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Interactive Machine Learning for GIS Systems

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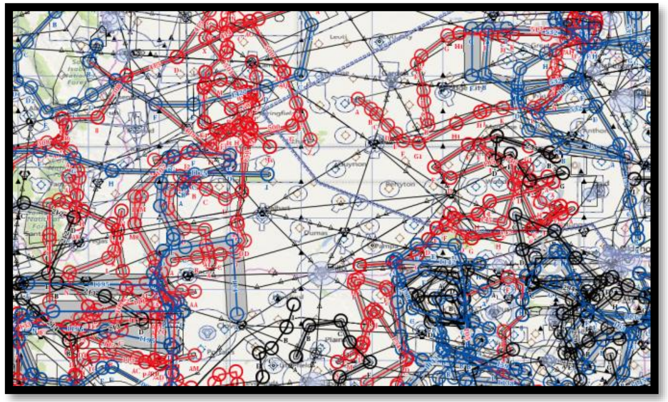
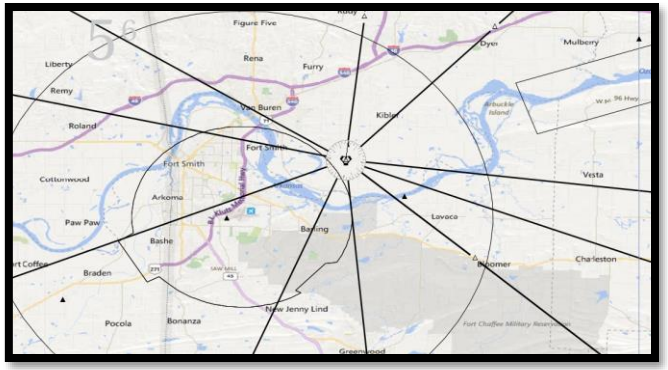
Problems in Automating Digital Map Displays

- Digital maps such are cumbersome to display perfectly
  - Automated region and object labeling is not always accurate
  - Layers that obfuscate each other, even at small scales
  - Impossible to account for every view of the map
  - Different users and situations need different views and layers

- There is no completely automated solution
  - Expert knowledge both from the data and analyst side are necessary for each map.





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Challenges in Machine Learning

- Machine learning can leverage today's computational power to generate better digital maps displays
- However, generating an accurate map automatically is not trivial

Challenges

- Training data:
  - Who's going to label?
  - How much is enough?
  - Do you even have enough?
  - Training overhead and turn-around time
- All or nothing solutions:
  - 99% accurate may not be good enough
    Counterproductive to correct classifier mistakes
- Concept Learning Challenges
  - Concept drift
    - Region of Interest
    - Data source sensor/calibration
  - Concept evolution
    - Mission requirements
    - New intelligence

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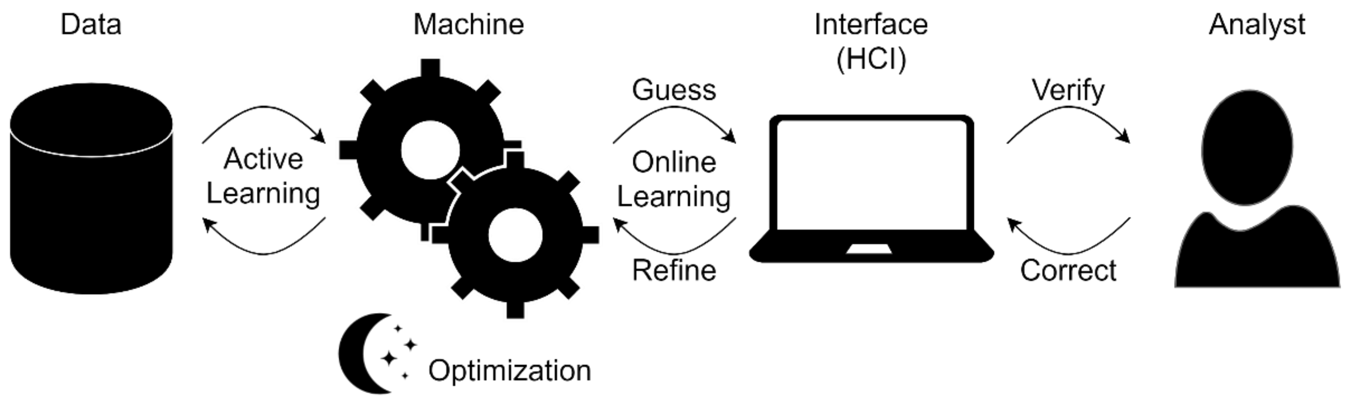
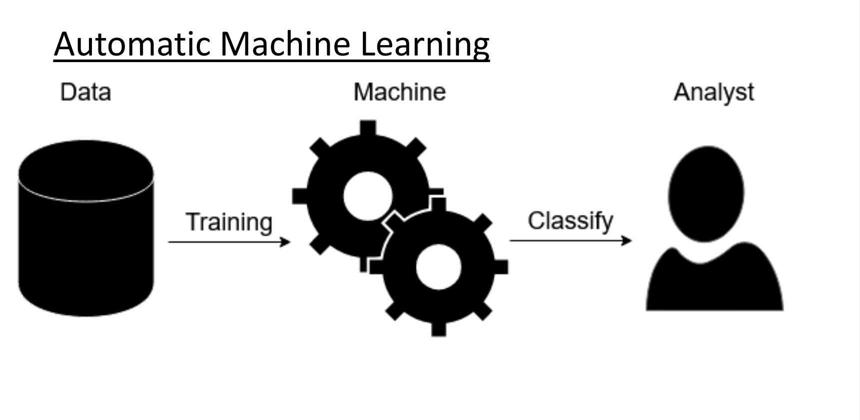
Interactive Machine Learning





AML typically one-way information flow from data to classifier to analyst

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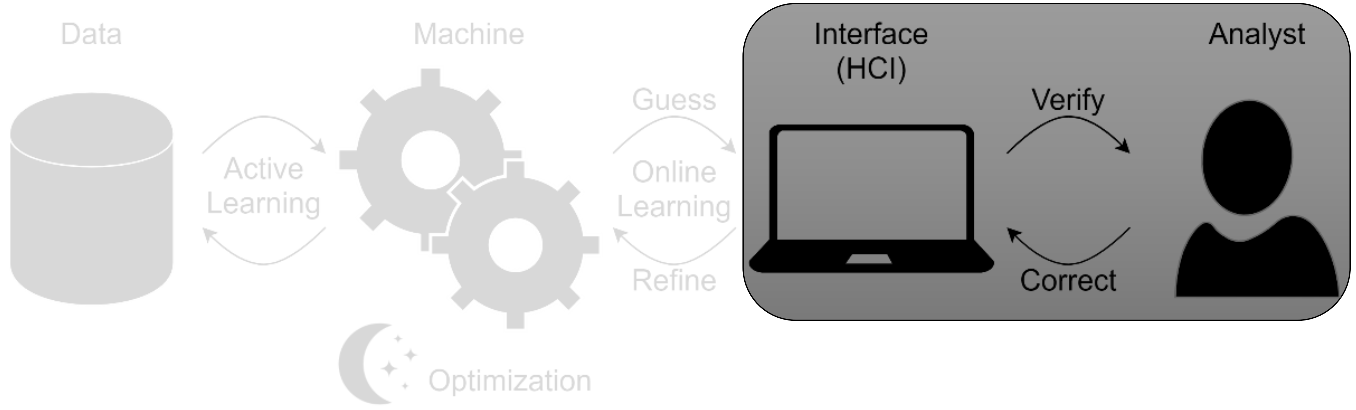
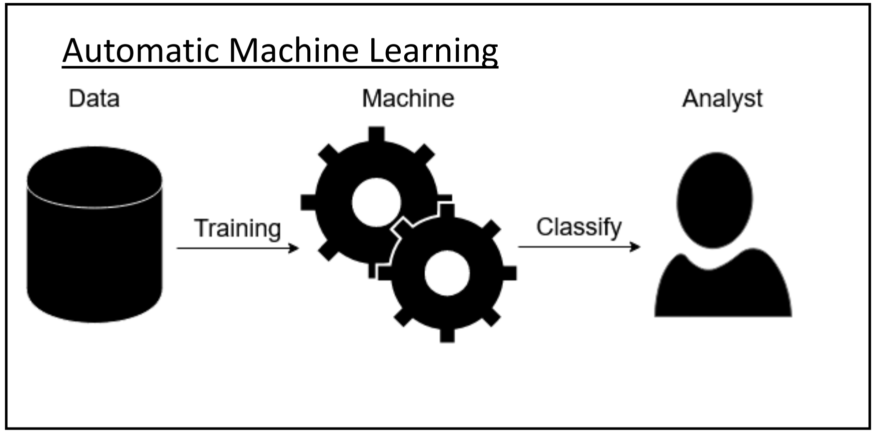


IML is centered around the analyst, who will actively verify and correct via an interface

- Solves all-or-nothing frustration
- Cold-start enabled



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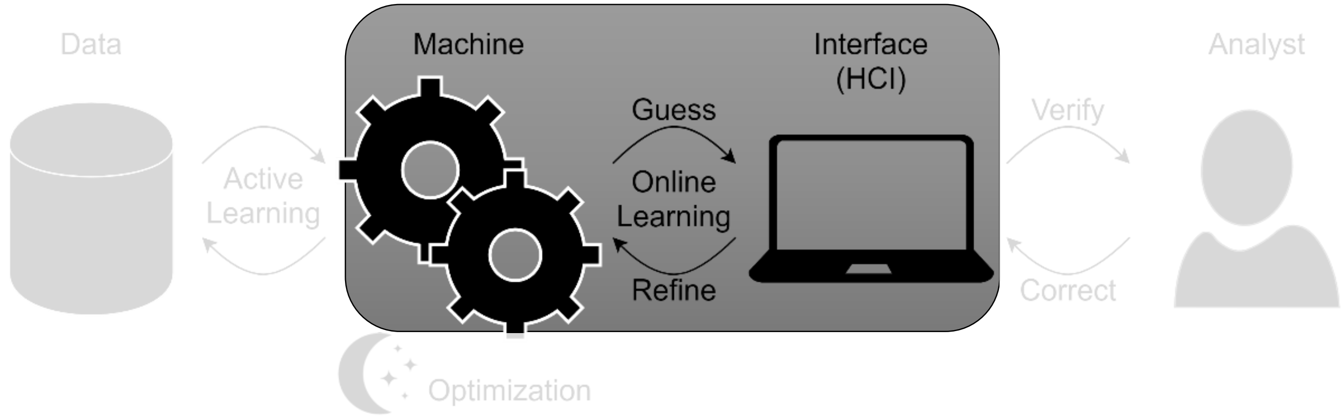

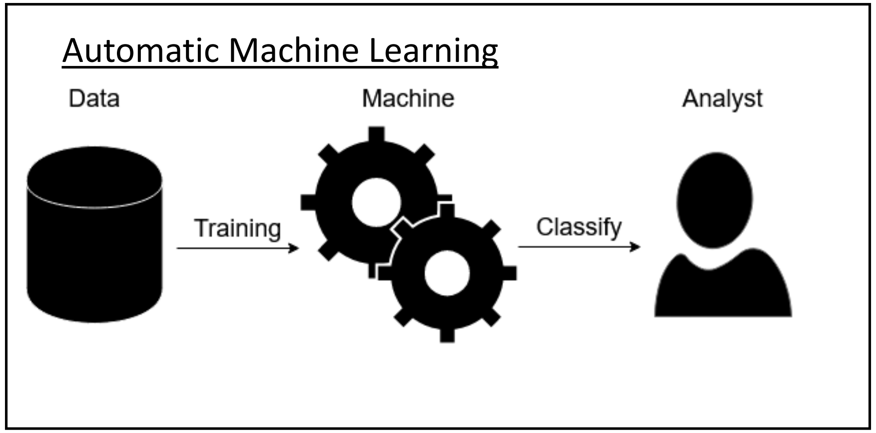

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- Concept drift & evolution

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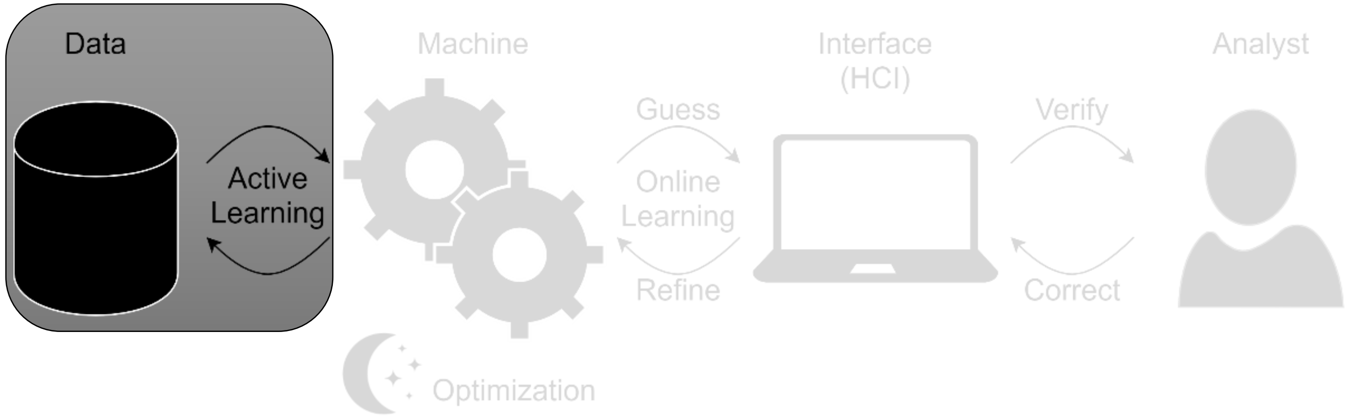

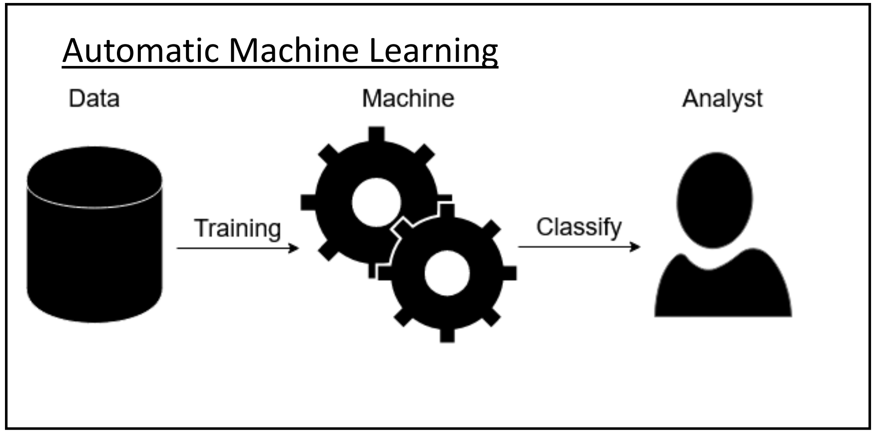

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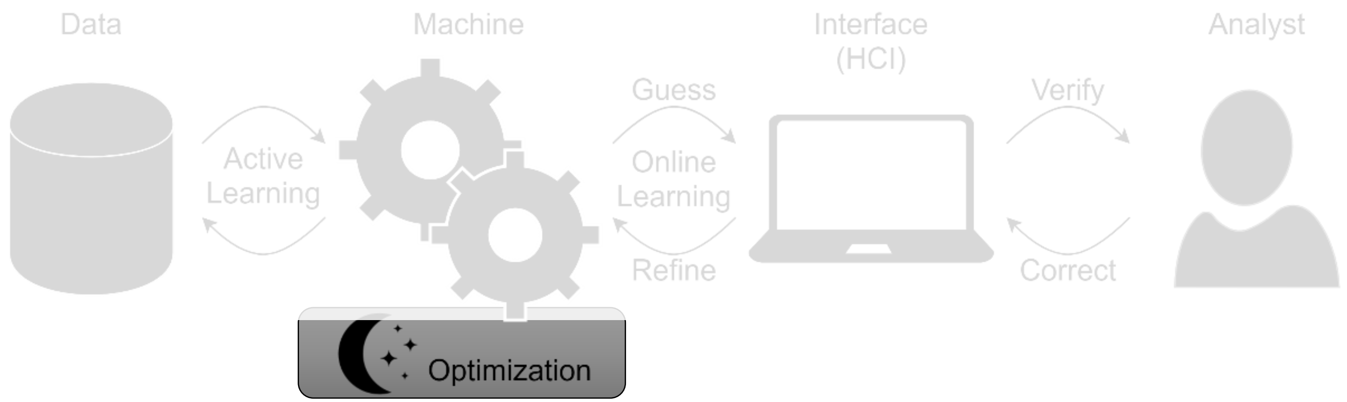

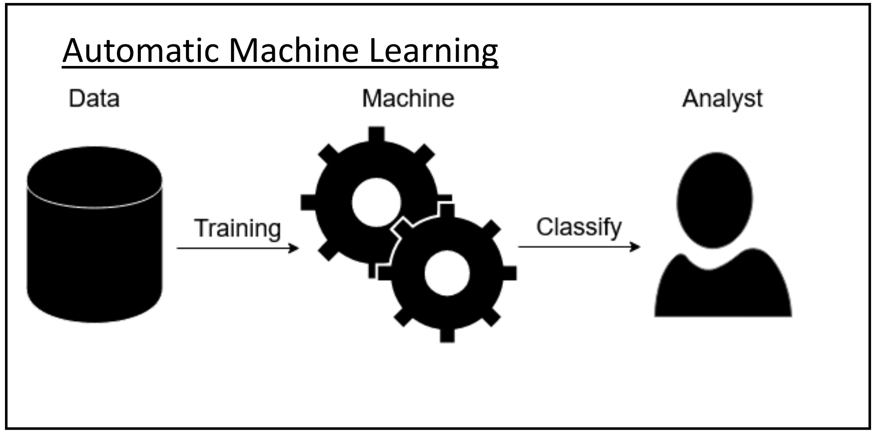

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When offline, optimization of IML model
- Analogous to AML

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Human-Attuned Machine Learning (HAML)

- Assumes human-in-the-loop for *active* and *online* training
  - ML takes an educated guess
  - User corrects, if necessary
  - ML immediately learns (trains) and guesses (classifies) again
  - Every guess has a confidence value
- Code-free approach
  - Maps may actively be trained within a GIS client
  - Can be as easy as clicking a “like” button
- Can use any ML implementation
  - Sometimes simple is best, sometimes advanced is necessary
  - Can support a high dimension of “feature” correlations
- Operational high-performance computing paradigm
  - Scales from a tablet to a supercomputer
  - Multicore-, GPGPU-, and cluster-enabled

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Example: Digital Map Editing (DME)

- The Problem: Automatic generation of a well made map is extremely difficult
  - Can get close to perfect
  - How do we handle imperfect cases?
  - Analyst is at the mercy of the map layout algorithm
  - May ask to have the layout algorithm changed
    - Cascading changes – domino effect
    - Long turnaround time

- Challenges
  - There are near-infinitely many ways to view a map
  - Need to capture user's preference somehow
  - The feature space of a digital map is not trivial

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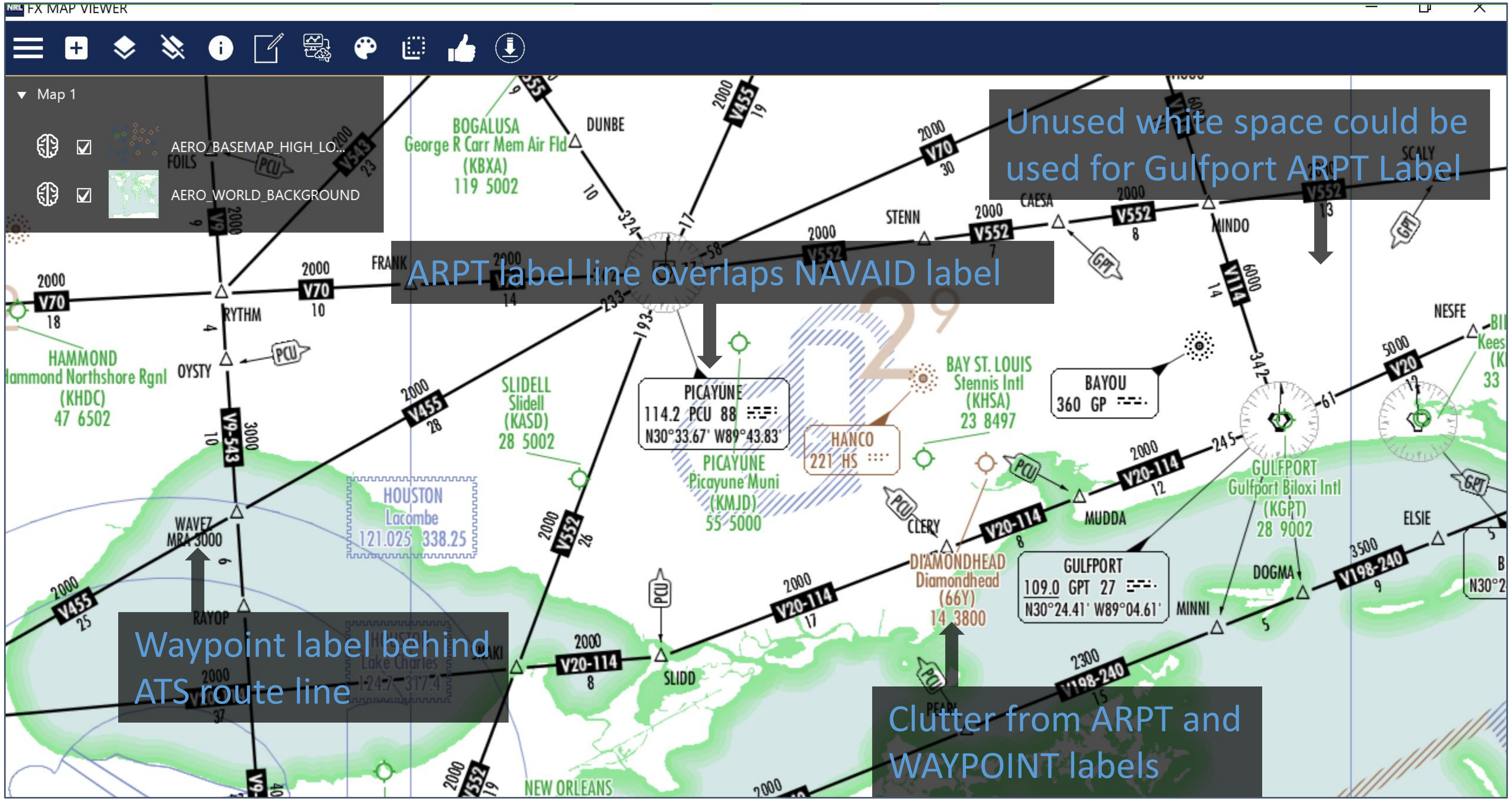
Snapshot is post-map layout algorithm



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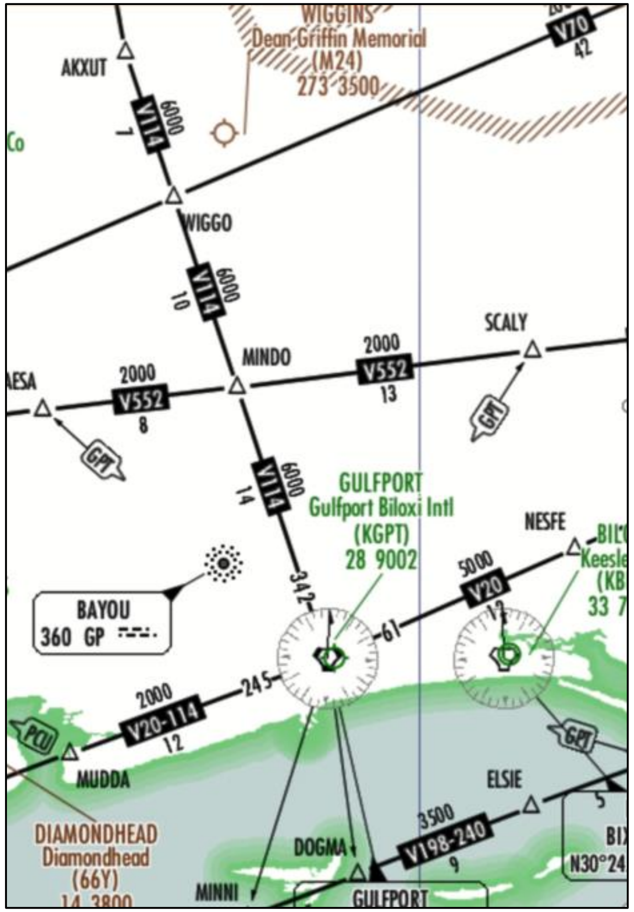
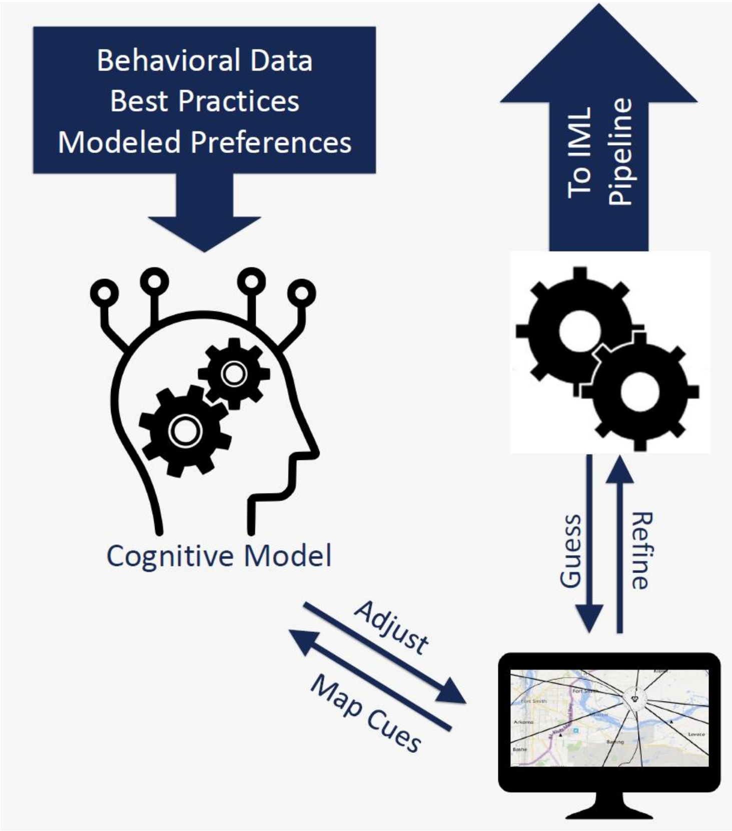
DME: The HAML Approach

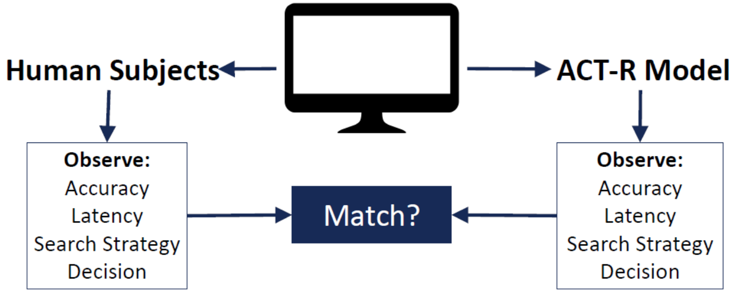
- Analyst edits inside the map-viewing client.
- AI implicitly learns label placements based on a user's preferences over time
    - Aggregates label placement preferences over different map-views
    - If more than one custom position exists for a label, the AI will use the custom position with the most similar map-view
    - AI will then remember these corrections for future label placements

- Challenge: Feature space can be very large, taking some time for model to converge.
    - Use modeled user feedback to supplement the HAML approach.



DME: Modeled User Preferences





Modeled user interactions seeks to emulate and understand the reasoning behind the customer's edits so that the preference may be propagated throughout the map

Example Label Placement Cues

Perceptual	Contextual	Other
• Salience • Label Density • Label Size • Spatial Distribution	• Label type • Relationship to nearby elements • Map purpose	• Preferences • Cartography Best Practices

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Example: Geographic Region Digitization (GRD)

- Digitize some geographic region of interest
- Annotated by a simple piecewise-linear polygon
- User clicks and drags to create and modify vertices, respectively

<u>Automatic Approaches Fall Short</u>

- Too much to correct
- Unintuitive parameters
- Unwieldy interface

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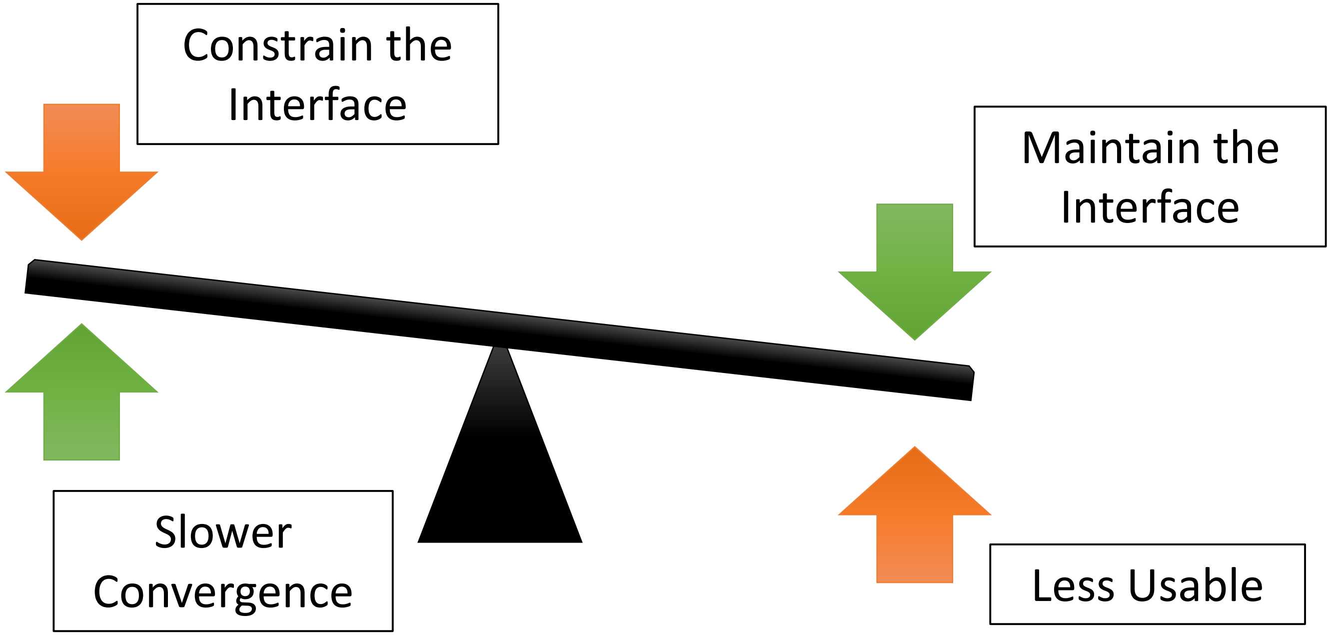
Constraining the Interface



Implementations of HAML are designed to maintain the delicate balance between usability and constrained problem spaces

Analogy: Autonomous Vehicles

Autonomous vehicles have been around for decades. The earliest were constrained to rails.

HAML constrains applications in a similar way to exploit autonomy given by modern machine learning.

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GRD: Constrained Interface

- A contour is instantiated
- The vertex is restricted to a *search space*
- The user drags the vertex to the correct location
- The machine learns by examining the search space
- Repeat until done!
- Techniques and results are published in the literature
    - 84% machine placement accuracy from cold start

Chris J. Michael, et al. 2019. *A General Framework for Human-Machine Digitization of Geographic Regions from Remotely Sensed Imagery*. In Proceedings of the 27th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (SIGSPATIAL ’19).

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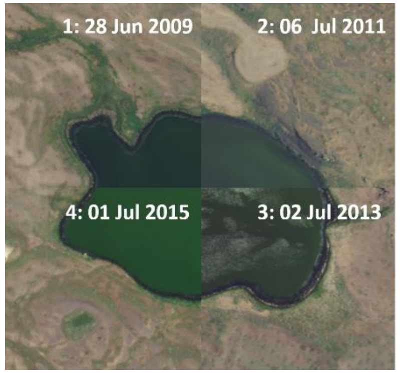
GRD: Calibrating Corrections

EFPL

EPPL

RPG

PPG



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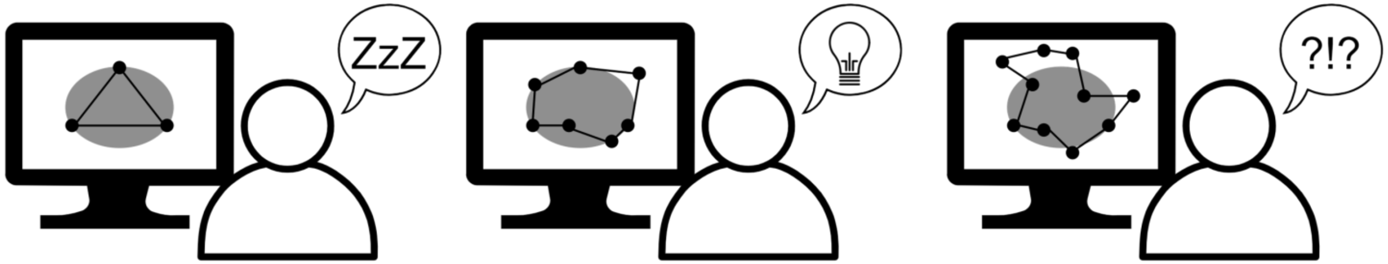
Cognitive Feedback

Goal: Understand cognitive load of analyst in HAML system.

- Too many incorrect guesses → Analyst will be slowed down and get frustrated.
- Not enough guesses → Analyst spends more time than necessary training model.

Approach: Measure productivity and improve human-machine team through:

- Self Reporting
- Implicit Feedback
- Modeled feedback



Underconfident Model	Cognitive-Attuned Model	Overconfident Model
ML learns too slowly	Productive human-machine team	High cognitive load

Chris J. Michael, et al. 2020. *On Interactive Machine Learning and the Potential of Cognitive Feedback*. Presented at the 2nd Workshop on Deep Models and Artificial Intelligence for Defense Applications (DMAIDA ‘20).

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Summary

- Many GIS applications benefit from a HAML approach
- HAML applications are complex systems that require systems engineering to create human-machine teams that best complement one another.
- Examples considered:
  - Airfield Change Detection (ACD)
  - Digital Map Editing (DME)
  - Geographic Region Digitization (GRAIT)

Ongoing Research:

- Modeling User Preferences
- Cognitive Feedback

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Questions

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