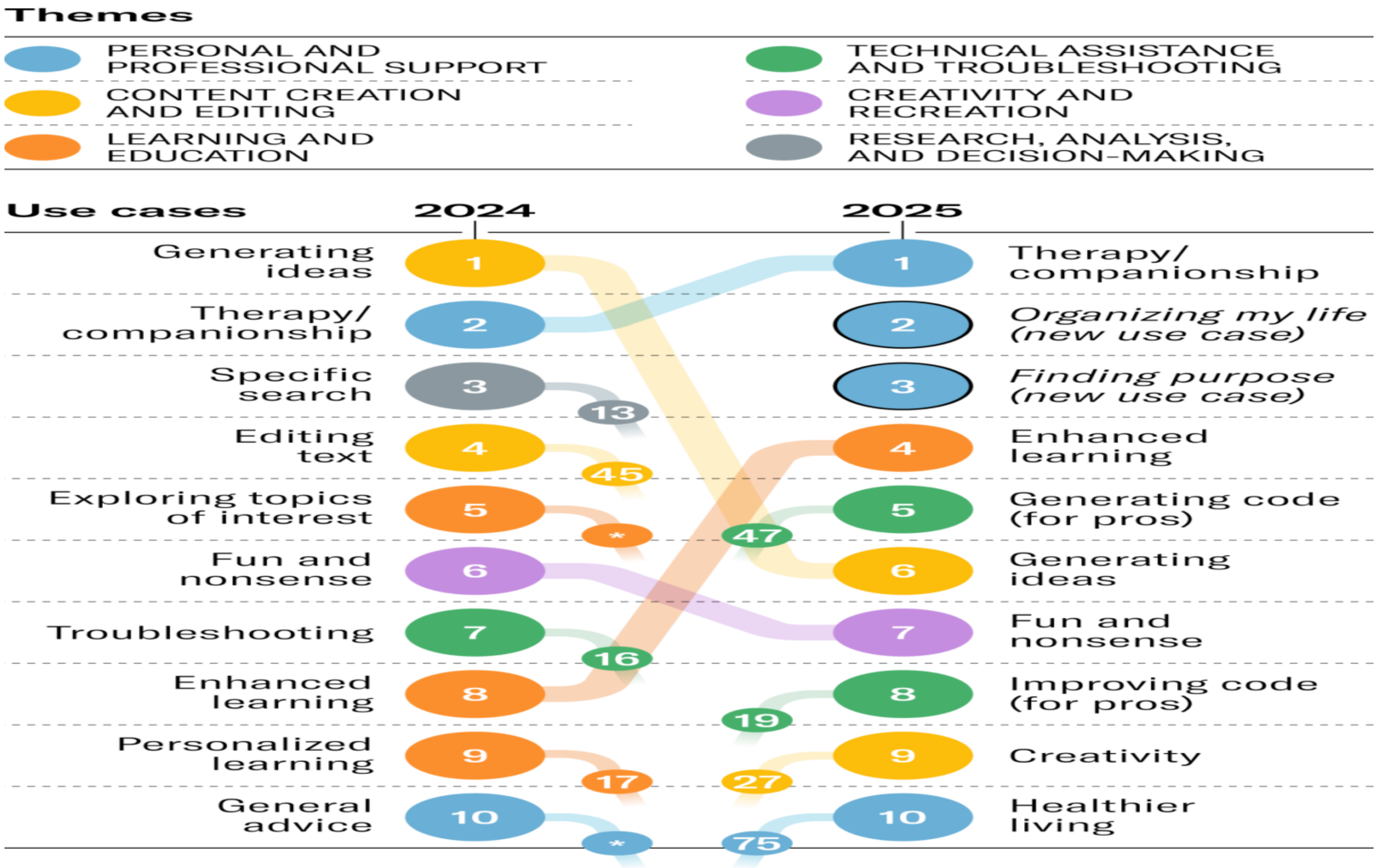


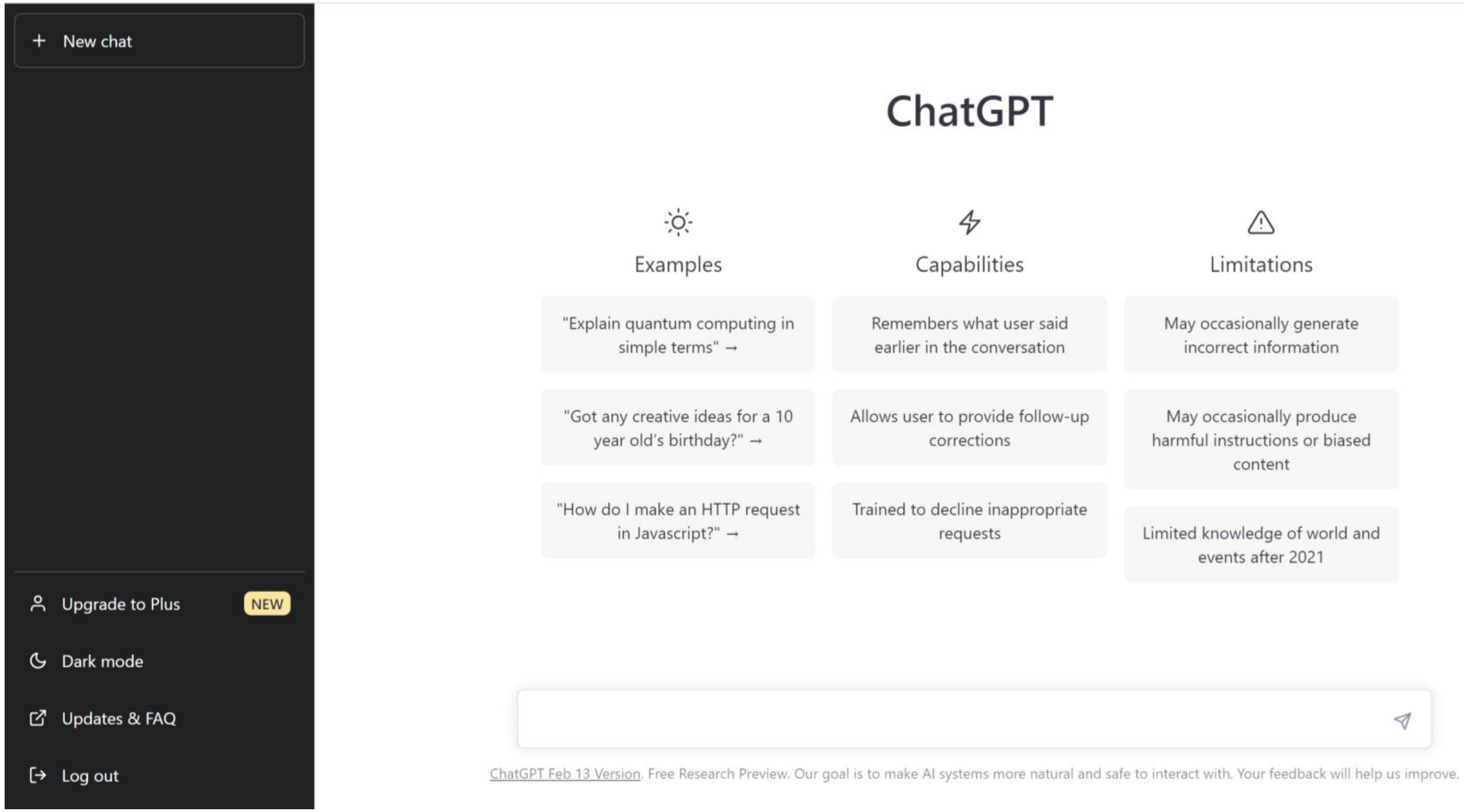
All In One Cheat Sheet
To Learn AI
Basic Roadmap
Mathematics for AI
• Calculus
• Linear Algebra
• Optimization Theory
• Statistics & Probability
Programming Fundamentals
• R (for Data Analysis)
• SQL (for Data Queries)
• Git (for version control)
• Python (NumPy, Pandas, Matplotlib)
Big Data Tools
• Hadoop, Spark
• Cassandra, MongoDB
• Apache Kafka (Streaming Data)
Data Engineering
• Cloud (AWS, GCP, Azure)
• ETL (Extract, Transform, Load)
• Data Warehousing (Snowflake, BigQuery)
Data Science
• Feature Engineering
• Exploratory Data Analysis (EDA)
• Data Cleaning & Preprocessing
• Data Visualization (Seaborn, Plotly, PowerBI)
AI IN A NUTSHELL
Artificial Intelligence (AI)
Machine Learning (ML)
Neural Networks
Deep Learning (DL)
Generative AI
Core AI Skills
Machine Learning (ML)
Deep Learning (DL)
Generative AI (GenAI)
(NLP)
Computer Vision
Model Deployment
Model Monitoring & Versioning
Reinforcement Learning
AI for Robotics
Explainable AI (XAI)
Core AI Concepts Explained
Machine Learning
Neural Network
Deep Learning
NLP
Computer Vision
Reinforcement Learning
Supervised Learning
Unsupervised Learning
Transfer Learning
GANs
Expert Systems
Cognitive Computing
Top Websites to Learn AI
• fast.ai
• ai.google
• kaggle.com
• coursera.org
• deeplearning.ai
• mygreatlearning.com
Best Datasets Repositories
• Kaggle
• Hugging Face Datasets
• UCI ML Repository
• Google Dataset Search
• OpenML
• Data.gov
YouTube Channels
• 3BlueBrown
• StatQuest with Josh Starmer
• CodeBasics
• Sentdex
• Two Minute Papers
• DeepLearningAI
Yannic Kilcher
AI Blogs to Follow
• Towards Data Science
• Machine Learning Mastery
• The Gradient
• arXiv ML papers
• Distill.pub
• Andrej Karpathy Blog
BLOG
Subscribe to Mindstream to learn AI for free → www.mindstream.news

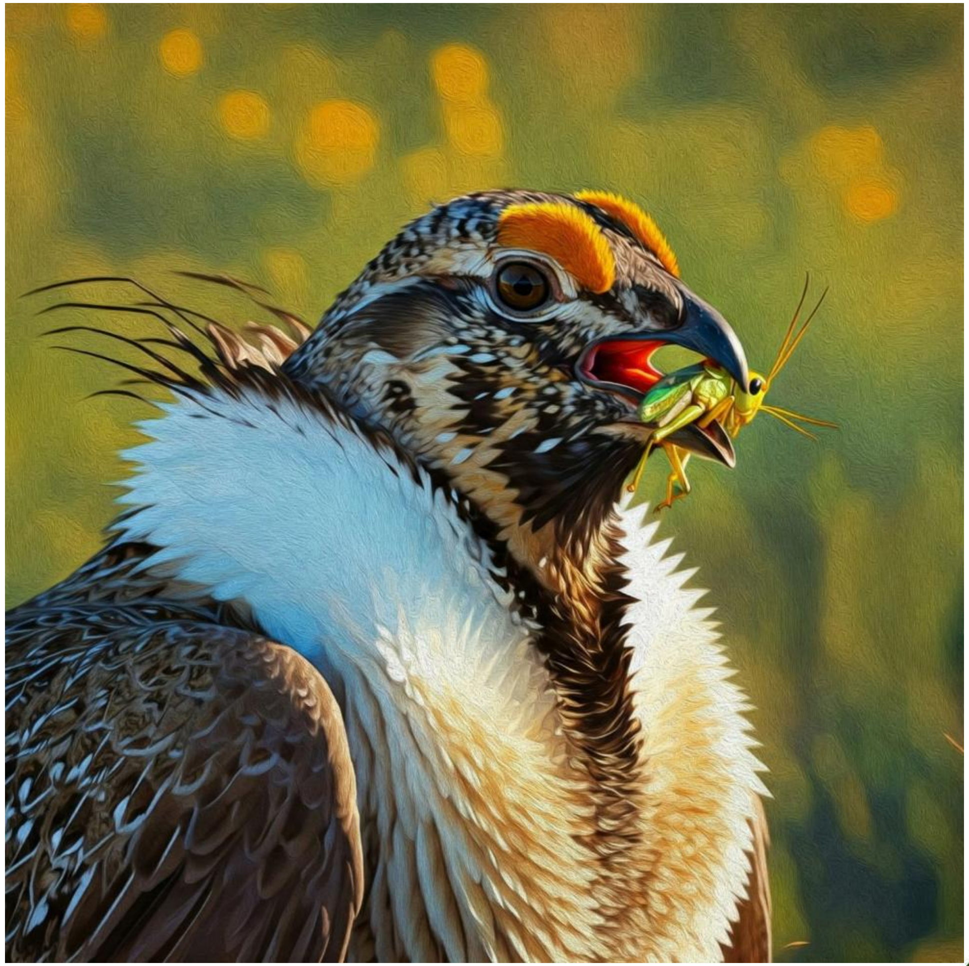
Top 10 Gen AI Use Cases

The top 10 gen AI use cases in 2025 indicate a shift from technical to emotional applications, and in particular, growth in areas such as therapy, personal productivity, and personal development.

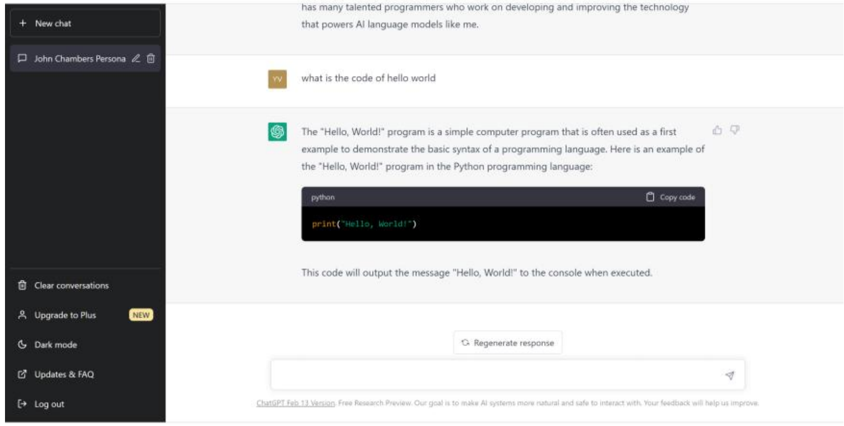


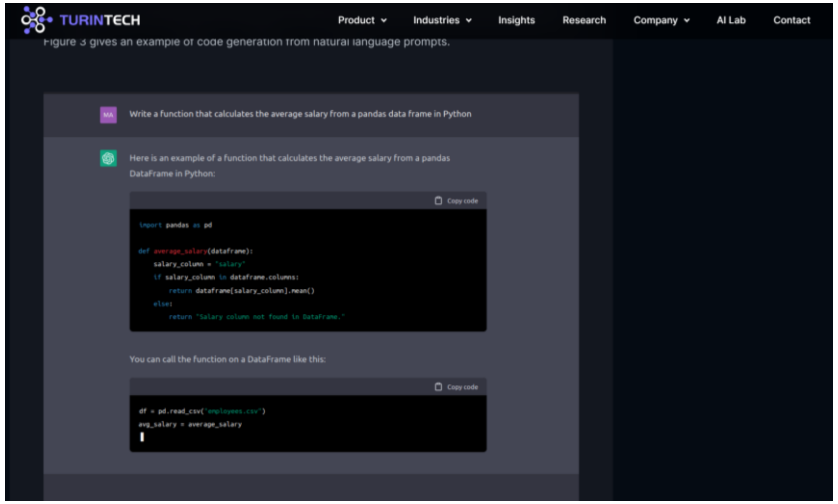
*Did not make list of top 100 in 2025
Source: Filtered.com

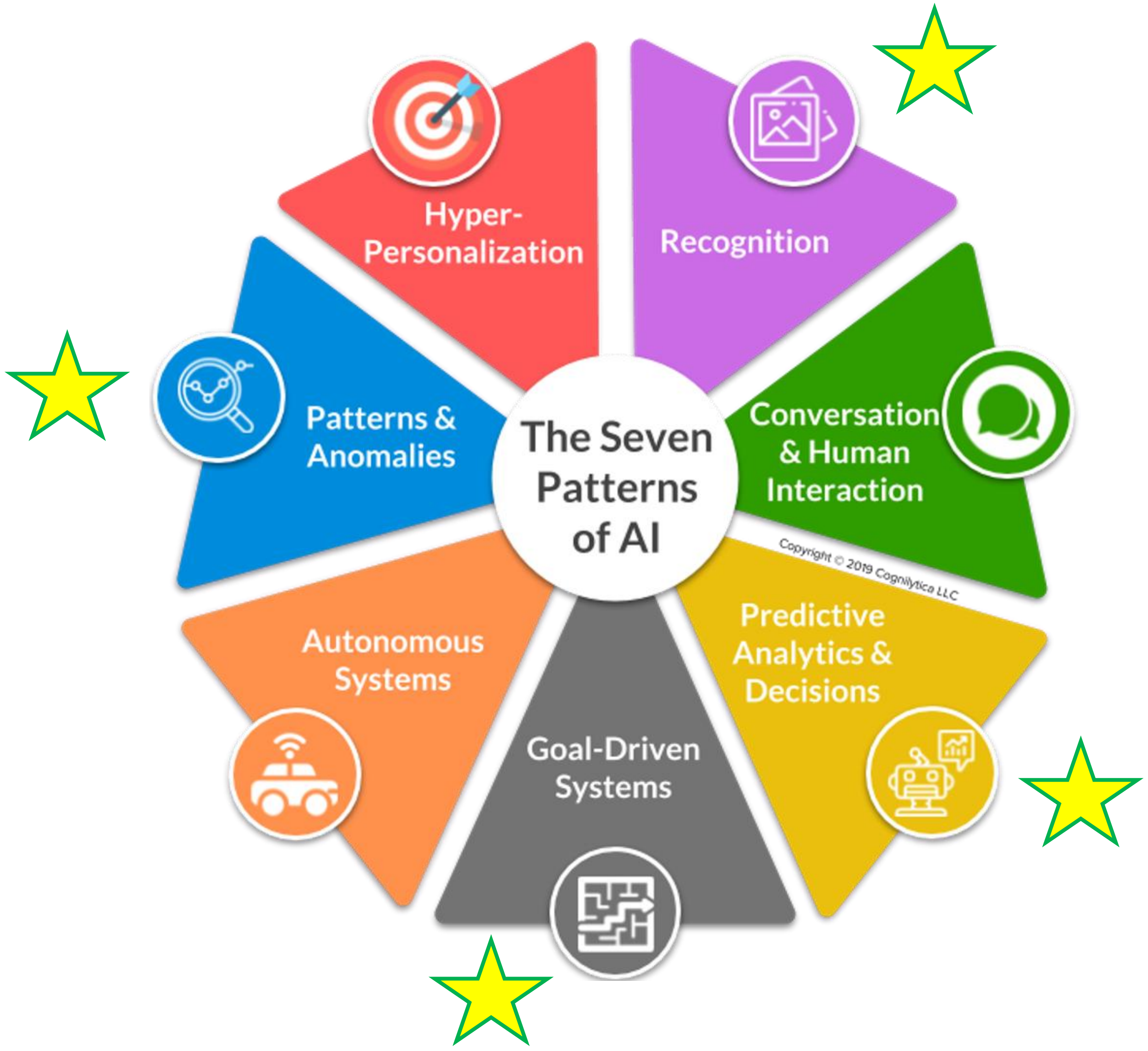

New chat
ChatGPT
Examples
"Explain quantum computing in simple terms" →
"Got any creative ideas for a 10 year old's birthday?" →
"How do I make an HTTP request in Javascript?" →
Capabilities
Remembers what user said earlier in the conversation
Allows user to provide follow-up corrections
Trained to decline inappropriate requests
Limitations
May occasionally generate incorrect information
May occasionally produce harmful instructions or biased content
Limited knowledge of world and events after 2021
Upgrade to Plus
NEW
Dark mode
Updates & FAQ
Log out
ChatGPT Feb 13 Version. Free Research Preview. Our goal is to make AI systems more natural and safe to interact with. Your feedback will help us improve.



- OpenAI Codex
- Tabnine
- CodeT5
- Polycoder
- Cogram
- GitHub Copilot
- DeepCode
- Kite
- TabNine
- CodeWP
- AskCodi
- Codiga
- Visual Studio IntelliCode
- PyCharm
- AIXcoder
- Ponicode
- Jedi
- Wing Pro






Hyper-
Personalization
Recognition
Patterns &
Anomalies
The Seven
Patterns
of AI
Conversation
& Human
Interaction
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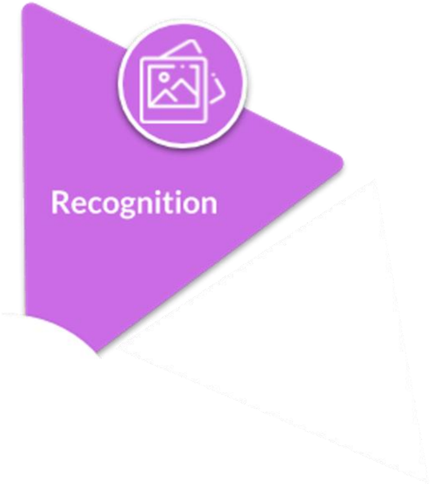
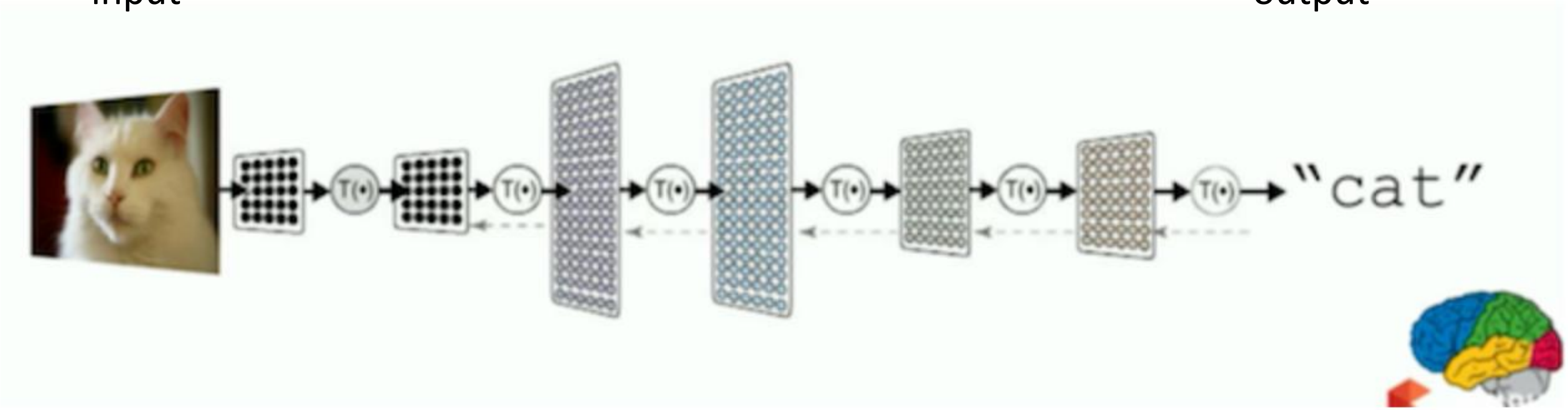
Predictive
Analytics &
Decisions
Autonomous
Systems
Goal-Driven
Systems

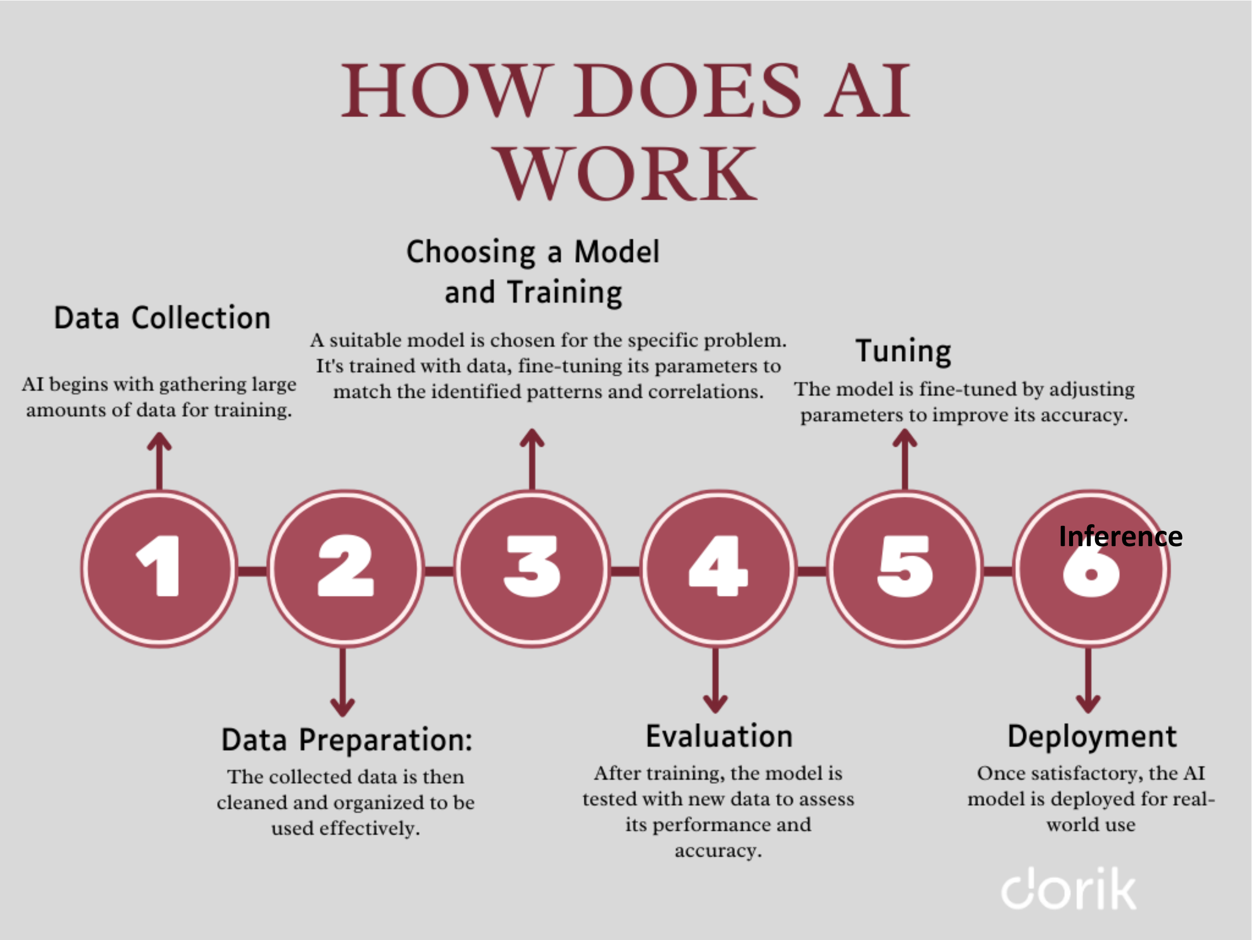

Recognition

input

output



- **Linear Algebra:** manipulation and analysis of pixel data
- **Calculus:** derive and optimize mathematical models for image processing tasks
- **Probability and Statistics:** analysis of image data, feature extraction, and classification
- **Fourier Transform:** filtering and edge detection
- **Convolution:** filtering and extract features


HOW DOES AI WORK
Choosing a Model and Training
A suitable model is chosen for the specific problem. It's trained with data, fine-tuning its parameters to match the identified patterns and correlations.
Data Collection
AI begins with gathering large amounts of data for training.
Tuning
The model is fine-tuned by adjusting parameters to improve its accuracy.
1
2
3
4
5
6
Inference
Data Preparation:
The collected data is then cleaned and organized to be used effectively.
Evaluation
After training, the model is tested with new data to assess its performance and accuracy.
Deployment
Once satisfactory, the AI model is deployed for real-world use
dorik

- 1 Euro = 1.04 Dollars
- x = 1.04y
- $$f_o = \frac{v + v_o}{v + v_s} f_s$$

f_o = observer frequency of sound
v = speed of sound waves
v_o = observer velocity
v_s = source velocity
f_s = actual frequency of sound waves

- Given a set of observations $(\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n)$, where each observation is a d-dimensional real vector, *k*-means clustering aims to partition the *n* observations into k $(\leq n)$ sets $\mathbf{S} = \{S_1, S_2, ..., S_k\}$ so as to minimize the within-cluster sum of squares (WCSS) (i.e. variance). Formally, the objective is to find:

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \|\mathbf{x} - \boldsymbol{\mu}_i\|^2 = \arg\min_{\mathbf{S}} \sum_{i=1}^{k} |S_i| \operatorname{Var} S_i$$

where $\boldsymbol{\mu}_i$ is the mean (also called centroid) of points in S_i, i.e.

$$\boldsymbol{\mu}_i = \frac{1}{|S_i|} \sum_{\mathbf{x} \in S_i} \mathbf{x},$$

$|S_i|$ is the size of S_i, and $\|\cdot\|$ is the usual L^2 norm . This is equivalent to minimizing the pairwise squared deviations of points in the same cluster:

$$\arg\min_{\mathbf{S}} \sum_{i=1}^{k} \frac{1}{|S_i|} \sum_{\mathbf{x},\mathbf{y} \in S_i} \|\mathbf{x} - \mathbf{y}\|^2$$

The equivalence can be deduced from identity $|S_i| \sum_{\mathbf{x} \in S_i} \|\mathbf{x} - \boldsymbol{\mu}_i\|^2 = \frac{1}{2} \sum_{\mathbf{x},\mathbf{y} \in S_i} \|\mathbf{x} - \mathbf{y}\|^2$. Since the total variance is constant, this is equivalent to maximizing the sum of squared deviations between points in *different* clusters (between-cluster sum of squares, BCSS).[1] This deterministic relationship is also related to the law of total variance in probability theory.

$$C_k = \frac{1}{P} \int_P x(t) e^{-i2\pi \frac{k}{P} t} \, dt$$

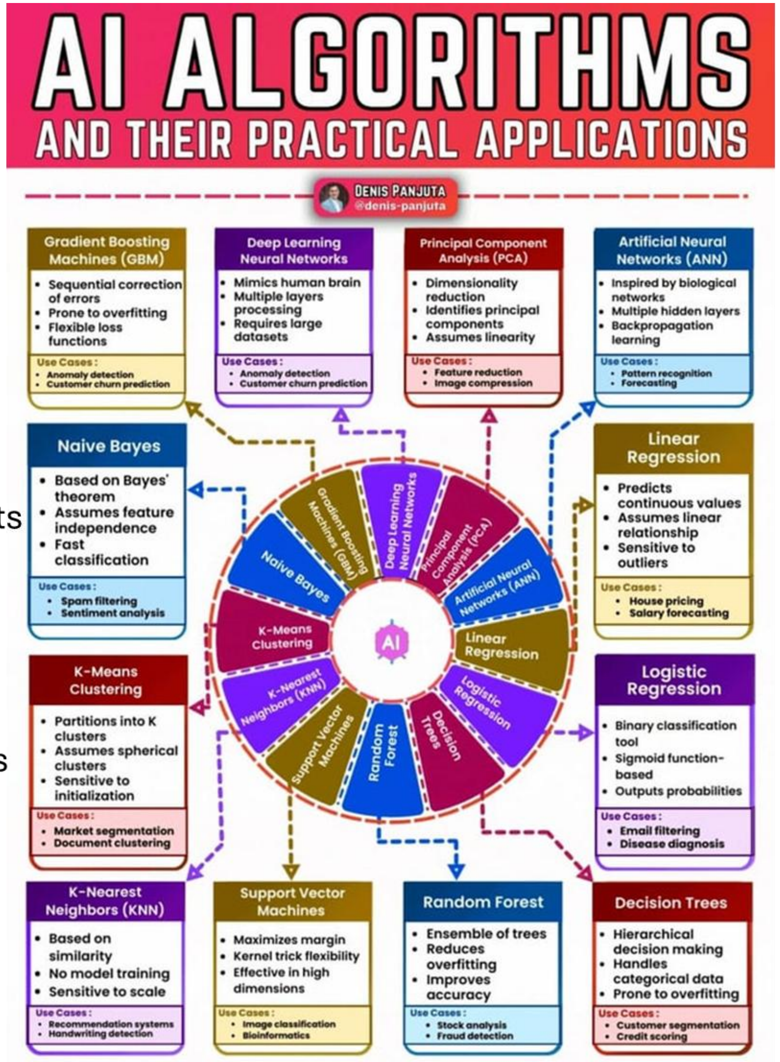
$$X_k = \sum_{n=0}^{N-1} x_n \cdot e^{-i2\pi \frac{k}{N} n}$$

Finding anomolies

Finding a cause based on results

Clustering – creating groups

Finding similarities



Recognizing things

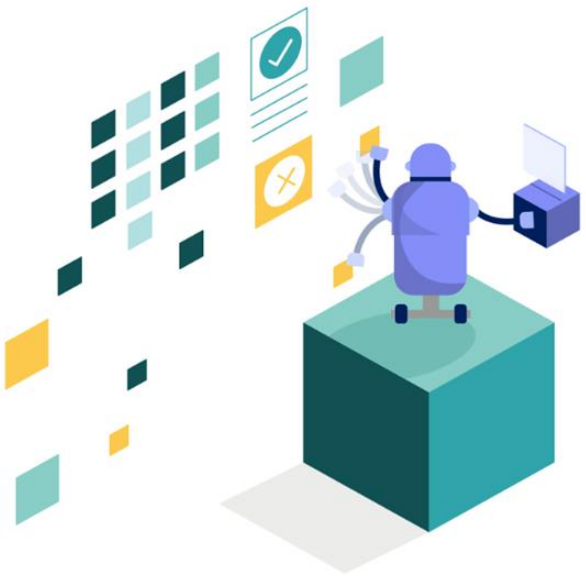
Making predictions

Filtering and Diagnosing

Making Decisions

Terms to Know	Meaning
Structured Data	Labelled and known data. Easy to interpret. Name, Address, price of item, etc.
Unstructured Data	Up to 90% of an organizations data! I don't know what it is, or it's not consistent. This is perfect for AI. AI can gather analytic info from structured data and 'recognize' it in unstructured data.
Supervised learning	Uses well-labeled structured data to 'learn' the pattern and define various classes for AI to 'recognize'. Sample data is fed into a neural network to 'train' the algorithm as to what data belongs into which category. By having a lot of use cases, the computer can then 'recognize' data to match the pattern to a class/category. The key is good training data !!
Unsupervised learning	Where the outcome is not known. AI finds a pattern that it learned/found itself and gives you that output that you then have to give a name.
Pattern recognition	looking at unstructured data and being able to categorize and recognize it. E.g. medical image, fingerprint, voice language, products in a video, etc.
Neural Network	Takes an input layer, puts it through various algorithm layers to produce an output layer. The concept of the artificial neural network was inspired by human biology and the way neurons of the human brain function together.
Deep Neural Networks, Deep Learning	Lots of layers of algorithms

Terms to Know	Meaning
Model	A computer program that uses data and algorithms to make decisions or predictions.
Generative AI or GenAI	AI that ‘generates’ something – instead of just analyzing or taking action on data, GenAI models PRODUCE something (such as text, images, blog posts, chat bots, program code, poetry, music tracks, sound effects, voice acting and artwork).
LLMs	Large Language Models
Deepfakes	Unauthentic content created with AI.
RAG	Retrieval Augmented Generation - Reduces hallucinations by retrieving data as needed instead of storing, increases accuracy
GAN	Generative adversarial network – GANs have a Generator and Discriminator. The Generator generates artificial data that looks like real data. The Discriminator determines if the data is real or fake and feeds information back to the Generator. Great for image creation.
Agentic AI	A type of artificial intelligence (AI) that can perform tasks independently with minimal human intervention. Agentic AI systems are designed to be goal-oriented and can accomplish tasks by creating a list of steps and carrying them out autonomously.
Digital Twins	A virtual replica of a physical object, process, or system that uses real-time data to simulate its behavior.



What is agentic AI?

Agentic AI, or autonomous AI, is a type of artificial intelligence that runs independently to design, execute, and optimize workflows – allowing enterprises to more effectively make decisions and get work done. AI agents can make decisions, plan, and adapt to achieve predefined goals - with little human intervention or completely autonomously.

What's the difference between agentic AI and traditional AI?

Self Learning – Self Working

Automation and Insights

Agentic AI

- Operates autonomously, making decisions and pursuing goals, asking for human guidance when needed
- Analyzes situations and finds the best path for moving forward
- Designs, executes, and optimizes workflows to achieve specific objectives
- Adapts to changes and continuously self-improves

Traditional AI

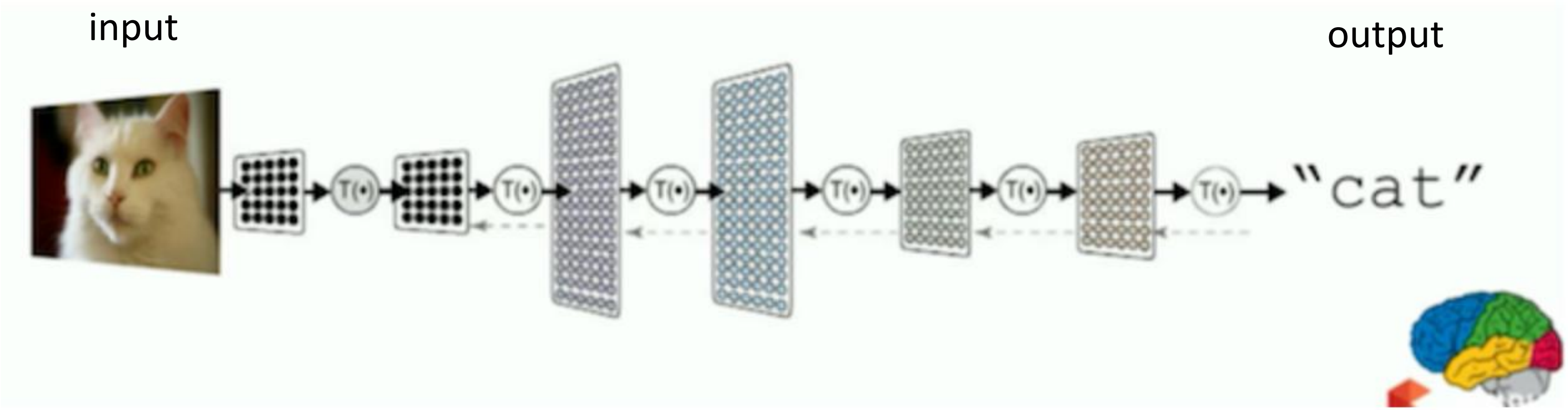
- Provides valuable insights based on data
- Is a key ingredient in more sophistic Agentic AI systems
- Automates or assists with specific, simple tasks
- Often requires manual retraining to adapt to changes in its environment

How does agentic AI work?

Define your objectives, and Agentic AI takes action – if a workflow exists to satisfy the intent, the agent can execute it. Sometimes, agents may design their own workflows on the fly – but always checking in with humans for support. If situations change along the way, AI agents can adapt their strategy for optimal results. Agentic AI is always looking ahead: anticipating needs, predicting outcomes, and proactively responding to opportunities.

Workflows = tasks / actions / order of actions

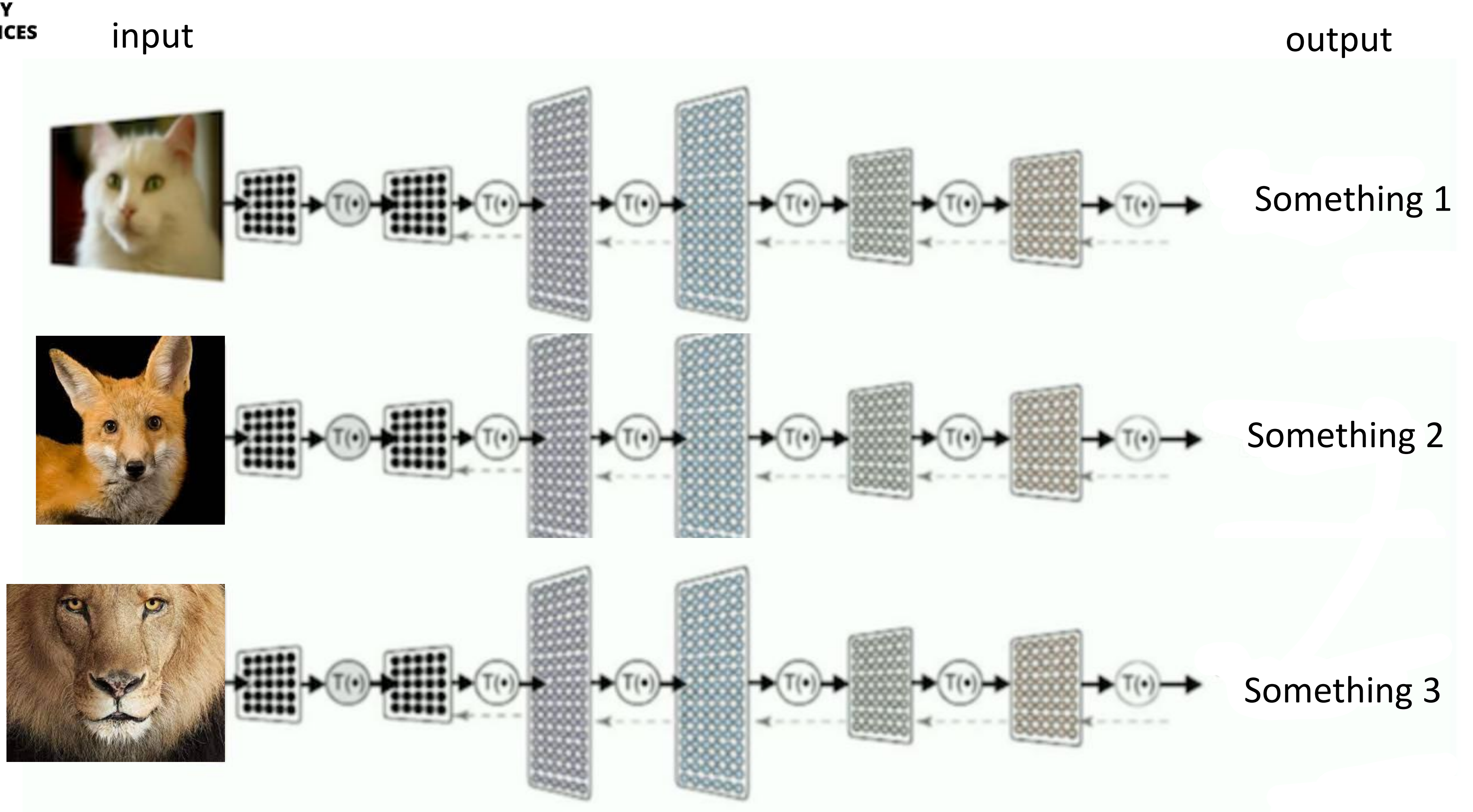
Neural Network Algorithm Layers
Supervised Learning



Hidden layers
(algorithms)
Deep Network

Based on having learned and trained on how a cat looks

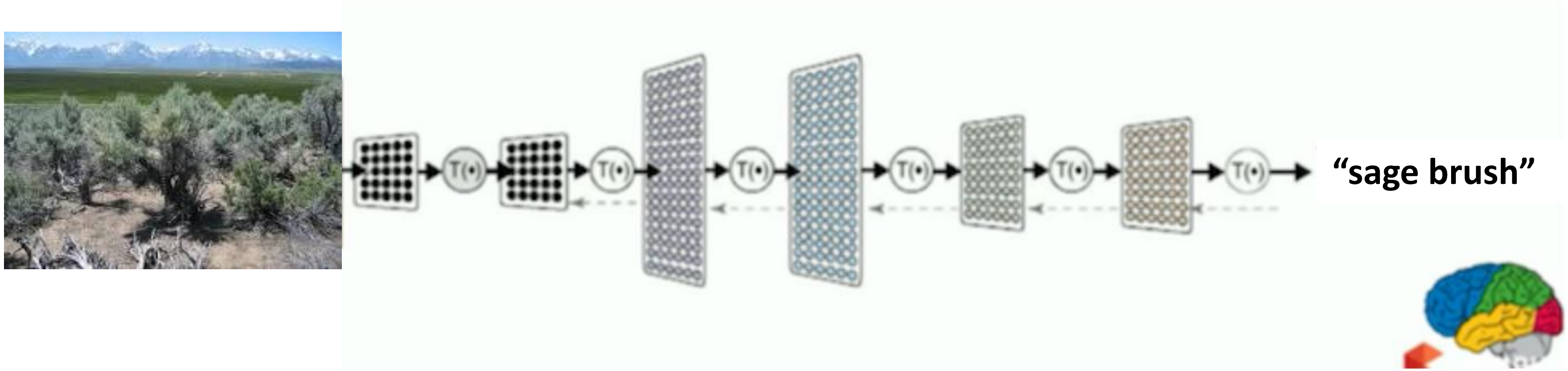
Neural Network – Unsupervised Learning



Hidden layers (algorithms), Deep Network - Deep Learning (lots of layers)

based on things to look for, without knowing a cat/fox/lion

Neural Network Algorithm Layers
Supervised Learning



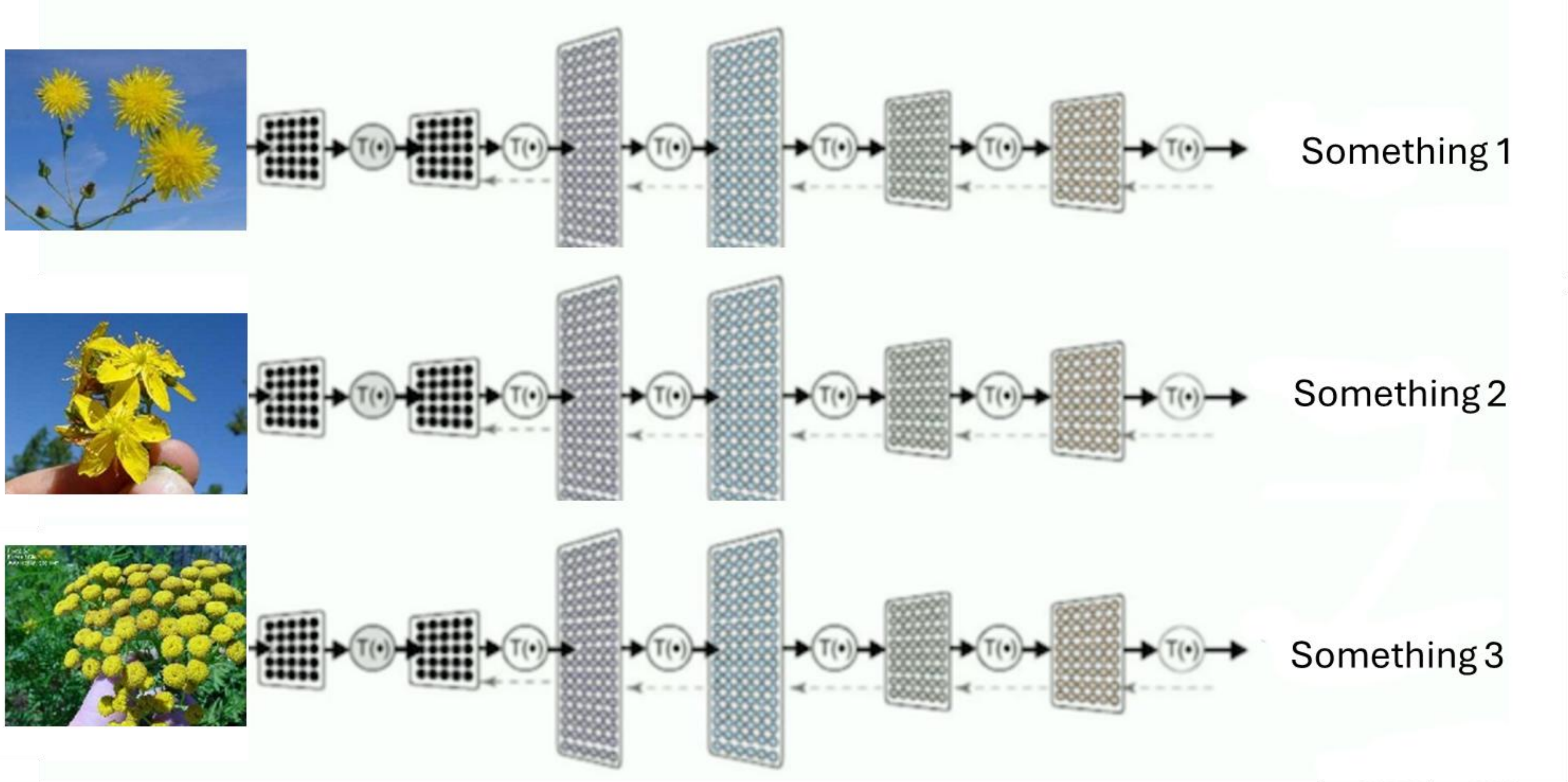
input

Hidden layers
(algorithms)
Deep Network

output

Based on having learned and trained on how a cat looks

Neural Network – Unsupervised Learning



input

Hidden layers
(algorithms)

output

Deep Network - Deep Learning (lots of layers)

based on things to look for, without knowing a cat/fox/lion

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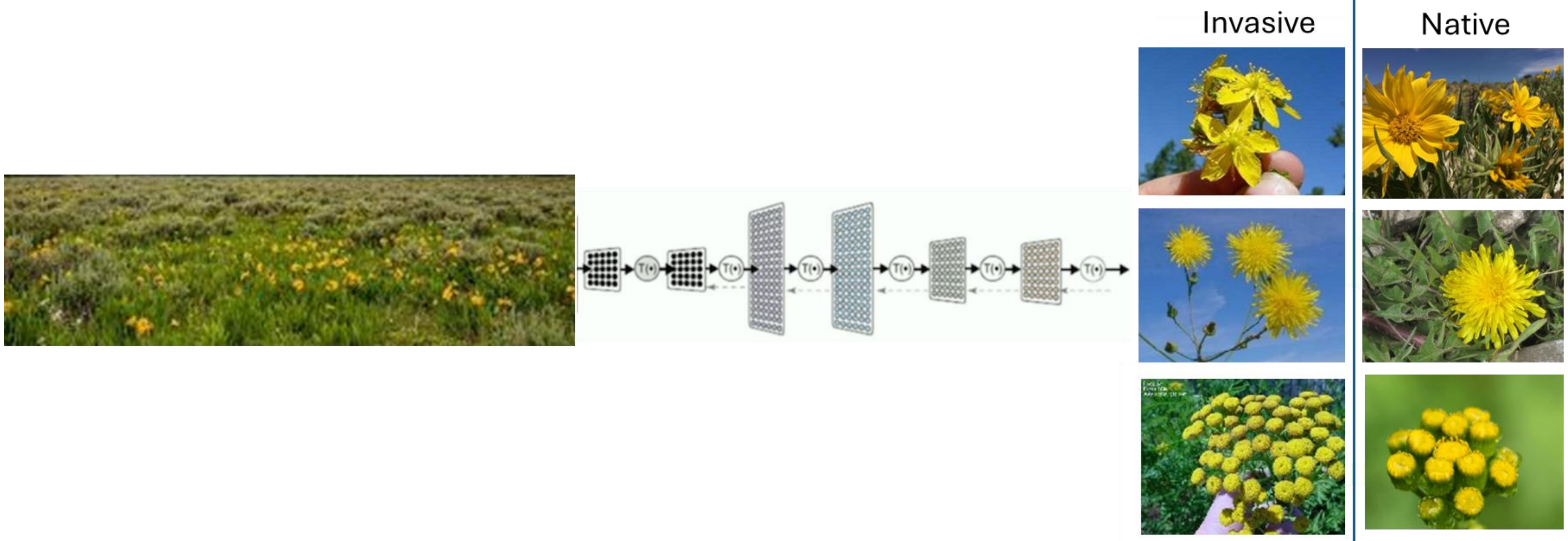

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Jody Grove, an operations supervisor for Chevron, tours a drilling site in New Mexico. (PHOTOGRAPH BY JOMANDO CRUZ)

AI | FEATURE

AI is Changing Oil Country—and Pumping Up Profits

The machinery in the vast Permian Basin is getting a lot more productive. And notably less noisy.

By Avi Salzman Follow
Nov 26, 2024, 3:30 am EST

ZACKS

APA & Palantir Collaborate to Oil and Gas Production With AI

November 27, 2024 — 08:54 am EST

Written by **Zacks Equity Research** for **Zacks** →

APA Corporation APA, a Houston, TX-based oil and gas exploration and production company, has expanded its partnership with **Palantir Technologies Inc.** PLTR. This move should deepen the company's collaboration to integrate AI-driven solutions across its extensive operations.

This multi-year, multimillion-dollar agreement shapes a relationship that started in 2021, marking a significant leap forward in the use of advanced artificial intelligence (AI) for optimizing production, operational planning and supply-chain management

The Economist

Menu Weekly edition The world in brief Search

Business | Pipe dreams

Oil bosses have big hopes for the AI boom

Data centres are fuelling demand for natural gas—for now

Fired up PHOTOGRAPH: DESIREE RIOS/NEW YORK TIMES/REDUX/EYEVINE

Nov 7th 2024 Share

THIS WEEK 180,000 people descended on Abu Dhabi to attend ADIPEC, the

JCO2

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GEOMARVEL HOME CLOUD PACKAGES SERVICES INDUSTRIES ABOUT US

Deep Learning for Wetland Mapping

GeoMarvel partnered with Chesapeake Conservancy to operationalize deep learning workflows for high resolution wetlands mapping. Deep learning (DL) is a technique within artificial intelligence (a central topic at Esri's Developer Summit & User Conference this year) that enables computers to process information similarly to how the human brain work

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Land Reclamation Management Utilizing Artificial Intelligence for Estimating Soil Properties

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ABSTRACT: In use of clayey soils for reclamation, the stability against slip and future consolidation settlement should be examined during and after reclamation. For these purposes, a practical reclamation management system has been developed based on three types of analysis: artificial intelligence (AI) estimation of soil properties such as compression index, consolidation coefficient and undrained shear strength, deposition shape analysis; and consolidation settlement analysis for clayey soils dumped from a hopper barge. The AI estimation of soil properties is characterized by use of a convolutional neural network (CNN) based on information such as soil source, wet density, and photographed image obtained before reclamation works. In this study the validity of each analysis model has been verified on an actual ...ped soils on the seabed, soil properties in the reclaimed ground

...CPT.

...osed neural network models to predict the factor of safety ...st slope failure in clayey soils based on the inclination and ... of slope, the angle of internal friction, cohesion and unit ...t of soil, the coefficient of pore water pressure, etc. Jang and ...l (2013) focused on the effects of geological parameters to the ...reak phenomenon in tunnel drilling, and applied a neural ...rk to predict overbreak by use of rock mass rating data. As for ... model with the performance of image recognition, Hata

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COMMENTARY

Artificial intelligence in soil science: Where do we go now?

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Abstract
Recognizing the fast advancement of artificial intelligence (AI) in soil science, the main objective of this commentary paper is to discuss how this technology is being incorporated into the discipline, focusing on the most common algorithms and their applications. Employing a discursive and reflective methodology, the article draws insights from the authors' expertise and opinions. The paper explores some ethical considerations and the potential impact of AI on the job market and calls for a balanced approach that maximizes the benefits of this technology while vigilantly

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Common AI Concerns

- Biases
- Hallucinations, Errors and Brand Damage
- Infusing Morality, Loss of Control
- Legal Issues (ownership of training data, etc.)
- Privacy
- Power Balance
- Availability of Data
- Environmental Concerns
- Cost, latency of LLMs,
- Humanity

ASRS
AMERICAN SOCIETY
OF RECLAMATION SCIENCES

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ECOLOGICAL SOLUTIONS

According to an Accenture report, A significant portion of executives believe that 75% of businesses risk going out of business in five years if they don't scale AI. (Accenture)

Only around 5% of businesses are currently using AI. (U.S. Census Bureau)

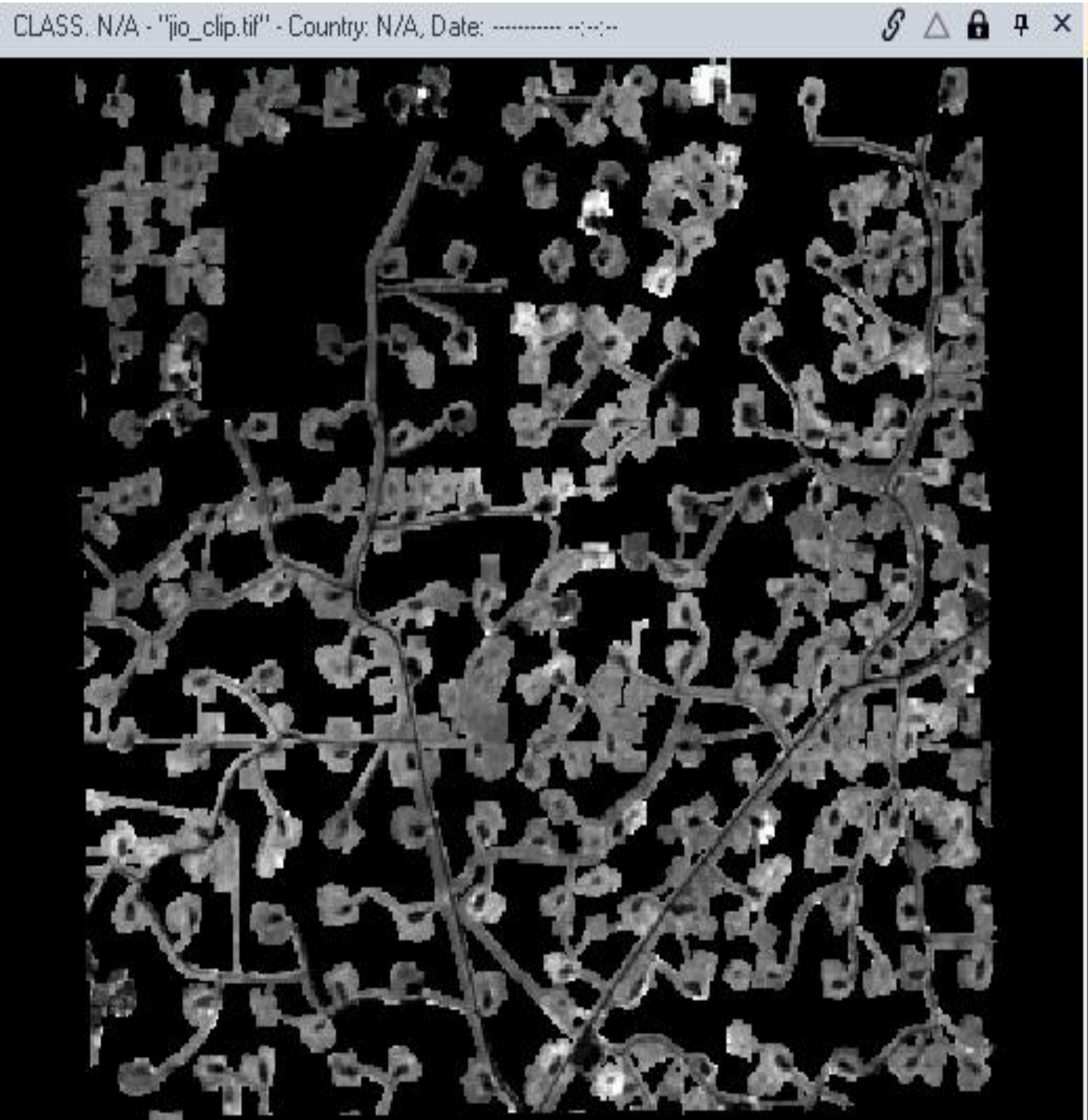
Who has time to think about AI for Land Reclamation?

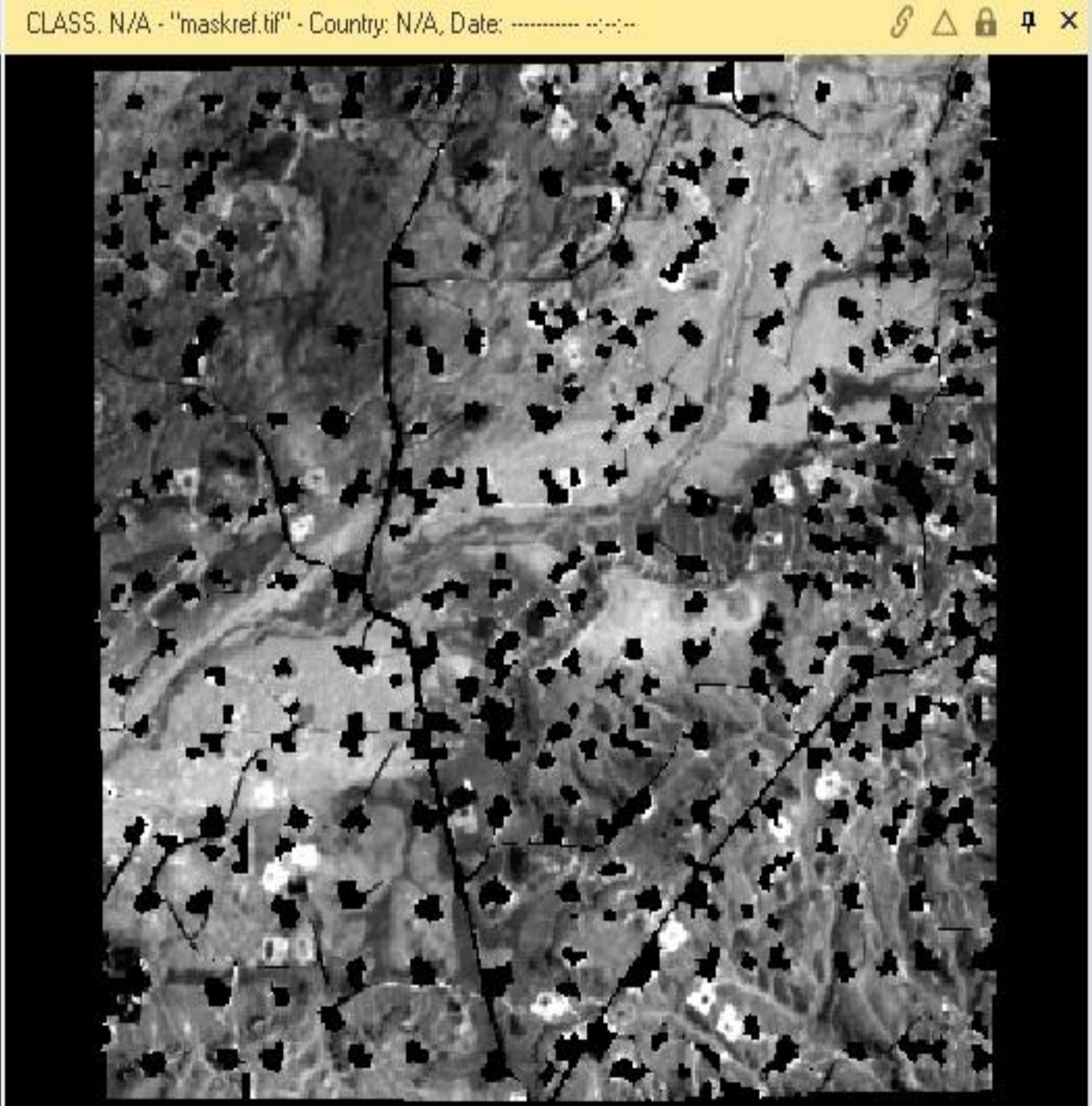
We have a business to run.

Applications to Reclamation

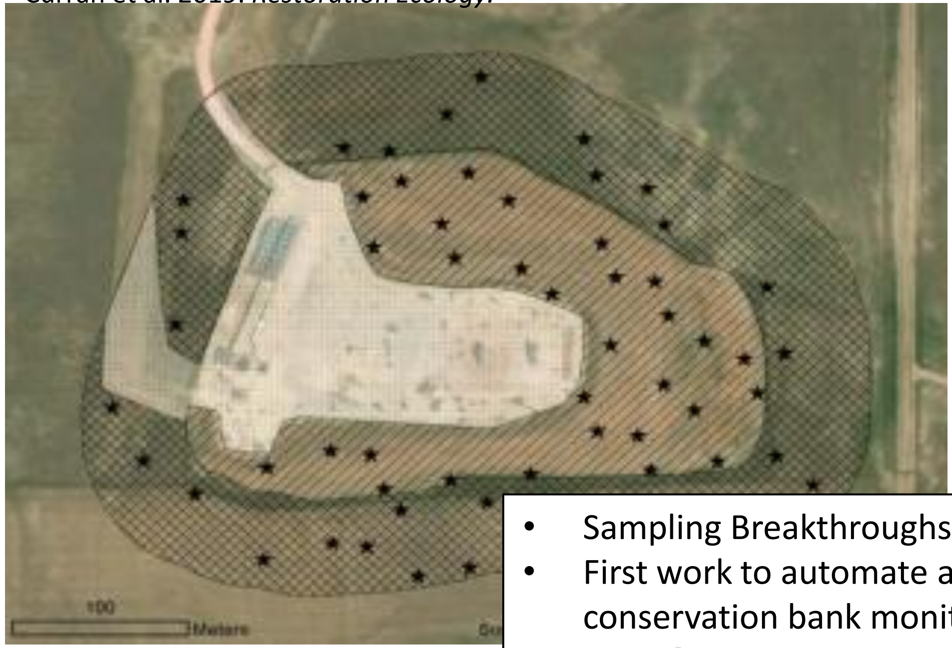
- Anomaly Detection
- Optimization
- Clustering
- Predictability
- Association Analysis
- Decision Making

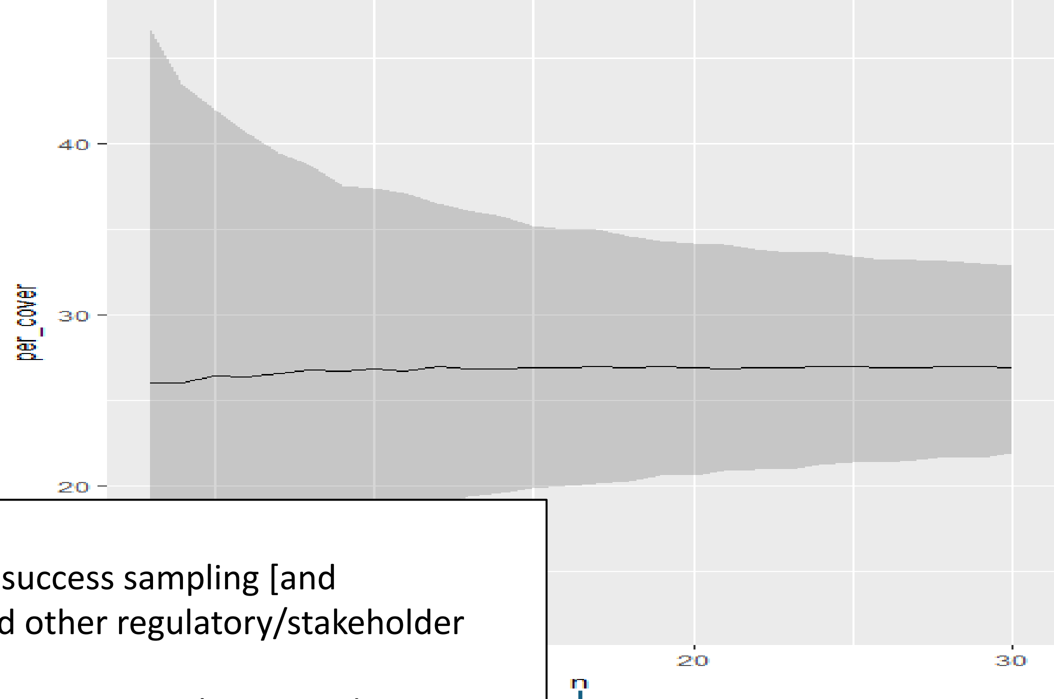
Anomaly Detection



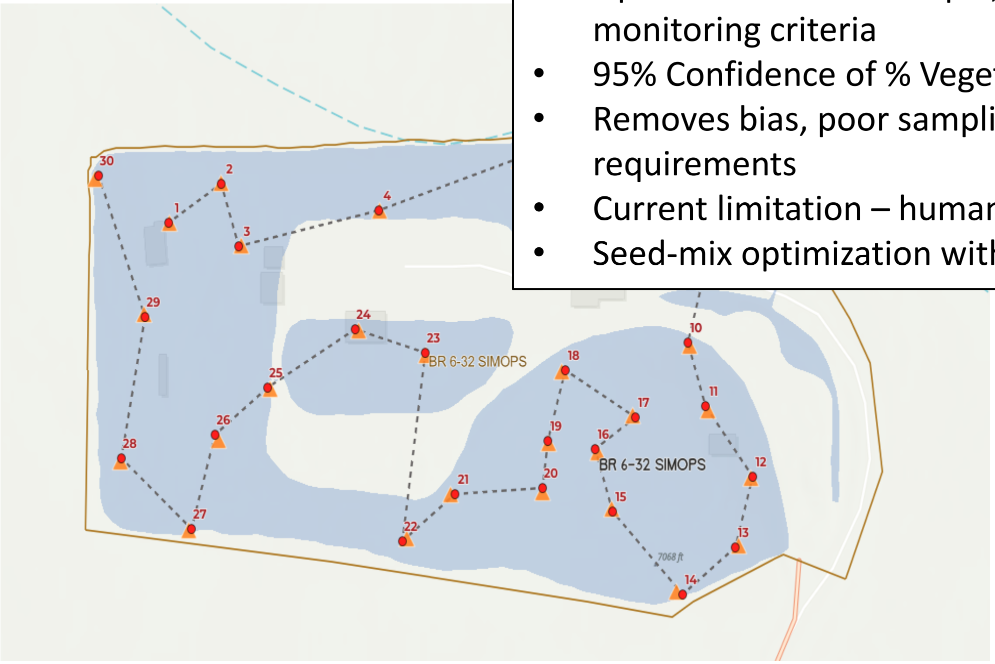


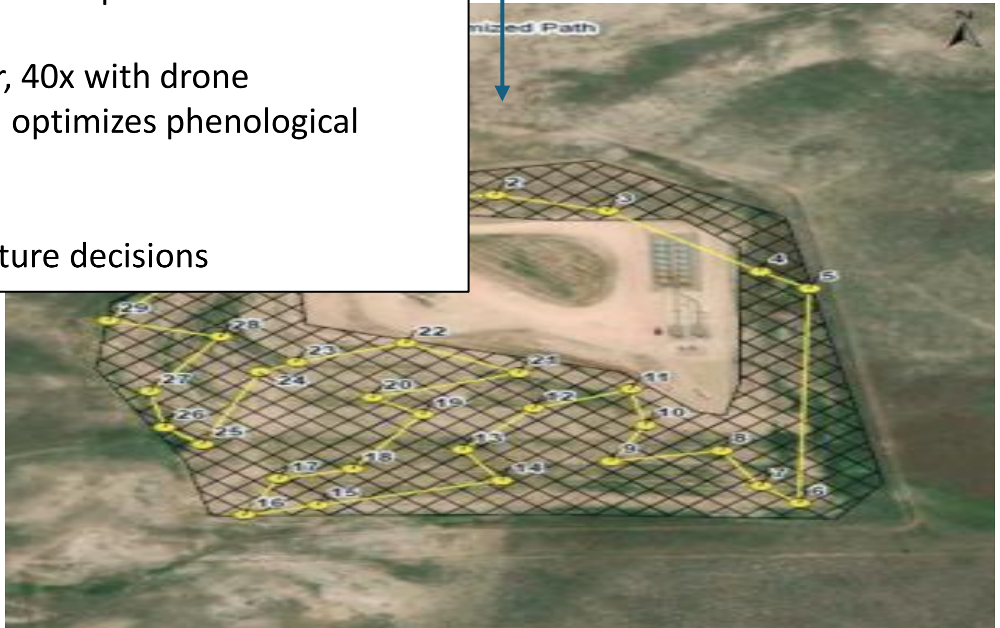
Curran et al. 2019. *Restoration Ecology*.





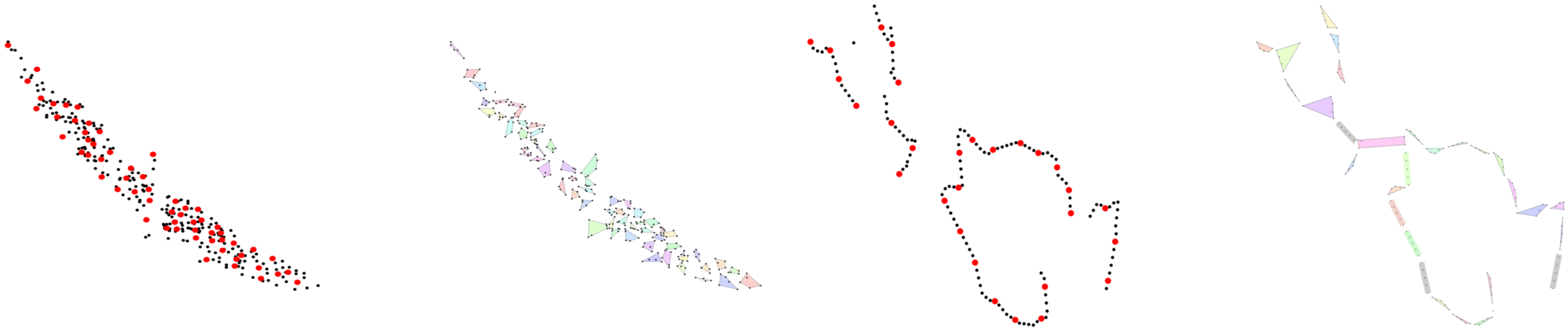
- Sampling Breakthroughs of Reclaimed Sites
- First work to automate and optimize reclamation success sampling [and conservation bank monitoring for sage-grouse and other regulatory/stakeholder needs]
- Optimize where to sample, distance, path within various compliance and monitoring criteria
- 95% Confidence of % Vegetation Coverage & 10x faster, 40x with drone
- Removes bias, poor sampling, and inconsistencies, and optimizes phenological requirements
- Current limitation – human-in-the-loop photo analysis
- Seed-mix optimization with high accuracy, informed future decisions



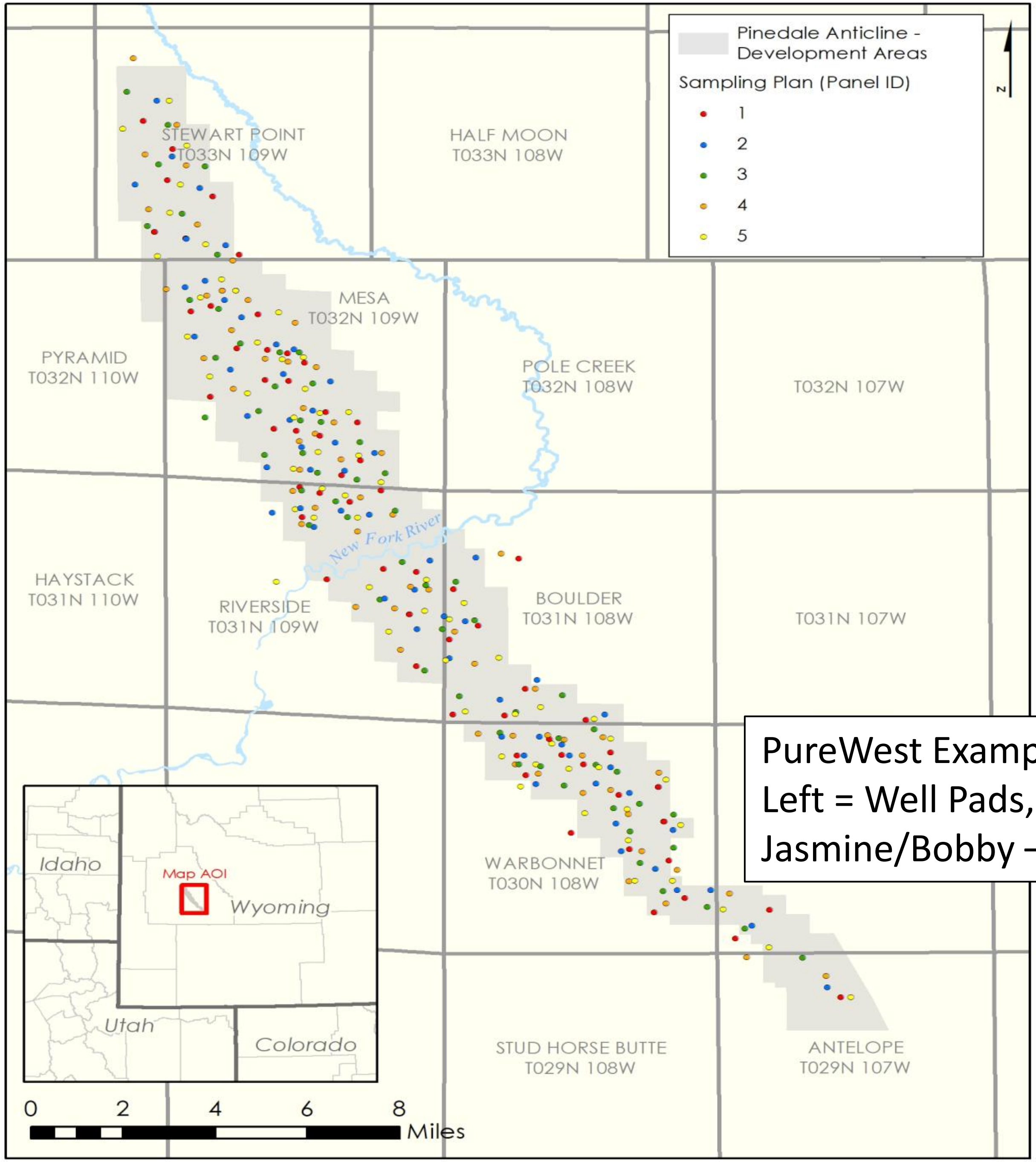


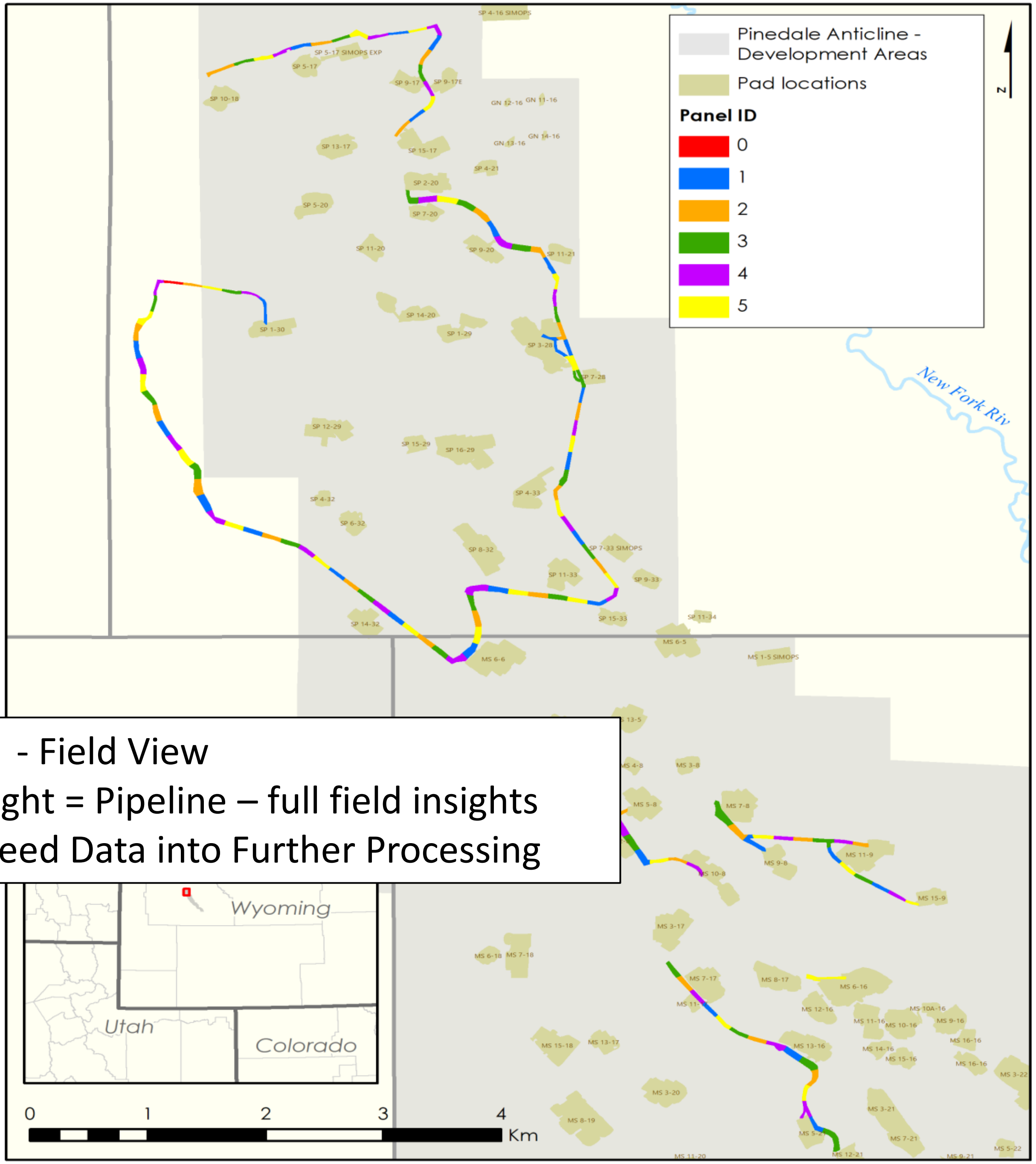
Curran et al. 2020. *Biodiversity*.

Long-term monitoring strategies for ecological reclamation programs using spatially balanced rotating panel designs



- Optimized sampling across entire field. Left = well pads. Right = pipeline
- Clustering (K-Means) by 20% of field to represent special coverage, seed mixes, 5 year location rotation, soil information, route optimization – creating like neighborhoods (triangles)
- Exceeds regulatory requirements, increases accuracy, saves time and money of monitoring





PureWest Example - Field View

Left = Well Pads, Right = Pipeline – full field insights

Jasmine/Bobby – Feed Data into Further Processing

ECOLOGICAL APPLICATIONS
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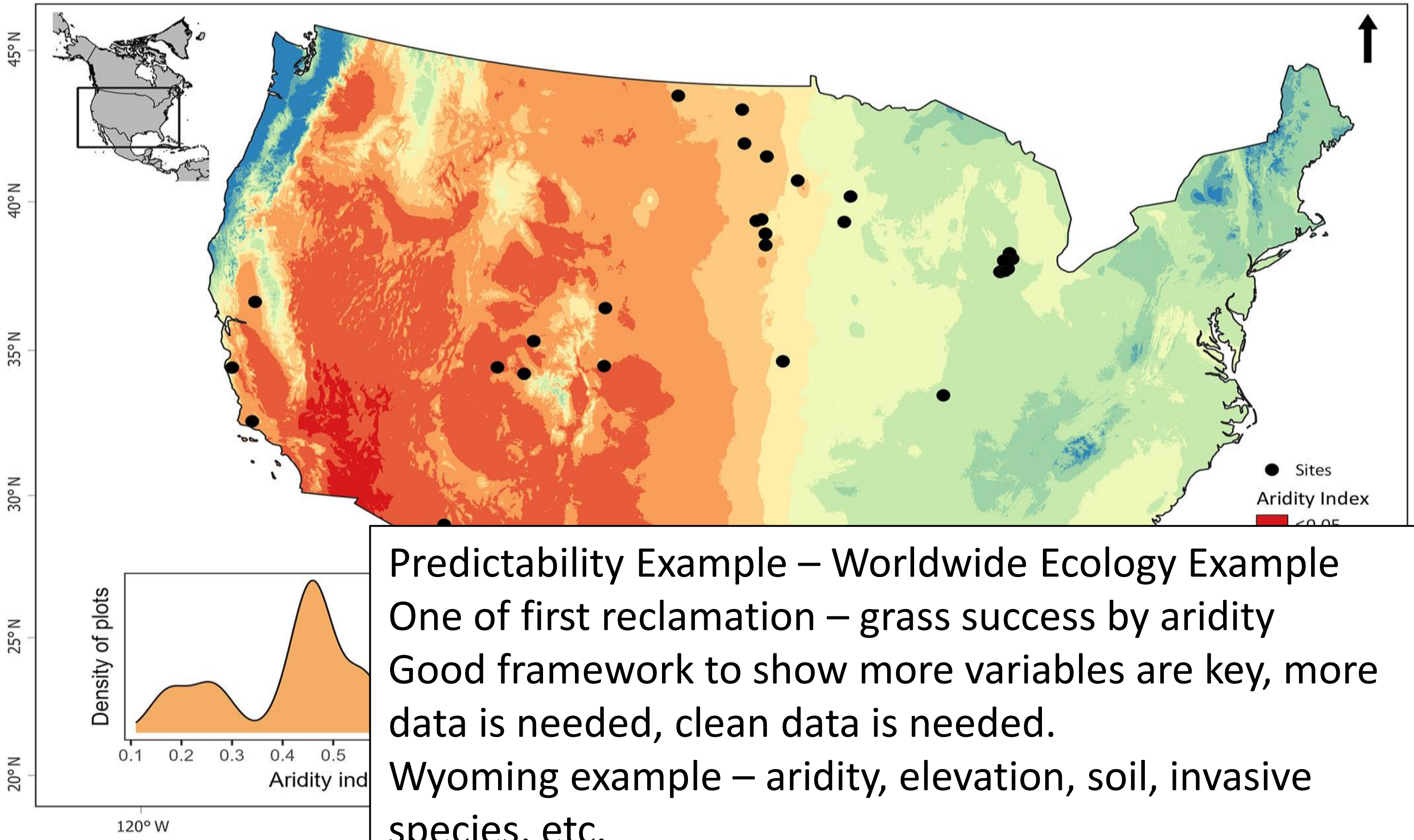
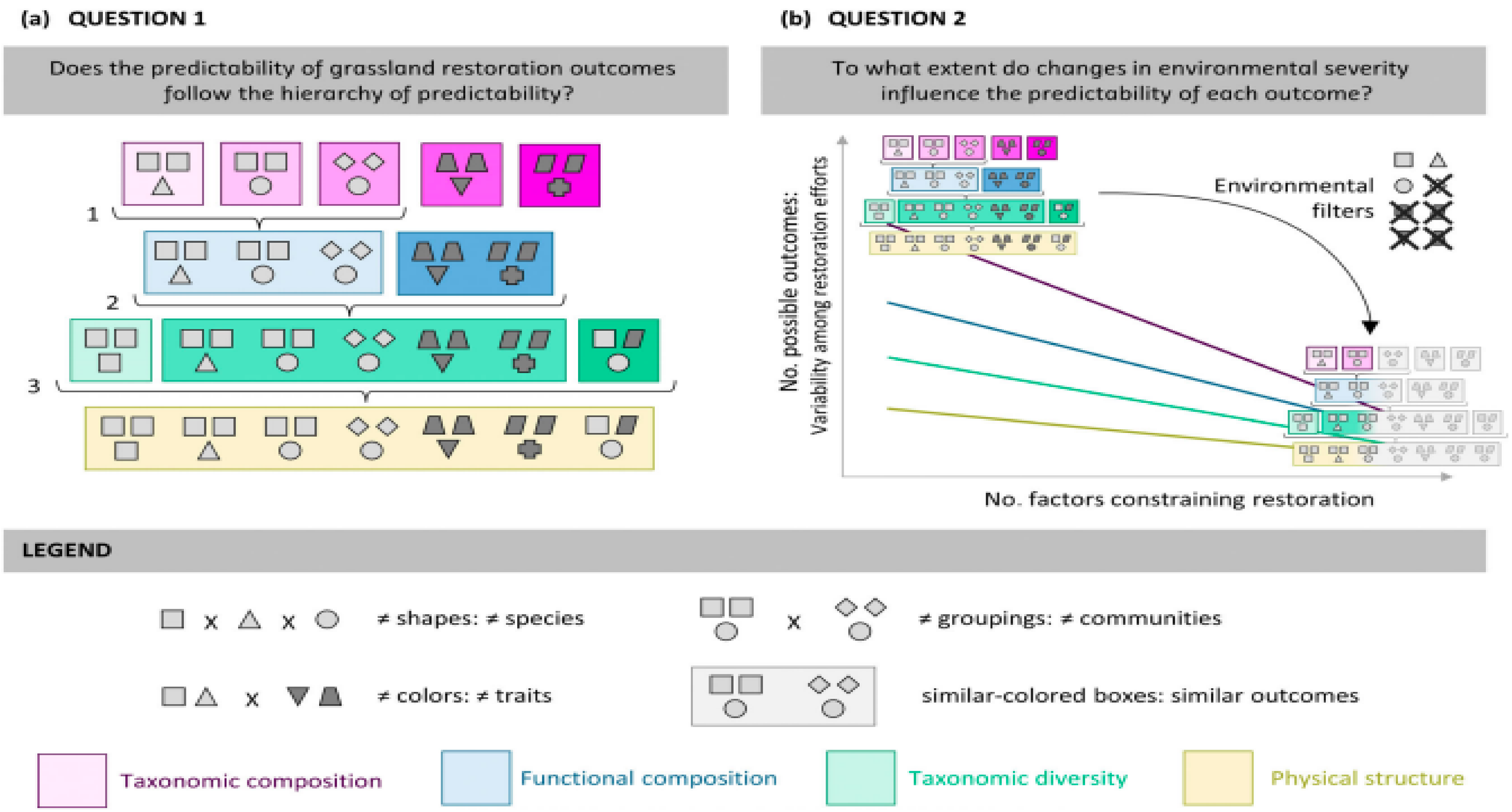
Testing the hierarchy of predictability in grassland restoration across a gradient of environmental severity

Diana Bertuol-Garcia, Emma Ladouceur, Lars A. Brudvig, Daniel C. Laughlin, Seth M. Munson, Michael F. Curran, Kirk W. Davies, Lauren N. Svejcar, Nancy Shackelford

- Similar reclamation practices yield different results
- The more limiting our environment, the less possible outcomes
- Coarse vegetation community properties may be more predictable than fine community properties
- Species traits may help predictability
- Reclamation practices may aid predictability
- Mixed results – highlights the need for sound monitoring programs



Predictability Example – Worldwide Ecology Example
One of first reclamation – grass success by aridity
Good framework to show more variables are key, more data is needed, clean data is needed.
Wyoming example – aridity, elevation, soil, invasive species, etc.



Bertuol-Garcia et al. 2023. *Ecological Applications*.

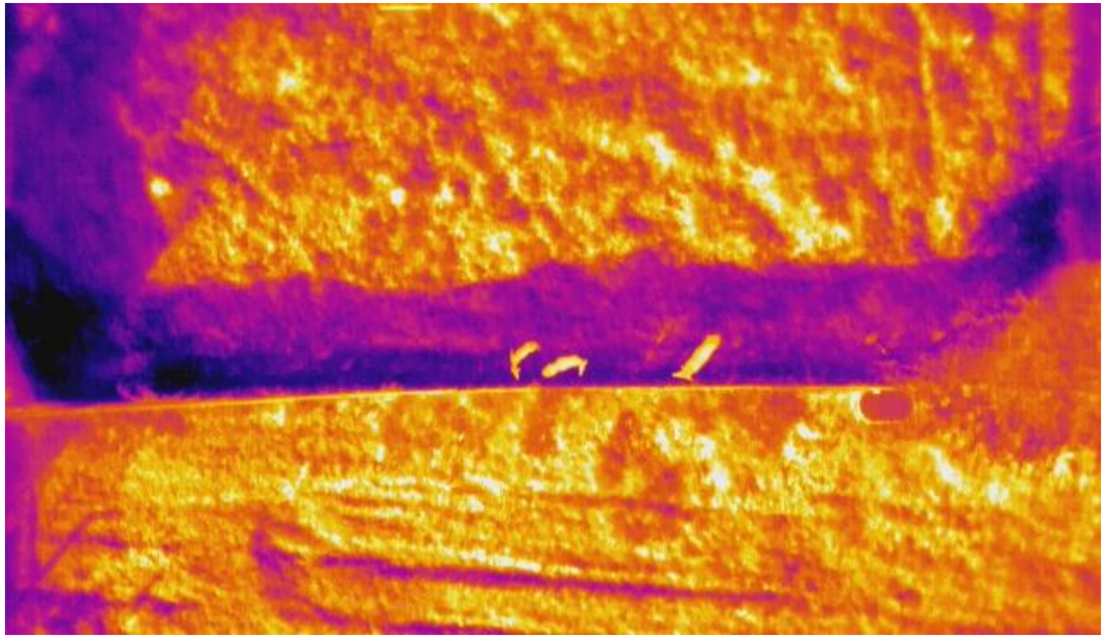


Image Processing

- Use of multispectral bands or various sensors may assist with wildlife monitoring
- Fusing visible and thermal imagery new, but promising
- Convolutional neural networks and deep residual networks also promising, with multi-layered ResNet architecture currently performing best

Association Analysis

	A	B	C	D	E	F	G	H	I	J	K	L
1	citrus fruit	semi-finish	margarine	ready soups								
2	tropical fru	yogurt	coffee									
3	whole milk											
4	pip fruit	yogurt	cream che	meat spreads								
5	other veget	whole milk	condensec	long life bakery product								
6	whole milk	butter	yogurt	rice	abrasive cleaner							
7	rolls/buns											
8	other veget	UHT-milk	rolls/buns	bottled bee	liquor (appetizer)							
9	pot plants											
10	whole milk	cereals										
11	tropical fru	other veget	white brea	bottled wat	chocolate							
12	citrus fruit	tropical fru	whole milk	butter	curd	yogurt	flour	bottled wat	dishes			
13	beef											
14	frankfurter	rolls/buns	soda									
15	chicken	tropical fruit										
16	butter	sugar	fruit/veget	newspapers								
17	fruit/vegetable juice											
18	packaged fruit/vegetables											
19	chocolate											
20	specialty bar											
21	other vegetables											
22	butter milk	pastry										
23	whole milk											
24	tropical fru	cream che	processed	detergent	newspapers							
25	tropical fru	root vegeta	other veget	frozen des	rolls/buns	flour	sweet spre	salty snack	waffles	candy	bathroom cleaner	
26	bottled wat	canned beer										

Association Analysis

Ecological Entomology

Royal Entomological Society

Methods

Market basket analysis of grasshopper (Orthoptera: Acrididae) assemblages in eastern Wyoming: a 17-year case study using associative analysis for ecological insights into grasshopper outbreaks

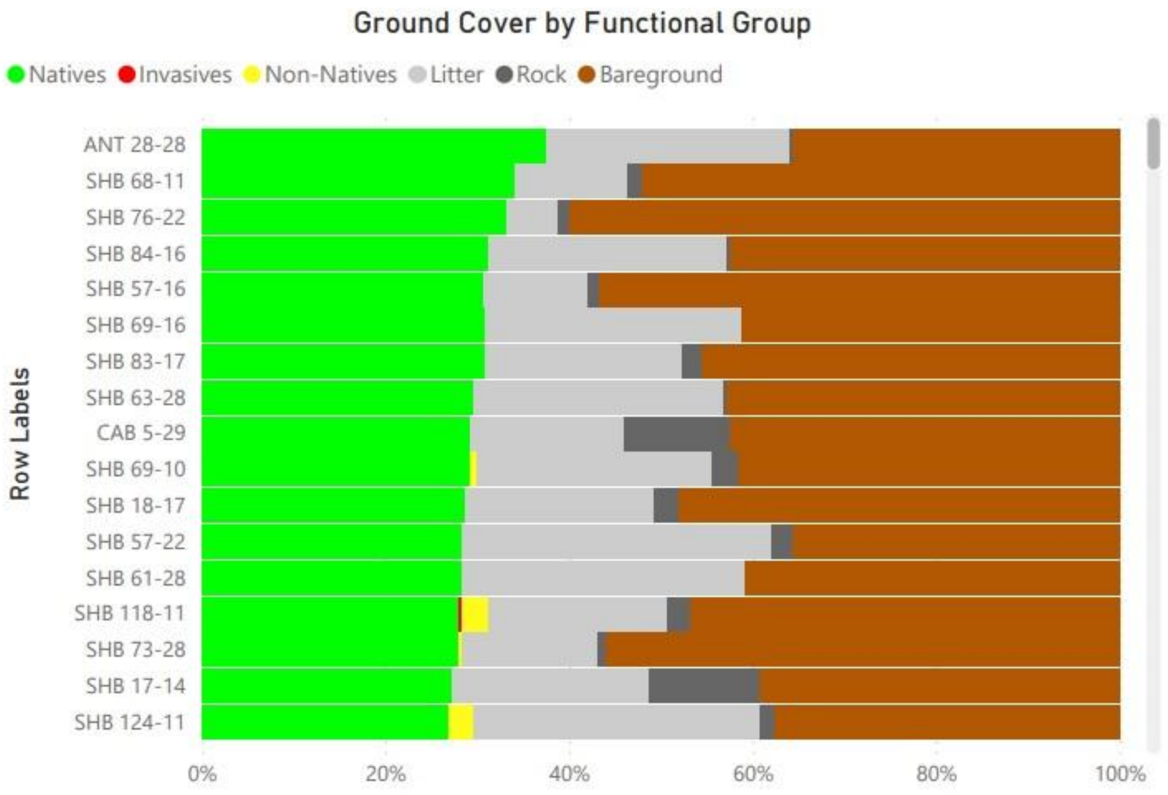
DOUGLAS I. SMITH, MICHAEL F. CURRAN, ALEXANDRE V. LATCHININSKY

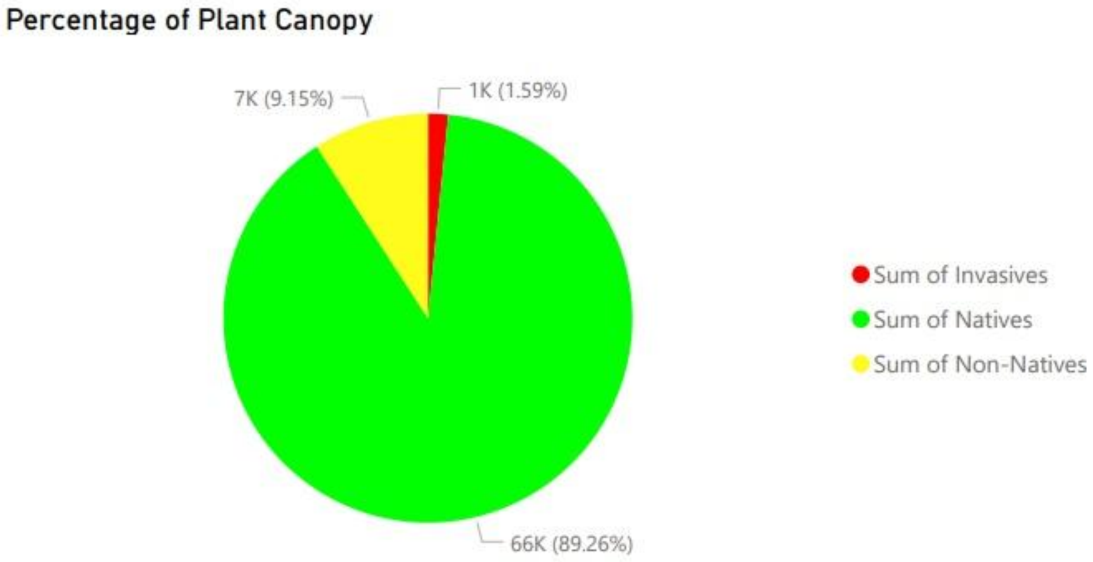
lhs	Yield	rhs	Support	Confidence	Lift
Melanoplus sanguinipes (HP, EH), *Phlibostroma quadrimaculatum* (SP, IH)	»	*Trachyrhachys kiowa* (SP, IH)	0.1	0.89	2.2
Ageneotettix deorum (MP, EH), *Melanoplus infantilis* (HP, IH), *Melanolus sanguinipes* (HP, EH)	»	*Trachyrhachys kiowa* (SP, IH)	0.14	0.88	2.1
Amphitonus coloradus (MP, EH), *Melanoplus infantilis* (HP, IH)	»	*Trachyrhachys kiowa* SP, IH)	0.11	0.85	2.1
Ageneotettix deorum (MP, EH) *Amphitornus coloradus* (MP, EH), *Melanoplus infantilis* (HP, IH)	»	*Trachyrhachys kiowa* (SP, IH)	0.1	0.85	2.1
Ageneotettix deorum (MP, EH), *Melanoplus infantilis* (HP, IH)	»	*Trachyrhachys kiowa* (SP, IH)	0.17	0.84	2.1

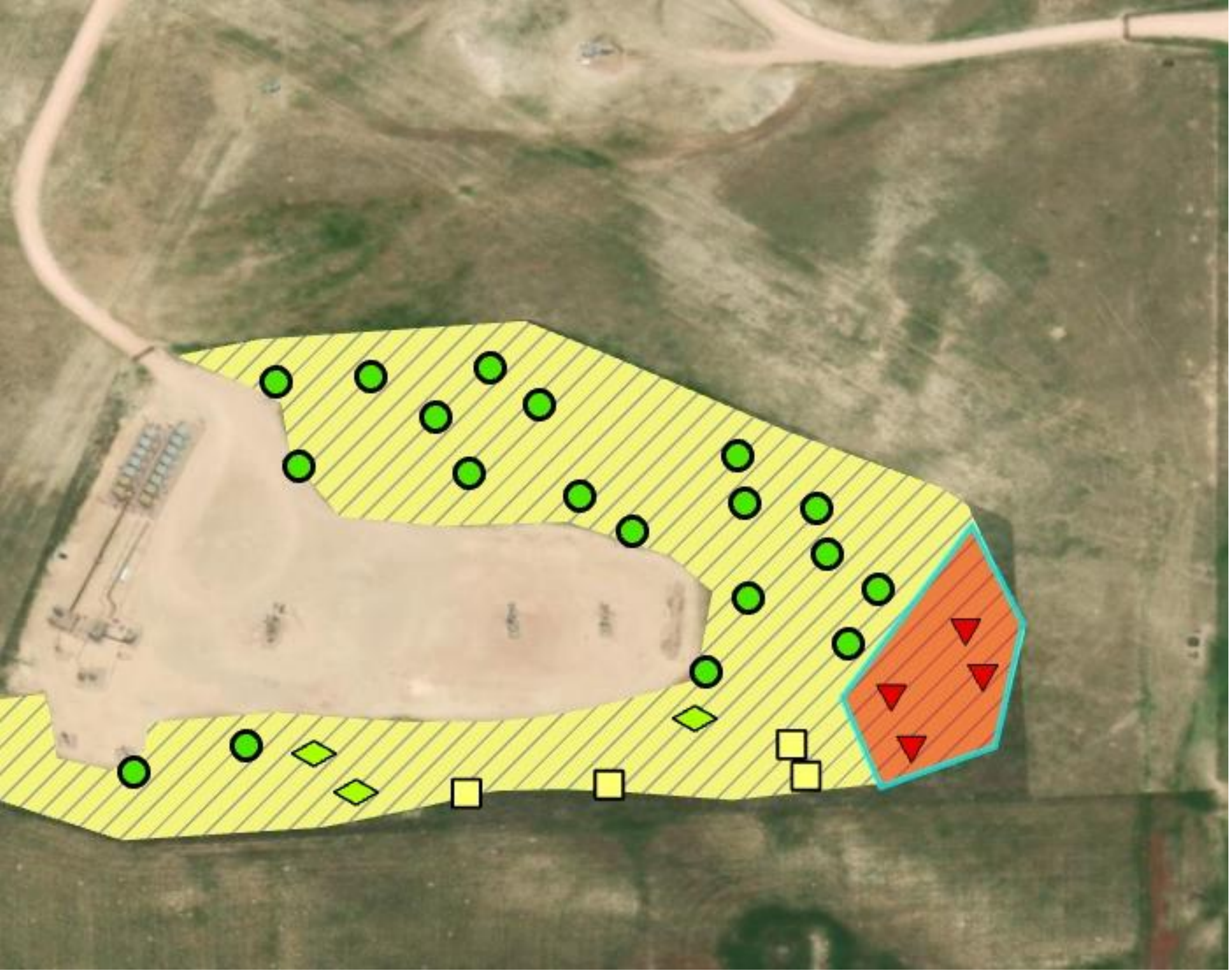
Decision Making

- Improved seed mixes
- What to spray?
- When to spray?
- Soil amendments, etc.

Example of a dashboard from Jonah (200 sites)







Legend

Native Vegetation

Native/Non-Native Mix

Non-Native Vegetation

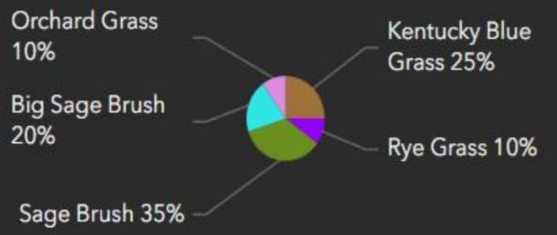
Invasive Vegetation

Reclamation Dashboard v2

Approval Table

BLM Approved	State Approved	PAPO Ap
No	Yes	N

Seeding Mix



1 of 2

Total Insect Abundance

79

1 of 2

Family Richness

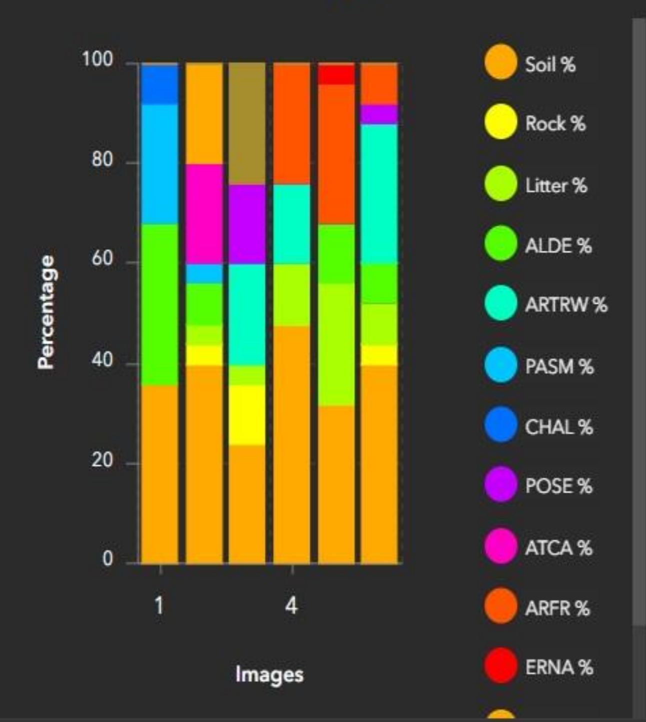
17

Criteria	Pass/Fail
TotalCover	Pass
ForbRichness	Fail
ForbDensity	Fail
ShrubRichness	Pass

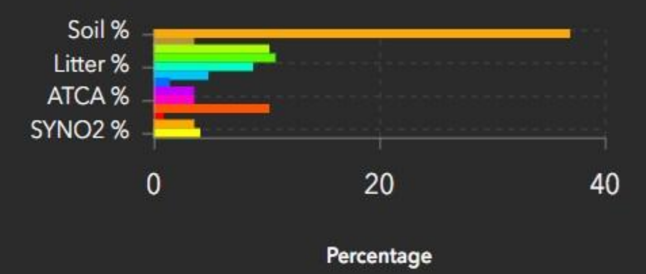
Pad List

Mesa 11-17

Ground Cover breakdown (by image)



Total Ground Cover (in map view)



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PUREWEST

Thank you

mike@abnovaecology.com