STEPS TOWARD ROBUST ARTIFICIAL INTELLIGENCE

Tom Dietterich
President, Association for the Advancement of Artificial Intelligence

Marvin Minsky (1927-2016)

Credit: Wikipedia CC BY 3.0

PROCEEDINGS OF THE IRE

Steps Toward Artificial Intelligence*

MARVIN MINSKY†, MEMBER, IRE

1961

Minsky: Difference between Computer Programs and People

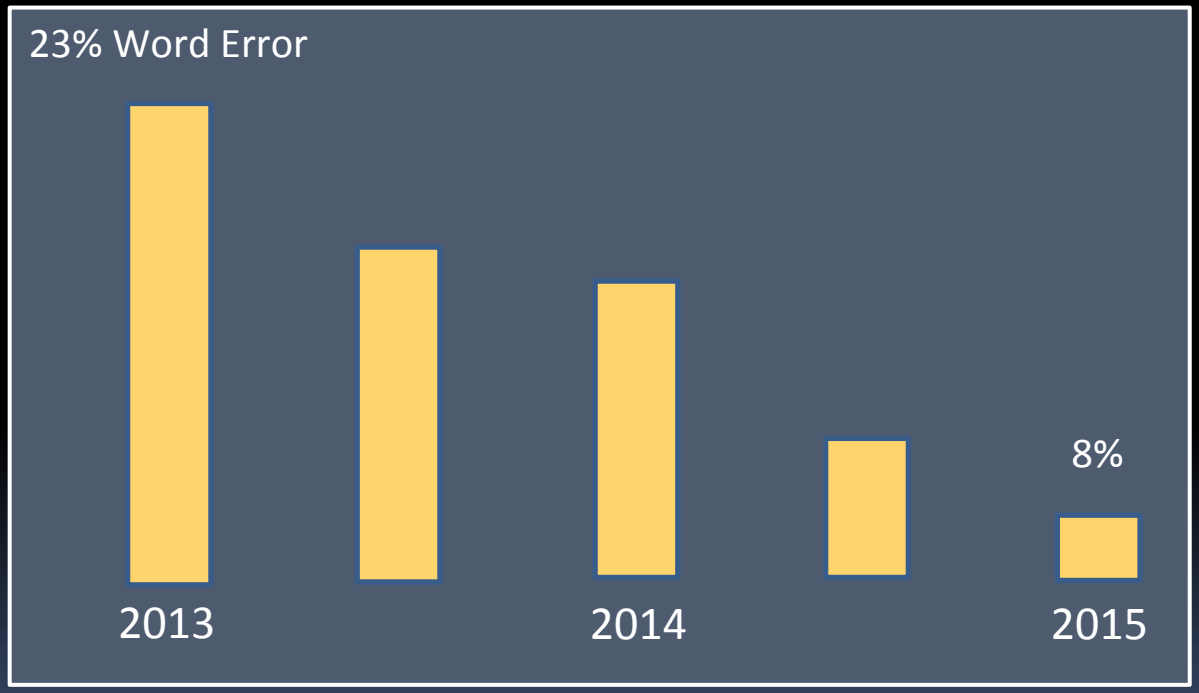
> “almost any error will completely paralyze a typical computer program, whereas a person whose brain has failed at some attempt will find some other way to proceed. We rarely depend upon any one method. We usually know several different ways to do something, so that if one of them fails, there's always another.”

Outline

- The Need for Robust AI
  - High Stakes Applications
  - Need to Act in the face of Unknown Unknowns
- Approaches toward Robust AI
  - Robustness to Known Unknowns
  - Robustness to Unknown Unknowns
- Concluding Remarks

Exciting Progress in AI: Perception

Google Speech Recognition



Credit: Fernando Pereira & Matthew Firestone, Google

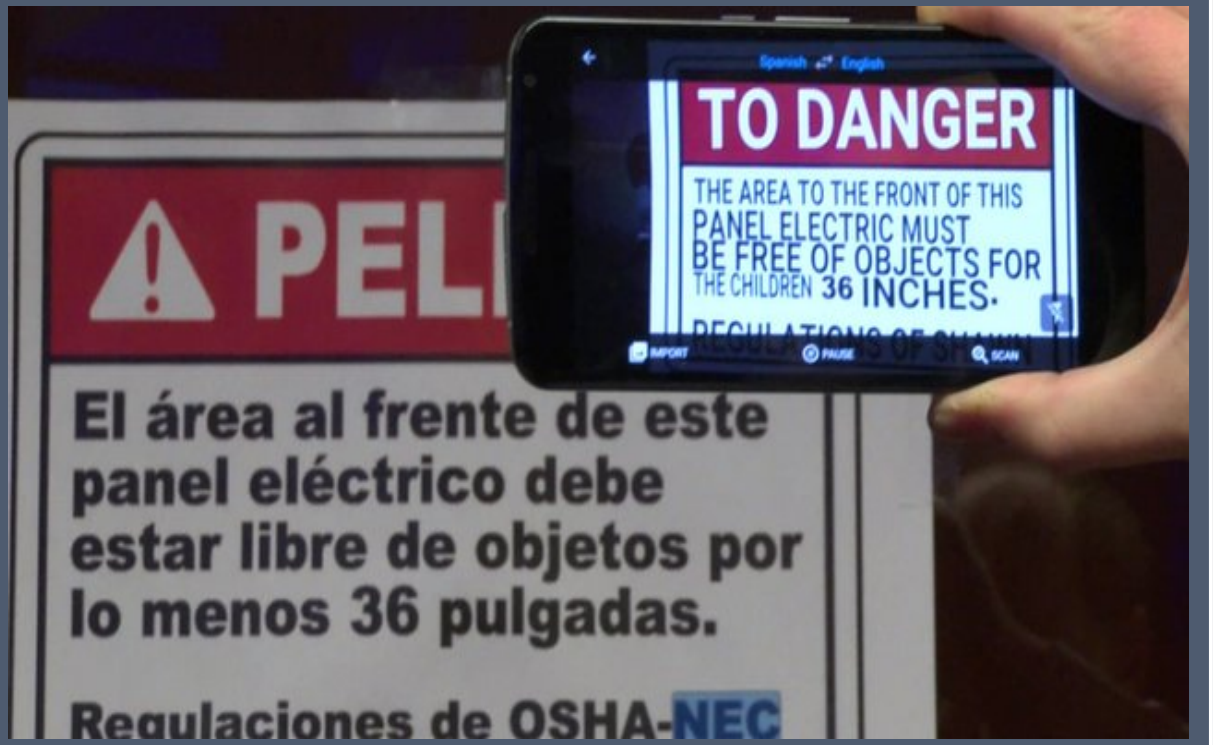
Image Captioning

"a black and white cat is sitting on a chair."

Credit: Jeff Donahue, Trevor Darrell

Perception + Translation

Google Translate from Images

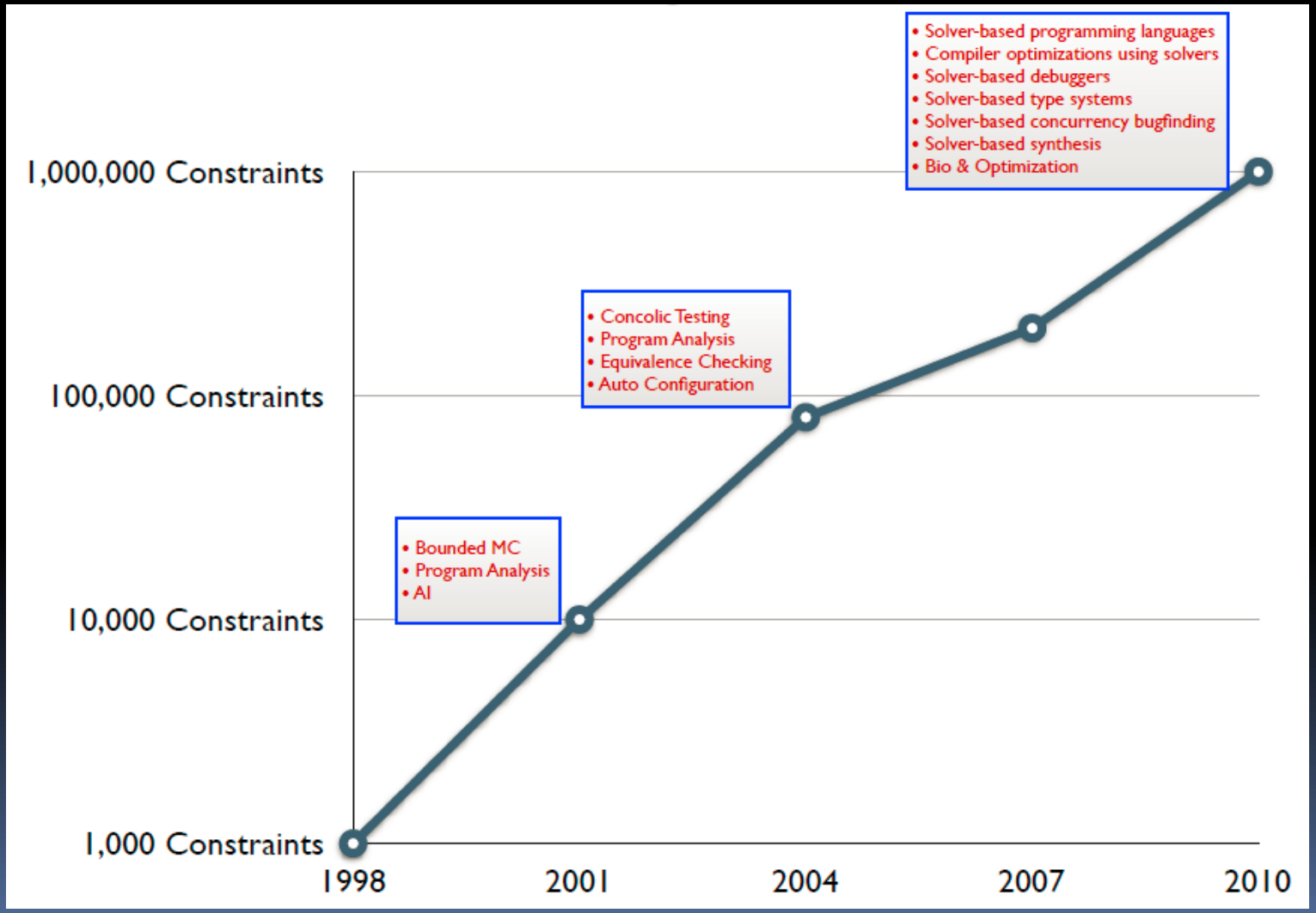


Credit: www.bbc.com

Skype Translator: Speech Recognition + Translation

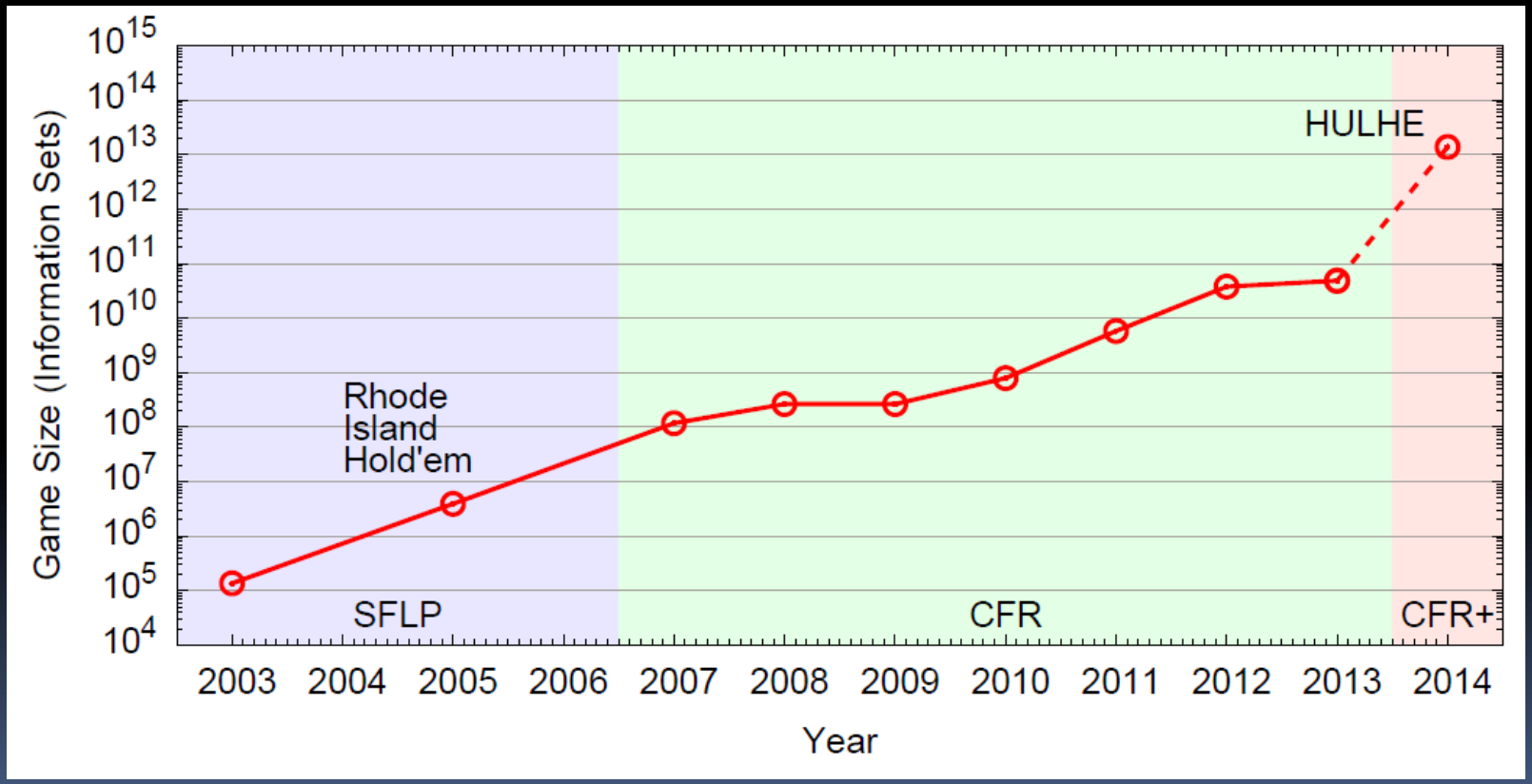
credit: Skype

Exciting Progress in AI: Reasoning (SAT)



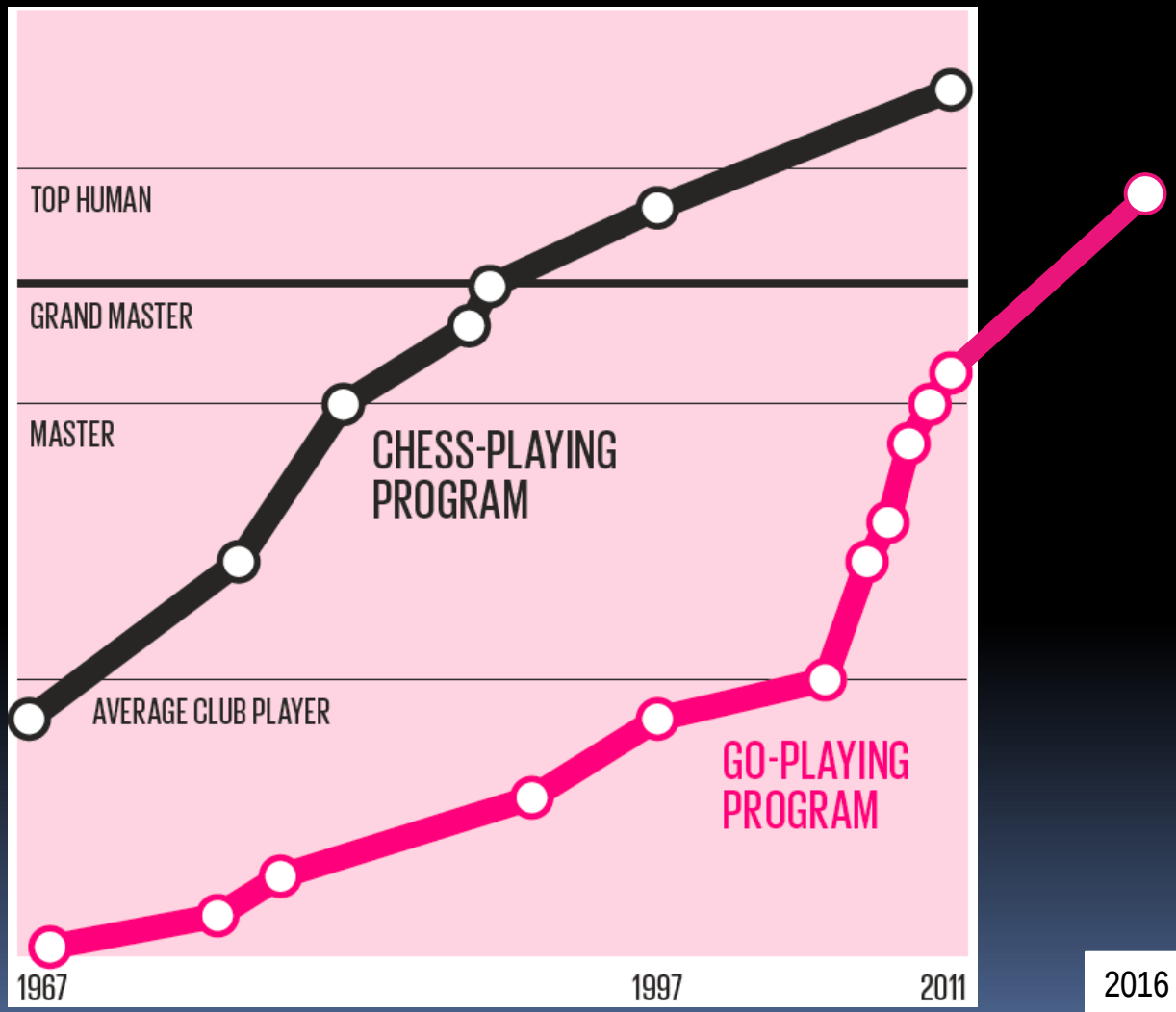
Credit: Vijay Ganesh

Exciting Progress: Reasoning (Heads-Up Limit Hold'Em Poker)



Credit: Michael Bowling

Exciting Progress: Chess and Go

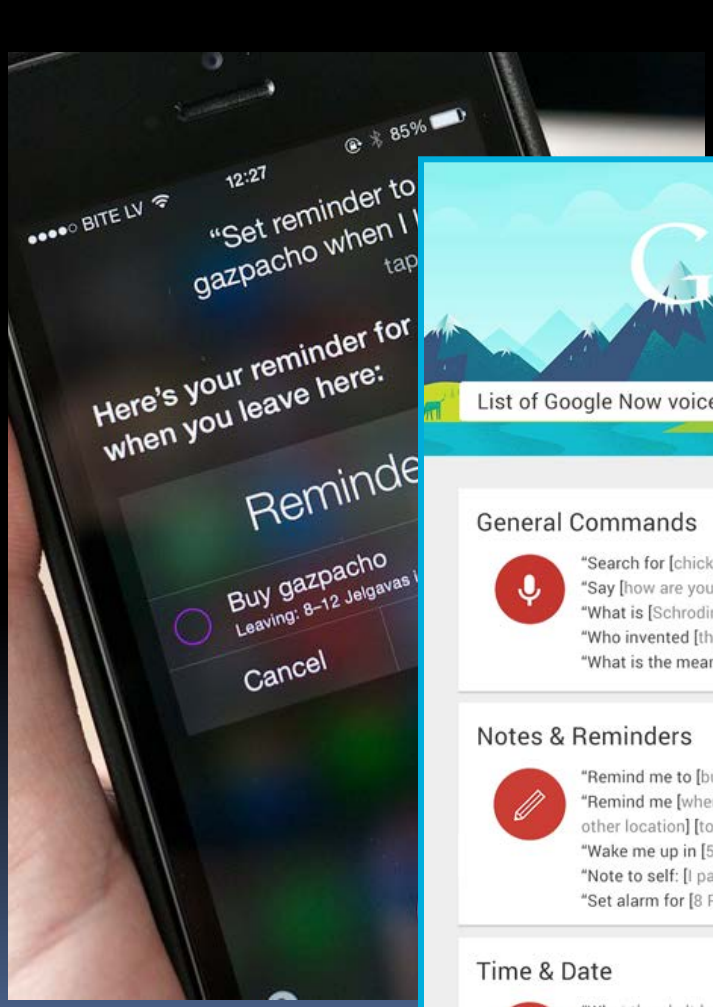


Credit: Martin Mueller

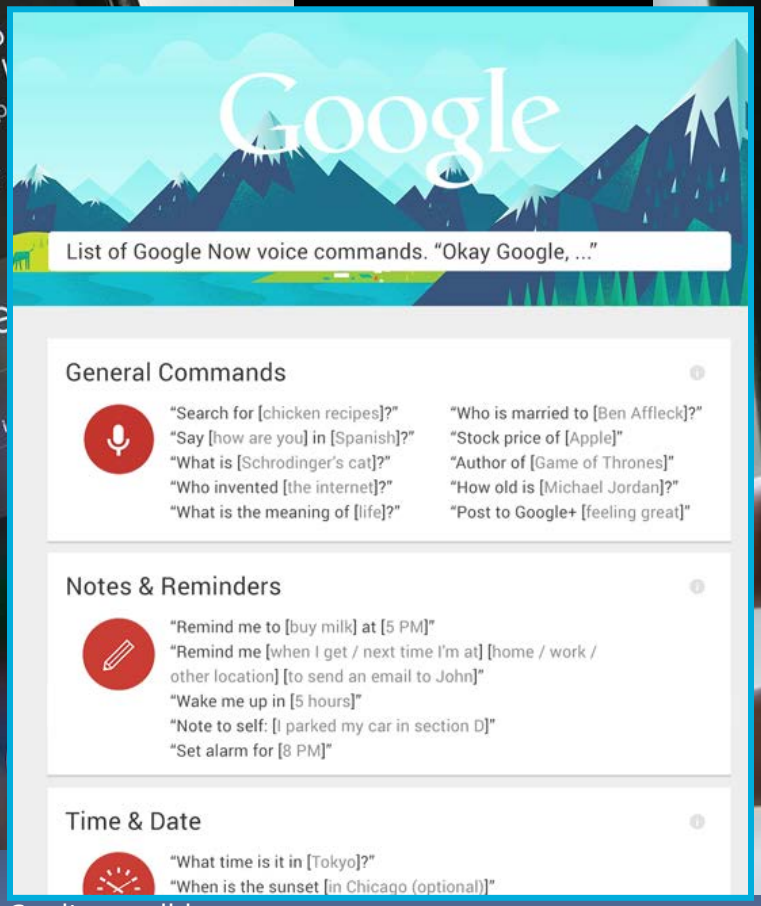
Silver, et al. (2016) *Nature*
Deep Learning +
Monte Carlo Tree Search

2016

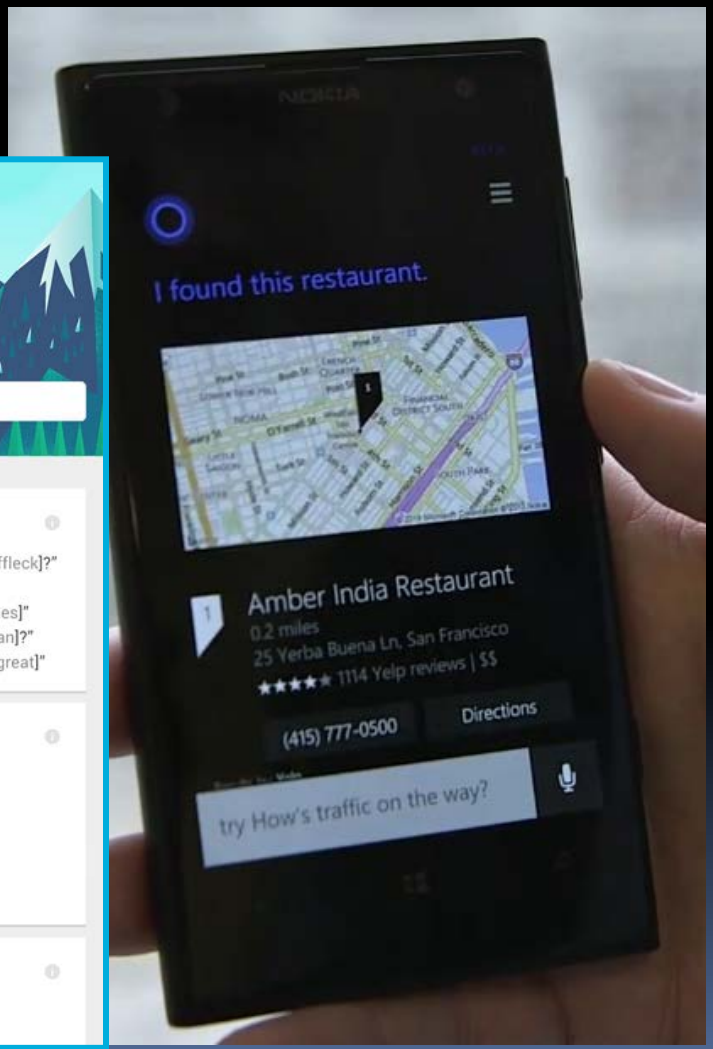
Personal Assistants



Credit: mashable.com



Credit:trendblog.net



Credit: The Verge

Technical Progress is Encouraging the Development of High-Stakes Applications

Self-Driving Cars

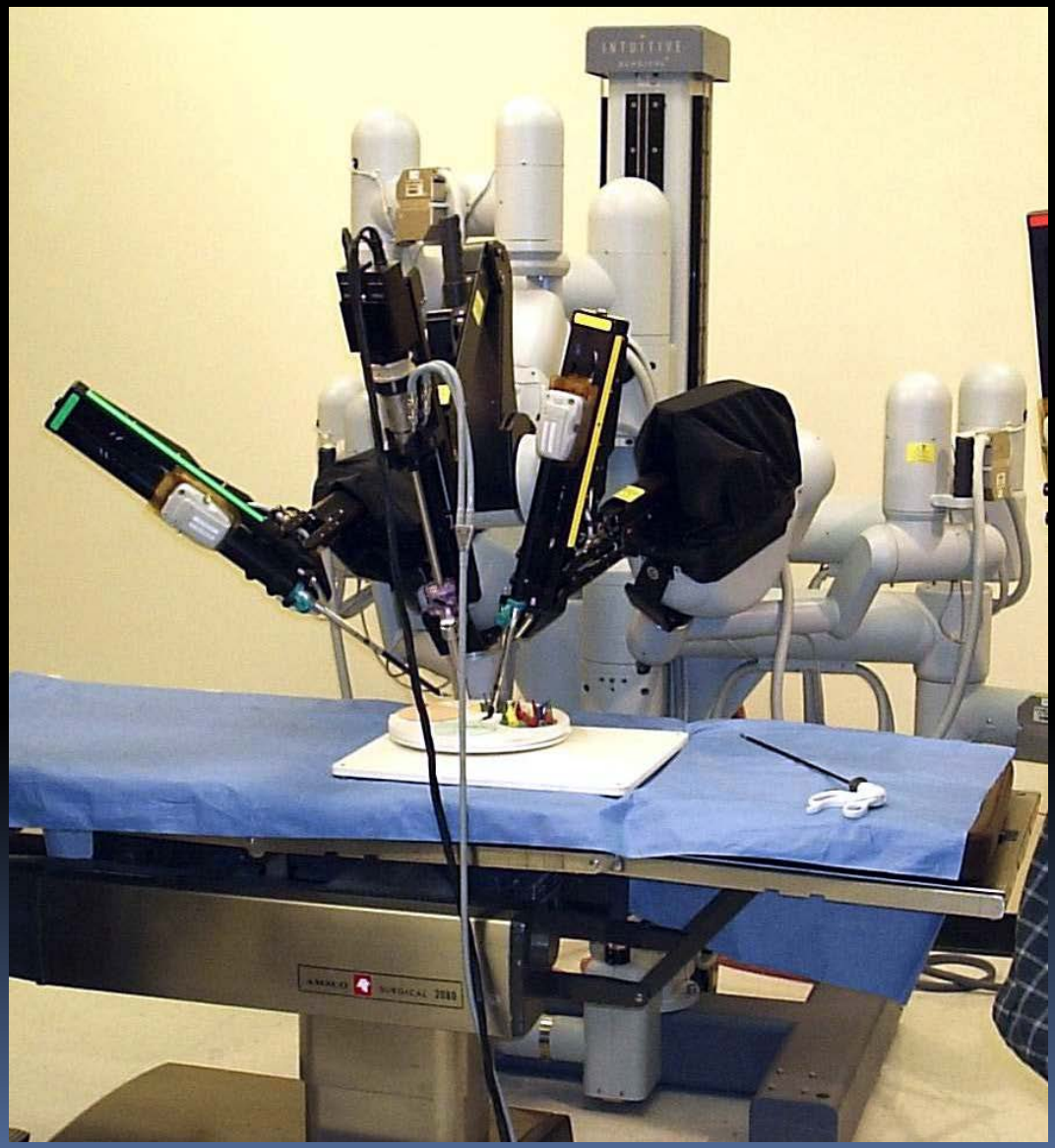
Credit: The Verge

Credit: delphi.com

Tesla AutoSteer

Credit: Tesla Motors

Automated Surgical Assistants



DaVinci

Credit: Wikipedia
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AI Hedge Funds

AI Control of the Power Grid

Credit: EBM Netz AG

Credit: DARPA

Autonomous Weapons

Northroop Grumman X-47B

Credit: Wikipedia

Samsung SGR-1

Credit: AFP/Getty Images

UK Brimstone Anti-Armor Weapon

Credit: Duch.seb - Own work, CC BY-SA 3.0

High-Stakes Applications Require Robust AI

- Robustness to
  - Human user error
  - Cyberattack
  - Misspecified goals
  - Incorrect models
  - Unmodeled phenomena

Why Unmodeled Phenoma?

- It is impossible to model everything
- It is not desirable to model everything

It is impossible to model everything

- Qualification Problem:
  - It is impossible to enumerate all of the preconditions for an action
- Ramification Problem:
  - It is impossible to enumerate all of the implicit consequences of an action

It is important to not model everything

- Fundamental theorem of machine learning

$$\text{error rate} \propto \frac{\text{model complexity}}{\text{sample size}}$$

- Corollary:
  - If sample size is small, the model should be simple
  - We must deliberately oversimplify our models!

Conclusion:

An AI system must act without having a complete model of the world

Digression: Uncertainty in AI

- Known Knowns
  - Theorem proving
  - Planning in deterministic, fully-observed worlds
  - Games of perfect information

Known-Knowns
1958-1980

Known Unknowns

- Probabilistic Graphical Models
  - Pearl (1988); Koller & Friedman (2009)
- Probabilistic Machine Learning
  - Murphy (2012)
- Planning in Markov Decision Problems
- Computational Game Theory

Known-Knowns
1958-1980

Known-Unknowns
1980-present

Unknown Unknowns

- Natural step on our trajectory toward robust AI

Known-Knowns
1958-1980

Known-Unknowns
1980-present

Unknown-Unknowns
1980-present

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Robustness Lessons from Biology

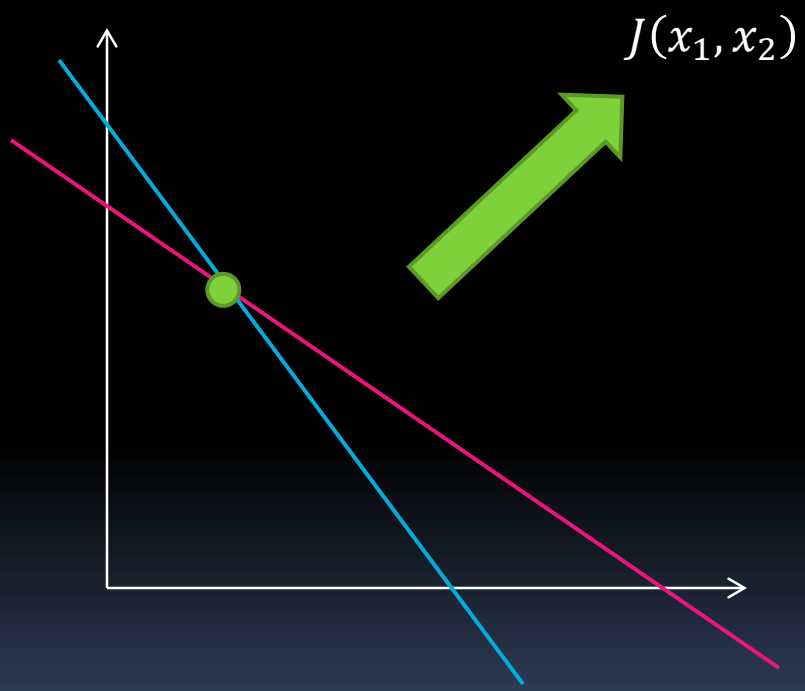
- Evolution is not optimization
  - You can't overfit if you don't optimize
- Populations of diverse individuals
  - A "portfolio" strategy
- Redundancy within individuals
  - diploidy/polyploidy = regressive alleles can be passed to future generations
  - alternative metabolic pathways
- Dispersal
  - Search for healthier environments

Approaches to Robust AI

- Robustness to Model Errors
  - Robust optimization
  - Regularize the model
  - Optimize a risk-sensitive objective
  - Employ robust inference algorithms
- Robustness to Unmodeled Phenomena
  - Expand the model
  - Learn a causal model
  - Employ a portfolio of models
  - Monitor performance to detect anomalies

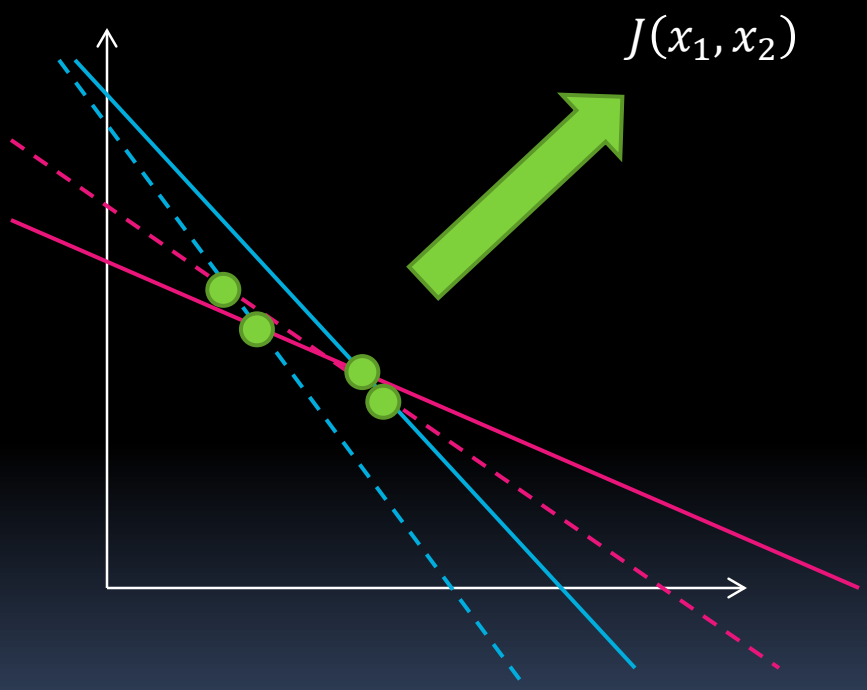
Idea 1: Robust Optimization

- Many AI reasoning problems can be formulated as optimization problems
- $\max_{x_1,x_2} J(x_1, x_2)$
- subject to
  - $ax_1 + bx_2 \leq r$
  - $cx_1 + dx_2 \leq s$



Uncertainty in the constraints

- $\max_{x_1,x_2} J(x_1, x_2)$
- subject to
  - $ax_1 + bx_2 \leq r$
  - $cx_1 + dx_2 \leq s$
- Define uncertainty regions
  - $a \in U_a$
  - $b \in U_b$
  - ...
  - $s \in U_s$



Minimax against uncertainty

- $\max_{x_1,x_2} \min_{a,b,c,d,r,s} J(x_1, x_2; a, b, c, d, r, s)$
- subject to
  - $ax_1 + bx_2 \leq r$
  - $cx_1 + dx_2 \leq s$
  - $a \in U_a$
  - $b \in U_b$
  - …
  - $s \in U_s$

Impose a Budget on the Adversary

- $\max_{x_1,x_2} \min_{\delta_a,\ldots,\delta_s} J(x_1, x_2; \delta_a, \ldots, \delta_s)$
- subject to
  - $(a + \delta_a)x_1 + (b + \delta_b)x_2 \leq (r + \delta_r)$
  - $(c + \delta_c)x_1 + (d + \delta_d)x_2 \leq (s + \delta_s)$
  - $\sum|\delta_i| \leq B$
  - $\delta_a \in U_a$
  - $\delta_b \in U_b$
  - …
  - $\delta_s \in U_s$

Bertsimas, et al.

Idea 2: Regularize the Model
Regularization in ML:

- Given:
  - training examples (x_i, y_i) for an unknown function $y = f(x)$
  - a loss function $L(\hat{y}, y)$: how serious it is to output $\hat{y}$ when the right answer is y?
- Find:
  - the model h that minimizes

$$\sum_i L(h(x_i), y_i) + \lambda \|h\|$$

loss + complexity penalty

Regularization can be Equivalent to Robust Optimization

- Xu, Caramanis & Mannor (2009)
  - Suppose an adversary can move each training data point x_i by an amount δ_i
  - Optimizing the linear support vector objective

$$\sum_i L(\hat{y}_i, y_i) + \lambda \|w\|$$

  - is equivalent to minimaxing against this adversary who has a total budget

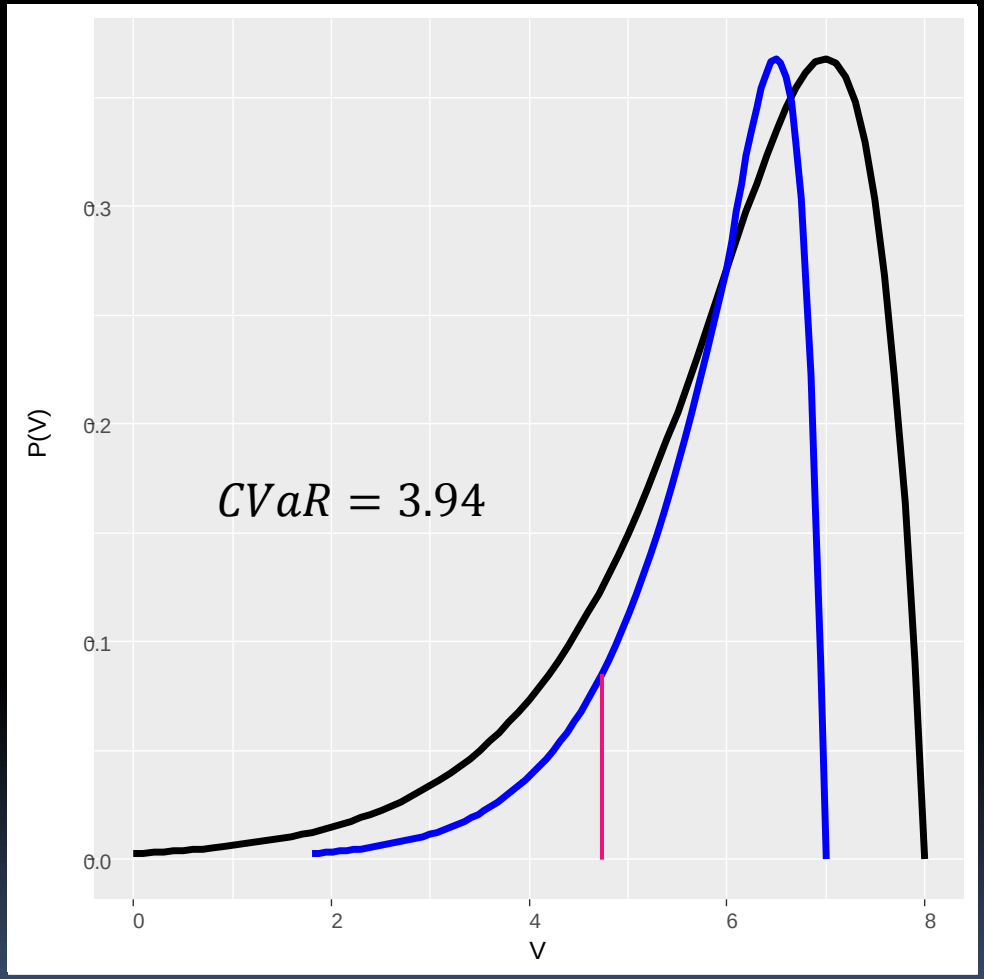
$$\sum_i \|\delta_i\| = \lambda$$

Idea 3: Optimize a Risk-Sensitive Objective

- Setting: Markov Decision Process
  - For $t = 1, \ldots, T$
    - agent observes world state s_t
    - agent chooses action a_t according to policy $\pi(s_t)$
    - world executes action a_t and moves to state s_{t+1} according to $P(s_{t+1}|s_t, a_t)$
    - agent receives reward $R(s_t, a_t)$

Idea 3: Optimize Conditional Value at Risk

- For any fixed policy π, the cumulative return $V^{\pi} = \sum_{t=1}^{T} R(s_t, a_t)$ will have some distribution $P(V^{\pi})$
- "Minimizing downside risks"
- The Conditional Value at Risk at quantile α is the expected return of the bottom α quantile
- By changing π we can change the distribution $P(V^{\pi})$, so we can try to push the probability to the right



Optimizing CVaR confers robustness

- Suppose that for each time t, an adversary can choose a vector δ_t and define a new probability distribution $P(s_{t+1}|s_t, a_t) \cdot \delta_t(a_t)$
- Optimizing CVaR at quantile α is equivalent to minimaxing against this adversary subject to a budget along each trajectory of

$$\prod_t \delta_t \leq \alpha$$

- Chow, Tamar, Mannor & Pavone (NIPS 2014)
- Conclusion: Acting Conservatively Confers Robustness to Model Errors

Idea 4: Robust Inference

- Credal Bayesian Networks
  - Convex uncertainty sets over the probability distributions at nodes
  - Upper and lower probability models
  - (Cosman, 2000; UAI 1997)
- Robust Classification
  - (Antonucci & Zaffalon, 2007)
- Robust Probabilistic Diagnosis (etc.)
  - (Chen, Choi, Darwiche, 2014, 2015)

Approaches to Robust AI

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Idea 5: Expand the Model

- Knowledge Base Construction
  - Cyc (Lenat & Guha, 1990)
- Information Extraction & Knowledge Base Population
  - NELL (Mitchell, et al., AAAI 2015)
  - TAC-KBP (NIST)
  - Robust Logic (Valiant; AIJ 2001)
- Learning Models of Actions in Planning and Reinforcement Learning
  - Gil (1994)

Idea 5: Expand the Model

- Risk:
  - Every new item added to a model may introduce an error
  - Inference may propagate these errors
  - The expanded model may not be more accurate than the original model
- Does not address the fundamental need to act robustly in incompletely-modeled environments

Idea 6: Use Causal Models

- Causal relations are more likely to be robust
  - Require less data to learn
    - [Heckerman & Breese, IEEE SMC 1997]
  - Can be transported to novel situations
    - [Pearl & Bareinboim, AAAI 2011]
    - [Lee & Honavar, AAAI 2013]

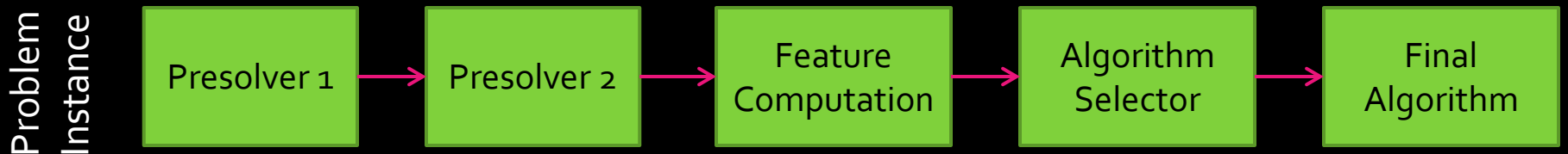
Idea 7: Employ a Portfolio of Models

"We usually know several different ways to do something, so that if one of them fails, there's always another."

--Marvin Minsky

Portfolio Methods in SAT & CSP

- SATzilla:

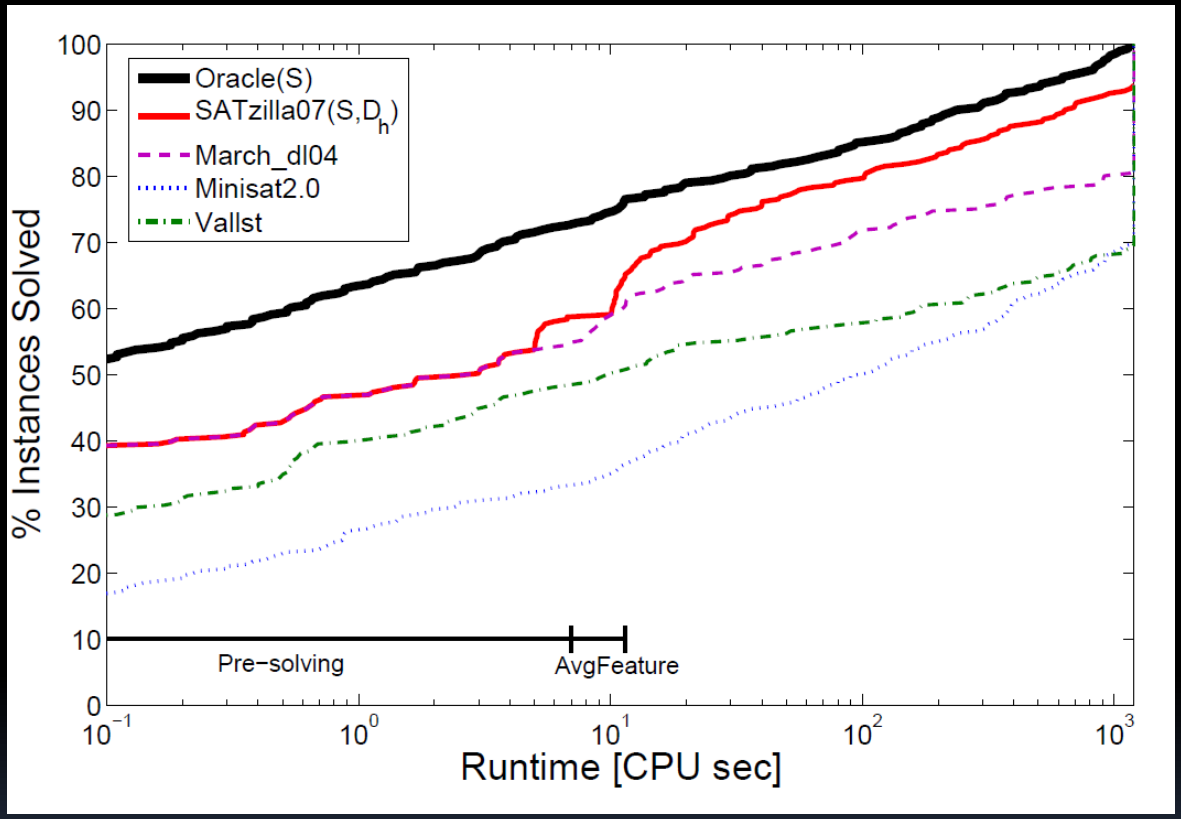


- Xu, Hoos, Hutter, Leyton-Brown [JAIR 2008]

SATzilla Results

- HANDMADE problem set
- Presolvers:
  - March_d104 (5 seconds)
  - SAPS (2 seconds)

Cumulative Distribution

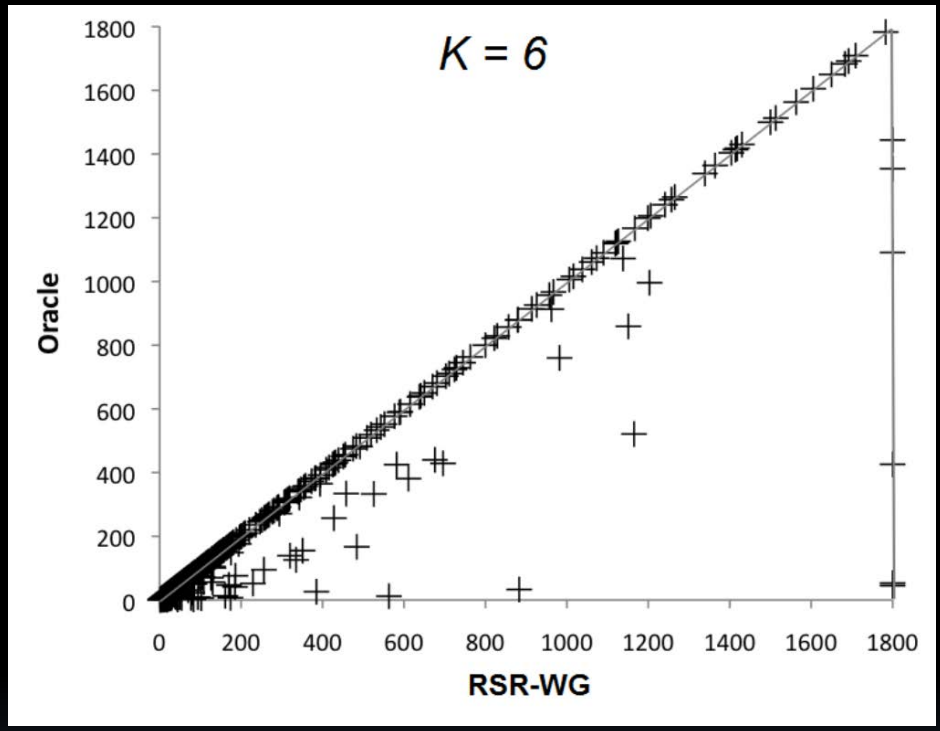


Xu, Hutter, Hoos, Leyton-Brown [JAI R2008]

Parallel Portfolios

- Any task where an algorithm can tell it has a solution
- Race the different algorithms in parallel
- Stop as soon as one algorithm reports a solution

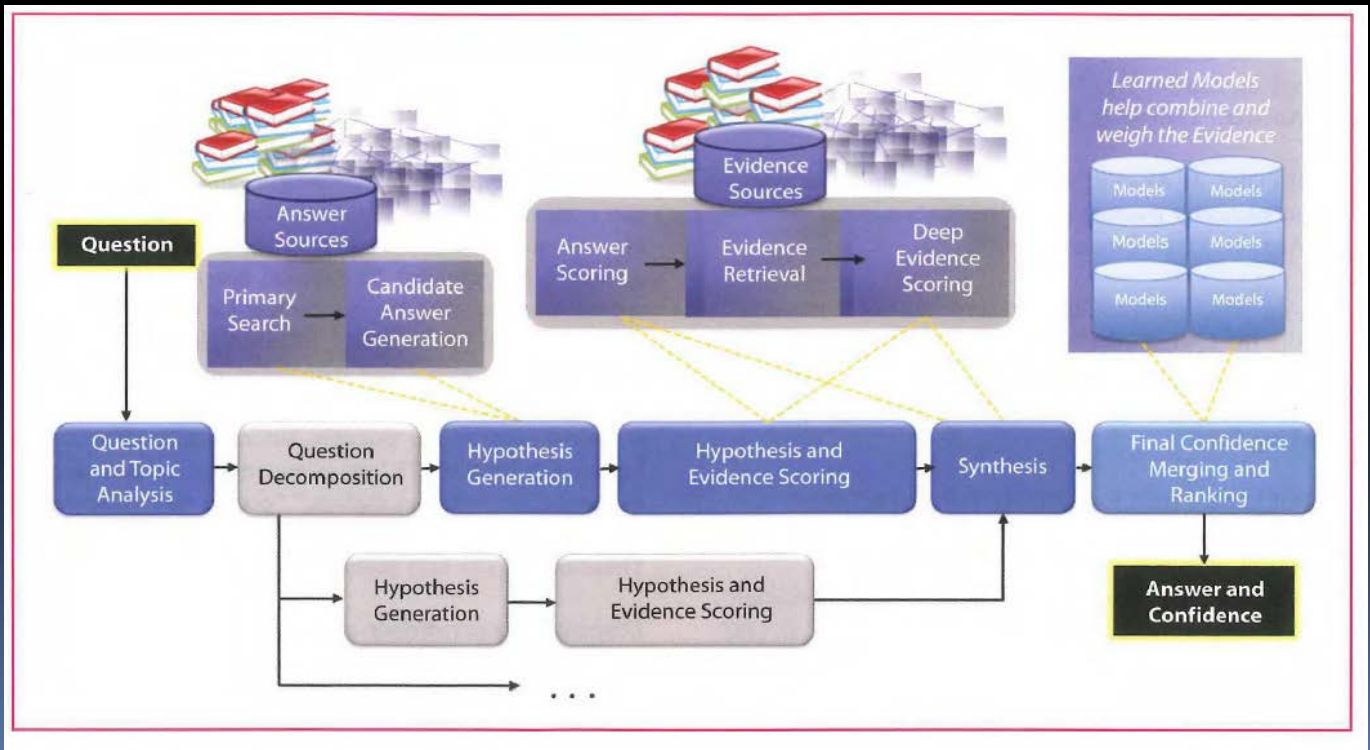
Runtime vs. Oracle



Yu & Epstein [LION 2012]. RSR-WG chooses a subset of methods via machine learning

IBM Watson / DeepQA

- Combines >100 different techniques for
  - analyzing natural language
  - identifying sources
  - finding and generating hypotheses
  - finding and scoring evidence
  - merging and ranking hypotheses



Ferrucci, IBM JRD 2012

Knowledge-Level Redundancy

- Minsky: “You don’t really understand something if you only understand it one way”

- Most AI systems only understand things one way:
  - Computer vision:
    - Object Appearance + human labels
  - Natural Language:
    - Word Co-occurrence statistics + human labels

“a black and white cat is sitting on a chair."

Multifaceted Understanding

- There is a person who is the cat's owner
- That person does not like the cat sitting on the chair
  - The cat is preventing a person from sitting on the chair
    - People often need to sit on chairs
  - The cat leaves hair on the chair
  - The cat is preventing the person from picking up the book
- The cat will soon not be on the chair
- The cat does this often

"a black and white cat is sitting on a chair."

Achieving Multi-Faceted Understanding

- We need to give our computers access to many different forms of experience
  - Performing tasks
  - Achieving goals through natural language dialogue
  - Interacting with other agents
  - Examples:
    - Minsky, “Learning Meaning” [1982 MIT TR]
    - Blum & Mitchell, “Multi-View Learning” [1998]
    - Lake, Salakhutdinov & Tenenbaum [Science 2016]

Idea 8: Watch for Anomalies

- Machine Learning
  - Training examples drawn from $P_{train}(x)$
  - Classifier $y = f(x)$ is learned
  - Test examples from $P_{test}(x)$
  - If $P_{test} = P_{train}$ then with high probability $f(x)$ will be correct for test queries

- What if $P_{test} \neq P_{train}$?

Automated Counting of Freshwater Macroinvertebrates

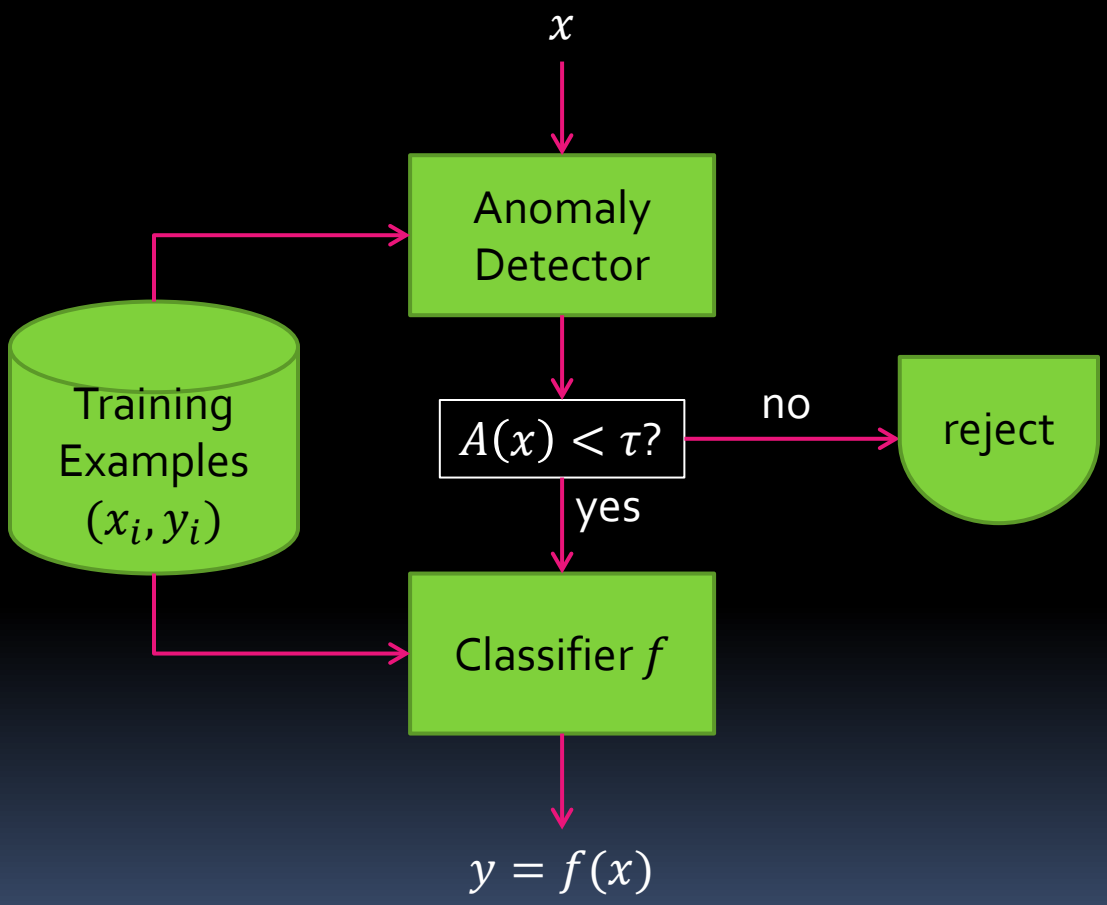
- Goal: Assess the health of freshwater streams
- Method:
  - Collect specimens via kicknet
  - Photograph in the lab
  - Classify to genus and species

www.epa.gov

Open Category Object Recognition

- Train on 29 classes of insects
- Test set may contain additional species

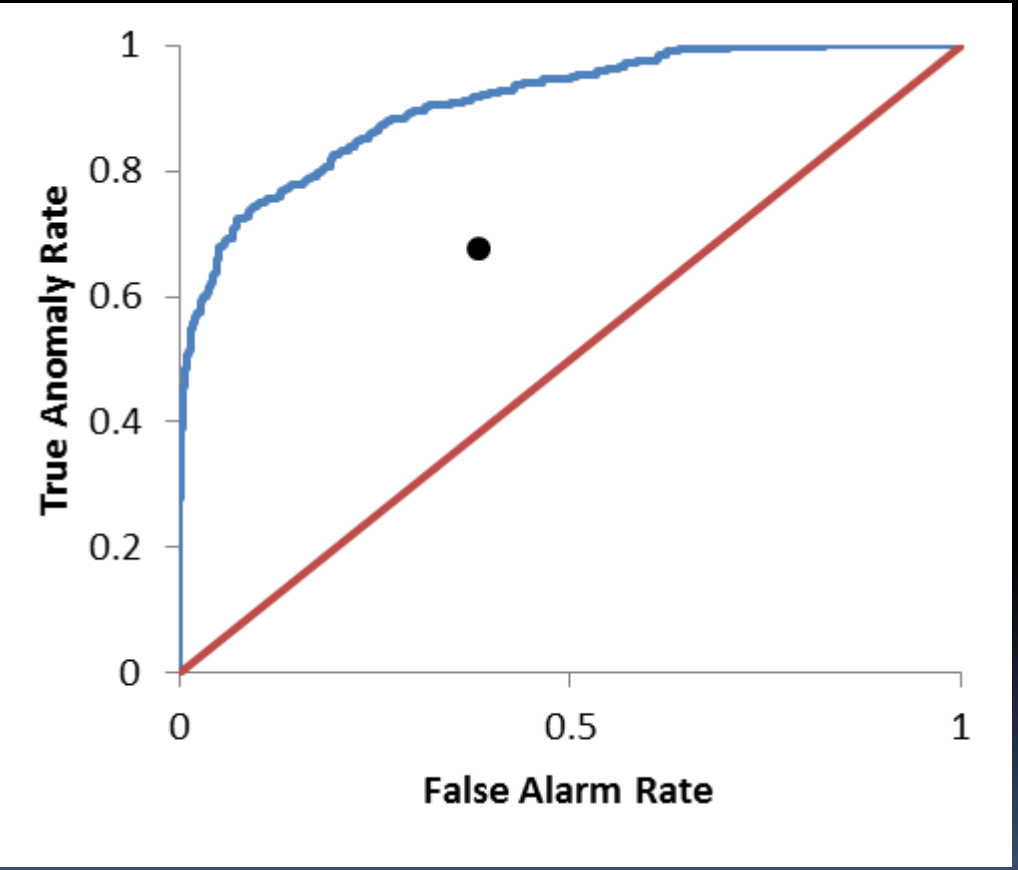
Prediction with Anomaly Detection



Source: Dietterich & Fern, unpublished

Novel Class Detection via Anomaly Detection

- Train a classifier on data from 2 classes
- Test on data from 26 classes
- Black dot: Best previous method



Anomaly Detection Notes

- We initially just used monochrome images
  - Feature selection studies showed this was sufficient
- But color is very useful for detecting novel classes
- Lesson: Use *all* of your features when looking for anomalies

Related Efforts

- Open Category Classification
  - [Salakhutdinov, Tenenbaum, & Torralba, 2012]
  - [Da, Yu & Zhou, AAAI 2014]
  - [Bendale & Boult, CVPR 2015]
- Change-Point Detection
  - [Page, 1955]
  - [Barry & Hartigan, 1993]
  - [Adams & MacKay, 2007]
- Covariate Shift Correction
  - [Sugiyama, Krauledat & Müller, 2007]
  - [Quinonero-Candela, Sugiyama, Schwaighofer & Lawrence, 2009]
- Domain Adaptation
  - [Blitzer, Dredze, Pereira, 2007]
  - [Daume & Marcu, 2006]

Open Questions

- Does robustness of the known model confer robustness to unmodeled variation too?
  - Regularization toward “safer” regions
- When an agent detects that it has entered an anomalous state, what should it do?
  - Is there a general theory of safety?

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Concluding Remarks

High Risk Emerging AI applications

... Require Robust AI Systems

AI systems can't model everything

... AI needs to be robust to "unknown unknowns"

Existing Approaches to Robust AI

- Robustness to Model Errors
  - Robust optimization
  - Regularize the model
  - Optimize a risk-sensitive objective
  - Employ robust inference algorithms
- Robustness to Unmodeled Phenomena
  - Expand the model
  - Learn a causal model
  - Employ a portfolio of models
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We have many good ideas

We need many more!

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Questions?