Reward Bonuses for Efficient, Effective Exploration  
(or, KWIK Learners at Play)

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Background (RL³)

• 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 $+1$.
• Example: 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 ($\epsilon$-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 $\leq +1 < +0$.
  - Adds a reward bonus for exploring.
  - Version of $R_{\text{MAX}}$ (Brafman & Tenneholtz)
- If we can KWIK learn it, we can use this information to drive behavior.
**R_{MAX} on the Shape Task**

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

**R_{MAX} Makes a KWIK Escape**

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

*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”. 

(Nouri)
Learn Surface Properties

• Learns the effect of its action on sand and wood. Uses the resulting model to plan shortest path.

  (Leffler, Edmunds, Littman)

R_{MAX} 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 bouncer who will stop a fight as soon as it breaks out.
• Pay $200 to repair the bar if a fight breaks out and no bouncer was hired.
• Pay $50 in opportunity cost and expel 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]
  - no fight
- [0,1]
  - fight
- [1,2,3,4]
  - no fight
- [1,4]
  - no fight
- [0,2,4]
  - no fight
KWIK Bound

• Will pay bouncer (“don’t know”) no more than \( n(n-1) \) 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.)
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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Do People Explore? (xkcd)

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?

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<th>Exploration style</th>
<th>Algorithm</th>
<th># of steps</th>
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<td>epsilon greedy</td>
<td>Q-learning</td>
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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.