Reward Bonuses for Efficient, Effective Exploration

(or, KWIK Learners at Play)

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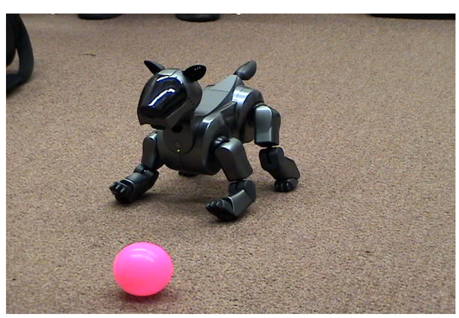
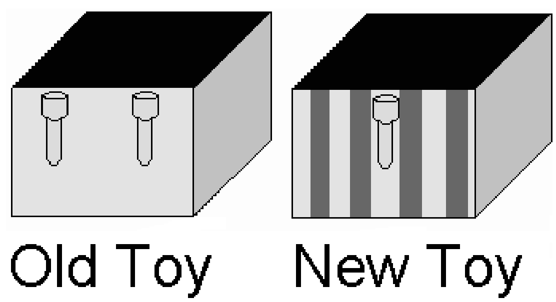
Background (RL^3)

- Creating algorithms that learn to behave.
- Model a learner, design an environment. (Backwards from psychology?)
- Interested in "in principle" learnability.
  - computational and experience complexity



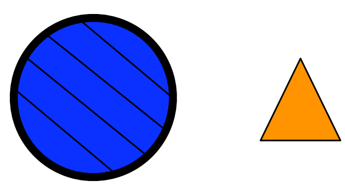
Motivational Data

- Statistics of play sensitive to confounding
- Show kid 2-lever toy (Schulz/Bonawitz 07).
  - Demonstrate both. Kid becomes interested in new toy.
  - Demonstrate them together. Kids stays interested in old toy.
- Experiment design intractable. How can play be computed?



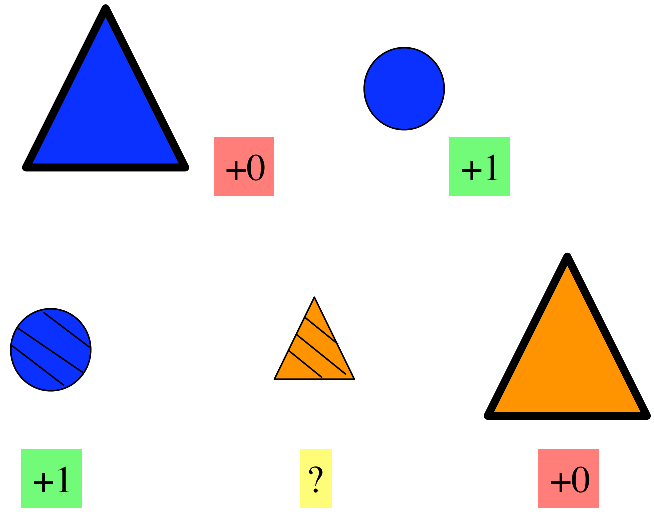
Motivating Example

- Let's imagine the world consists of shapes.
- Four attributes:
  - striped / solid
  - big / little
  - blue / orange
  - circle / triangle



- Each shape is either rewarding +1 or not +0 .
- Critical assumption: *Only one attribute matters.*
- Each round: Select shape from a collection, get the associated reward.

Let's Play



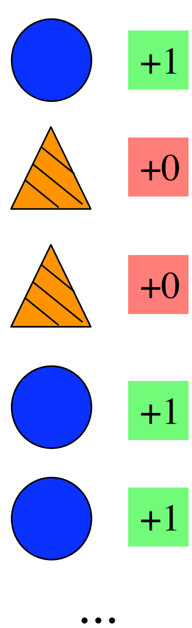
Which to Choose?

- +1 vs. +0 → +1
- +1 vs. ? → +1
- +0 vs. ? → ?
- Like assigning a value of 0.5 to ? and always choosing the highest scoring shape.
- Results in maximum total reward.
- Critical for learner to *know when it knows* the value.
- Contrast with classical machine learning…

PAC Learning

- Classic machine-learning paradigm is PAC (probably approximately correct).
- A learner is efficient in the PAC model if it can make accurate predictions after seeing a small set of labeled examples. Critical assumption: Examples are drawn iid.
- Commits to a single hypothesis based on the statistics of the training examples.
- A vicious adversary can make a PAC learner get very low reward.

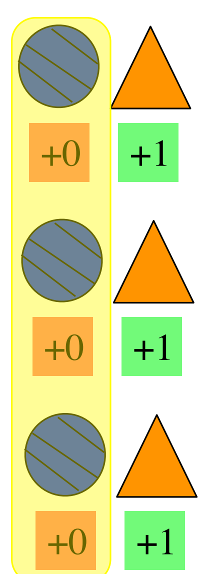
Nasty Example for PAC



PAC learner now picks a hypothesis

Could be:

- blue = +1
- circle = +1
- solid = +1



KWIK Learning

- We devised a different model, which we call KWIK learning (Knows What It Knows).
- A KWIK learner cannot make miscategorization errors, but it can choose not to label some examples.
- However, there is a bound on the number of times the learner can opt out. So, it needs to glean something substantial from each example.
- No training/testing distinction.

Decisions Can Be Hard

- Using a KWIK algorithm and preferences of +1 < ? < +0 leads to optimal decisions.
- Things are not always so simple.
- Let's say each round of the game has an associated reward multiplier.
- Now, it can be better to prefer a ? to a +1 .
- <u>Example</u>: Next trial has a huge multiplier.
- Can formulate optimal behavior in a Bayesian framework–computationally intractable.

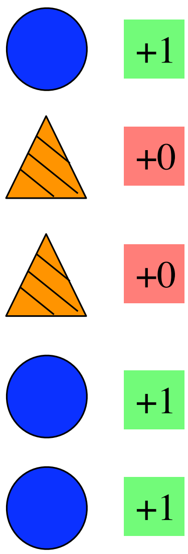
Experience-Efficient Learning

- Decision maker interacts with the world.
- We call an action a "mistake" if it is not a step of a nearly optimal (ϵ-optimal) behavior.
- With high probability ($1-\delta$), the number of mistakes should be small compared to the complexity of the environment.
- Such an approach is "experience efficient".

Implications and Solution

- Easier than if requiring optimal behavior.
- But, still challenging.
- Must balance exploration/exploitation.
- One solution: KWIK learn while behaving assuming ? ≤ +1 < +0 .
  - Adds a reward bonus for exploring.
  - Version of R_{MAX} (Brafman & Tenneholtz)
- If we can KWIK learn it, we can use this information to drive behavior.

RMAX on the Shape Task



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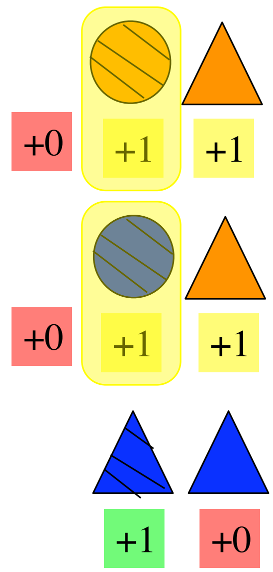
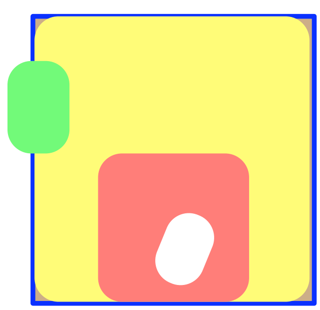
KWIK learner doesn't pick a hypothesis, changing over time.



RMAX Makes a KWIK Escape

Task: Exit room using bird's-eye state representation.



schematic

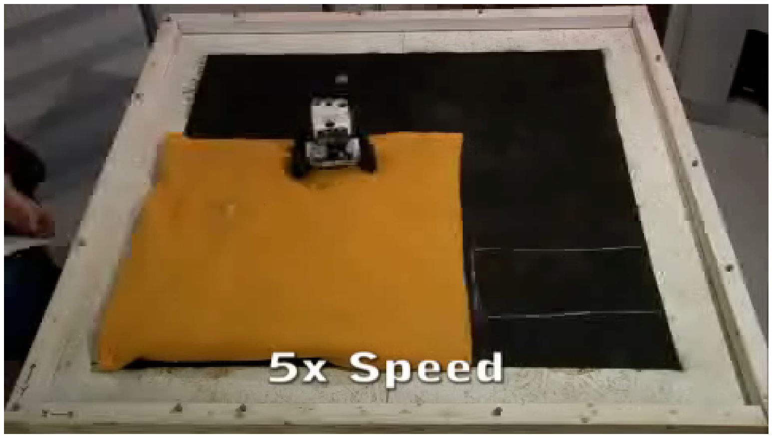
(Nouri)

Details: Discretized 15x15 grid x 18 orientation (4050 states);
6 actions: forward, backward, turn L ,turn R, slide L, slide R.

Prefer unknown to "known bad".

Learn Surface Properties

- Learns the effect of its action on sand and wood. Uses the resulting model to plan shortest path. (Leffler, Edmunds, Littman)



RMAX Observations

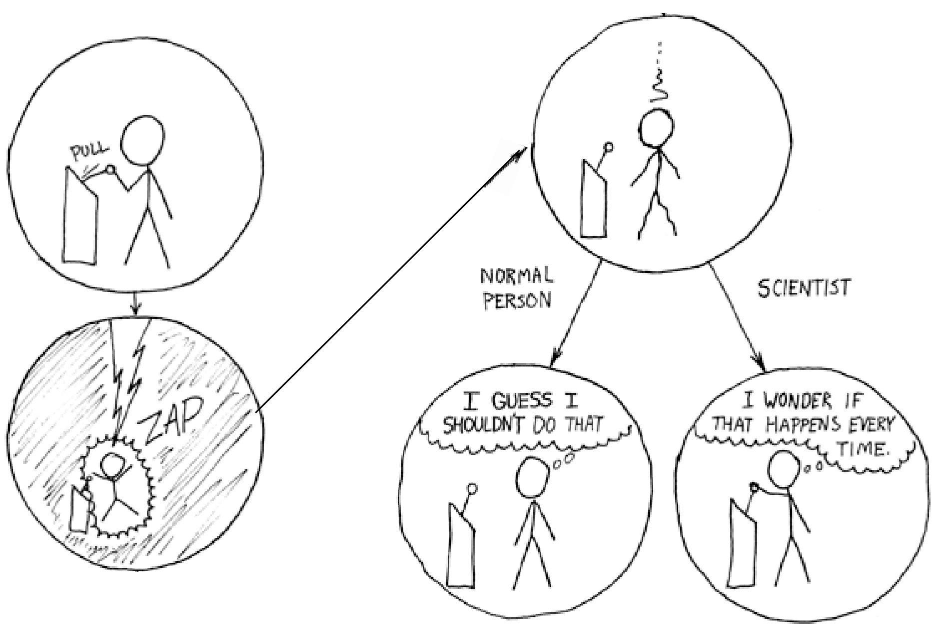
- Actively balance exploration/exploitation.
  - Provable near-optimality, bounded exploration.
- Don't have to make explicit experiments!
  - Difficult, and unnecessary for this objective.
- Works in diverse decision-making algorithms
  - uncertainty put on a value scale
  - decisions driven off of value judgments
- Doesn't "consciously" know if an action is for information or reward gathering.

Final Thoughts

Many hypothesis classes KWIK learnable:

- coin flip probability
- Dynamic Bayes net probabilities given graph
- degree *k* Dynamic Bayes net
- *k* Meteorologist problem
- *k*-CNF
- *k*-depth decision tree
- unions of KWIK-learnable classes

Do People Explore? (xkcd)



Wrap Up

- Goal: Algorithms that learn to behave.
- To provide learning algorithms with guarantees of near-optimality, devised a new learning setting, KWIK.
- The learner can influence exploration/exploitation in a decision maker by adding artificial rewards to unknown states.

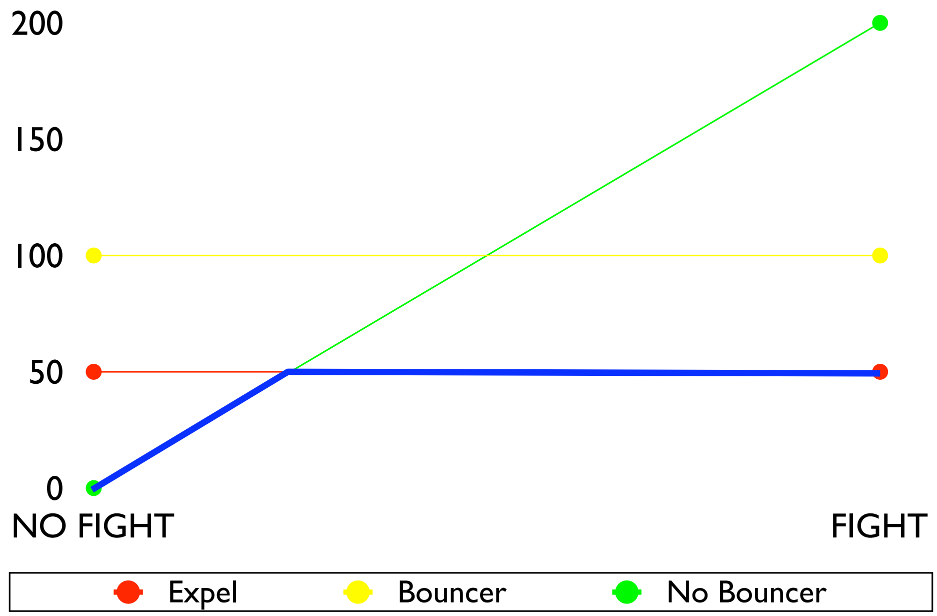
Extended Fanciful Example

We own a bar. There's a collection of n=5 regular customers. One is belligerent (not sure who). One is a peacemaker (not sure who). Each night, we see who comes to the bar. A fight breaks out if the belligerent one is there and the peacemaker is not.

After we see who has arrived, we can:

- Pay $100 for a <u>bouncer</u> who will stop a fight as soon as it breaks out.
- Pay $200 to repair the bar if a fight breaks out and <u>no bouncer</u> was hired.
- Pay $50 in opportunity cost and <u>expel</u> the whole group before they even enter the bar.

Costs of Choices By Outcome



Example Interaction

- [0,2,3]
  - no fight
- [1,3]
  - no fight
- [3]
  - *no fight*
- [0,3,4]
  - fight
- [2,3]
  - *no fight*
- [1,2,4]
  - *no fight*
- [0,4]
  - *fight*
- [0,2,3,4]
  - no fight
- [1,3,4]
  - no fight
- [0,2,4]
  - *no fight*
- [0,1]
  - *fight*
- [1,2,3,4]
  - *no fight*
- [1,4]
  - *no fight*

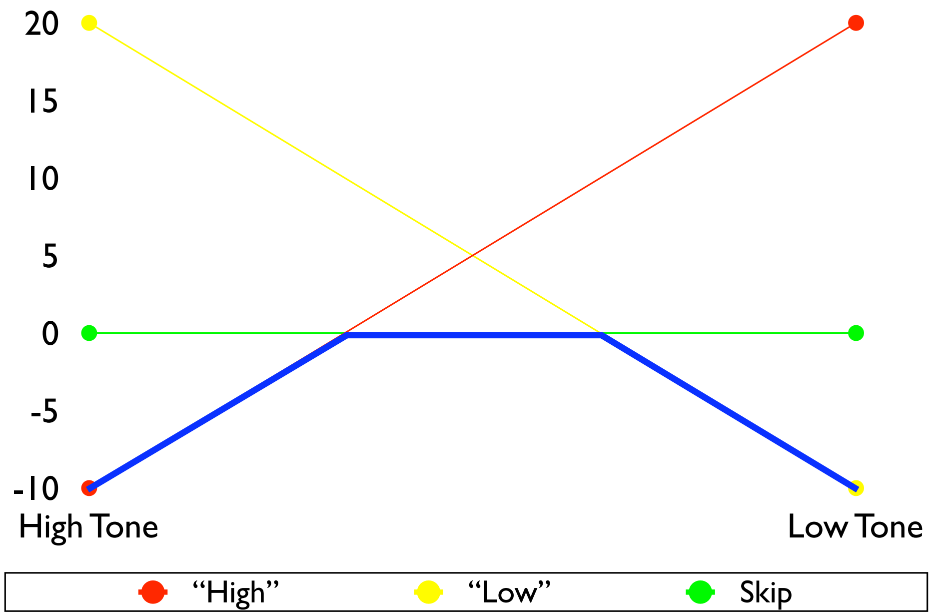
KWIK Bound

- Will pay bouncer ("don't know") no more than $n(n\text{-}1)$ times. Might overpay by $100.
- Every other trial is optimal!
- Same overpay cost as active learning, in spite of the lack of control over the examples.
- Better than mistake bound or PAC approaches.

Some KWIKer Than Others

- Given a classification task with a high cost of being wrong, can a subject learn to choose an "I don't know" response to move on to a new question?
  - Porpoises, spider monkeys, people can do it.
  - Rats* and pigeons haven't.
- Not really the same… "I don't know" is actually the right answer for some inputs. (Not part of learning, per se.)

Costs of Choices By Outcome



Building Block for Learning

- One scenario of general interest follows.
- Imagine learner can perceive a set of candidate causes.
- Imagine it knows that exactly one is responsible for the output.
- Concretely,
  - *n*-bit input, one bit (unknown) controls output
  - one output distribution if bit is on, another if off
  - Learn complex structure by same idea: one hypothesis controls output...

Why So Hard?

- Given the data, you can estimate the probability the output is 1 given any of the input bits. Even the wrong ones.
- Which should we believe?
- One with lowest prediction error.
- If two bits are correlated, prediction error will be similar... Need to notice when they

Exploring Approximations to Models of Exploration

apologies to Adam Sanborn

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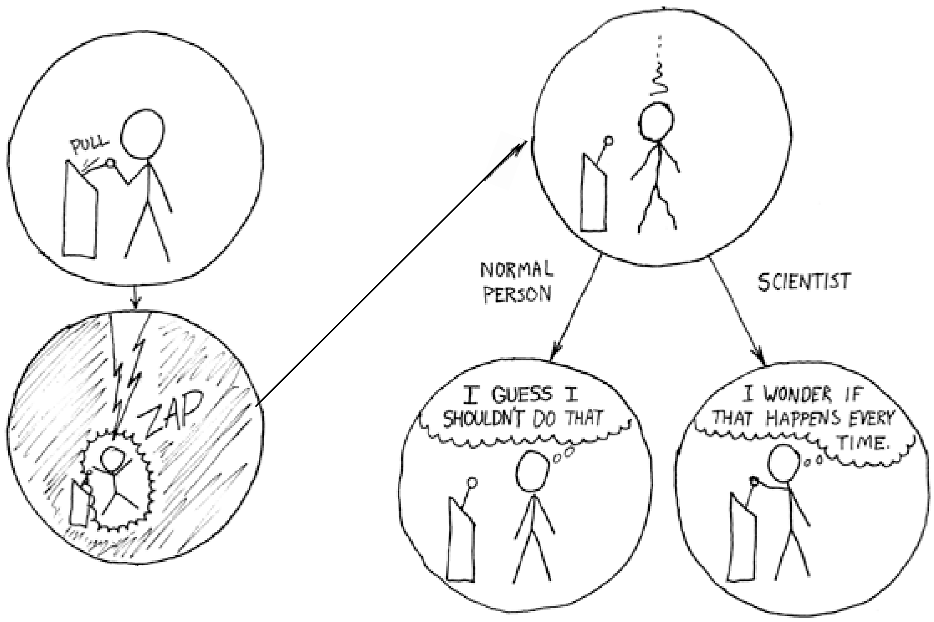


Importance of Exploration

- Exploring is risking low-outcome decisions to obtain high-outcome decisions.
  - Necessary for finding optimal decisions.
  - Probably needed for finding satisficing decisions.
- Perhaps a higher order decision.
- Can interact with representation issues.
- What could happen? What will happen?

Demo

- win the mystery game...

Comparison

- Taxi problem (Dietterich)
- Taxi: How long until optimal behavior?

Exploration style	Algorithm	# of steps
epsilon greedy	Q-learning	47157
count on states	Flat Rmax	4151
count on features	Factored Rmax	1839
count on interaction	Objects	143
whatever people do	People	50

Views of Exploration

- Ad hoc: Trying something crazy now & then.
- Bayesian: Act optimally given current uncertainty and future information.
- PAC-MDP: Act near optimally (w.h.p.) on all but a small number of steps.
- Regret: Converge to optimal, total loss grows slowly.

None quite right.

Demo #2

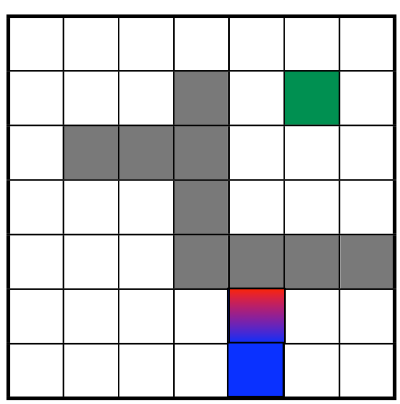
- What do you learn?

PAC-MDP

- Can exploit the structure to learn fast!
  - Knows nothing matters: Rmax.
  - Know some feature matters: RAM-Rmax.
  - Knows which feature matters: RAM-Rmax.
  - Know the wall: No learning needed.
- KWIK learning underlies fast learners.
- *Enthymematic*!
  - Where do these assertions come from?
  - What if they hold only partially?

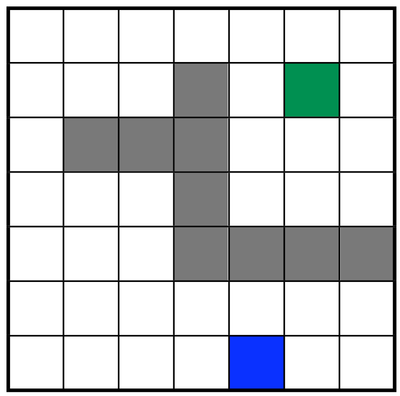
It's Not Easy Getting Creamed

- Standard PAC-MDP algorithms can't say:
  - I know you told me all states independent,
  - but every wall I've seen has been painful.
  - Can I just walk around now, please?



PAC-MDP with Bayesian Priors

- With a prior that all similar colored squares are the same, we can bound the chance generalization will lead to sub-optimality.
- Idea: Don't worry about it if it's small!



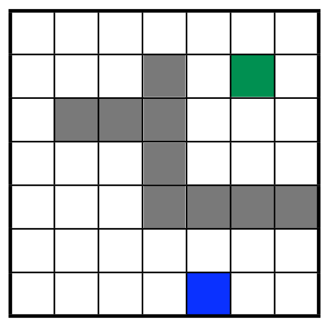
BOSS: Algorithmic Approach

- Maintain a posterior.
- Sample models from the posterior.
- Solve each one.
- Assume the best of sampled set is right.
- Act accordingly until something surprising.

- If set big, guarantee near optimality (whp).

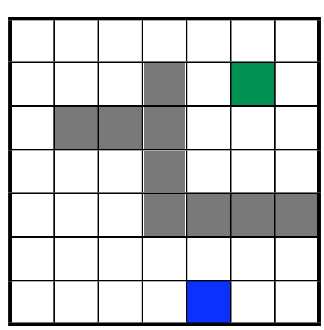
Priors Change Learning Alg

- Gray always wall: No learning
- Each gray independent: Rmax
- Grays always like each other: RAM-Rmax
- Sometimes independent/not: New alg.



Learn Prior: Learn to learn

- These priors themselves can be learned.
- Techniques like those discussed earlier in a "transfer" setting seeing related problems.



Conclusion

- Humans don't solve NP hard problems.
- Observations of impressive behavior imply we've framed the problem wrong.
- Happily "stealing" from cognitive science to create better learning algorithms.