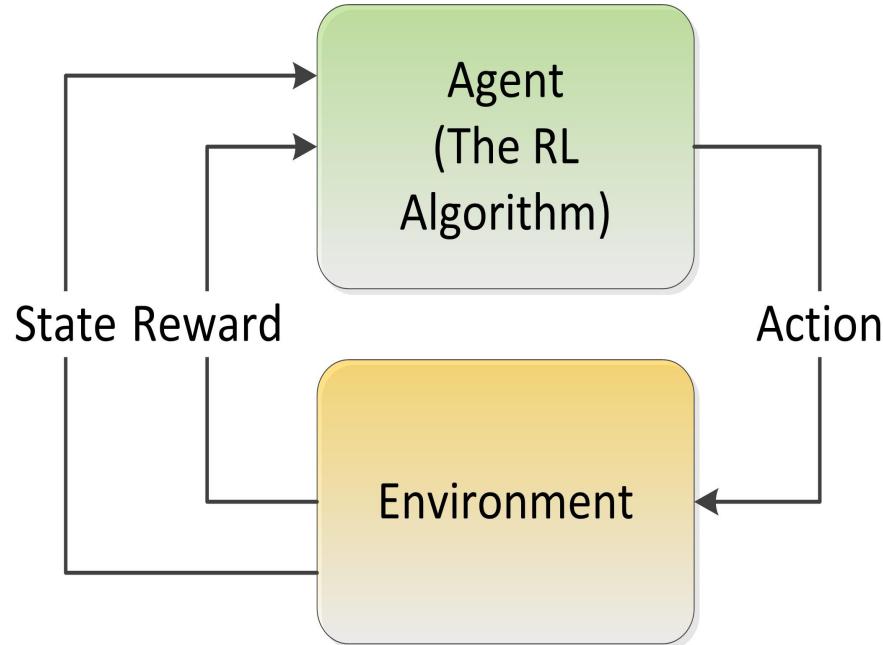
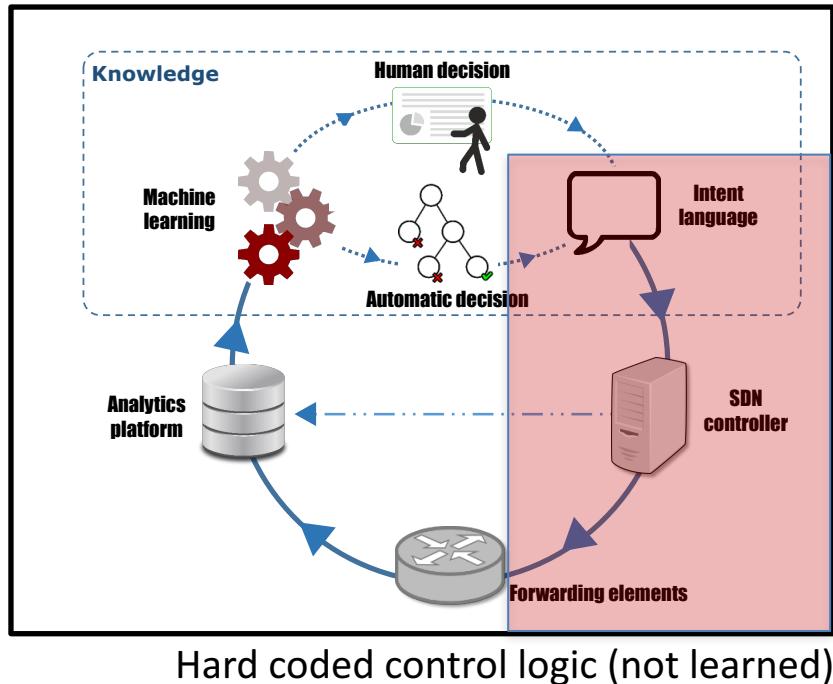


# So What Do We Need To Do?

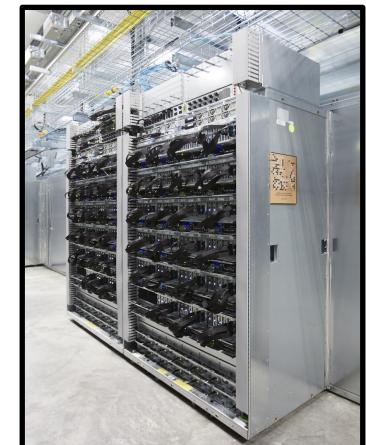
- Find a Useful Theory of Networking
  - As opposed to ad-hoc approaches
  - Again, consider the success of convolutional neural networks
  - What is the “interlingua” for networking?
- Public Data Sets
- Skill Sets
  - But watch out
  - <https://papers.nips.cc/paper/5656-hidden-technical-debt-in-machine-learning-systems.pdf>
- Apply state of the art machine learning algorithms
- Build ML platforms and associated automation
- Explainable end-to-end systems
- Learn control not just prediction

# Learning Control?

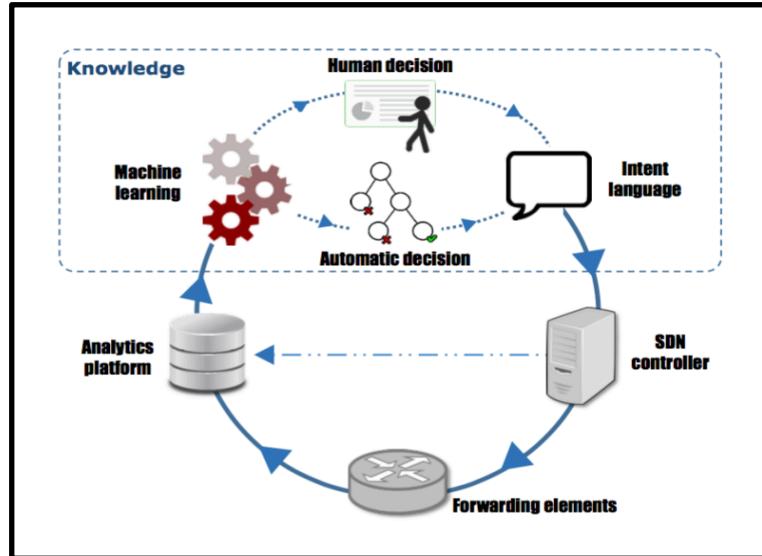
*Reinforcement Learning Meets Monte Carlo Tree Search and Deep Learning*



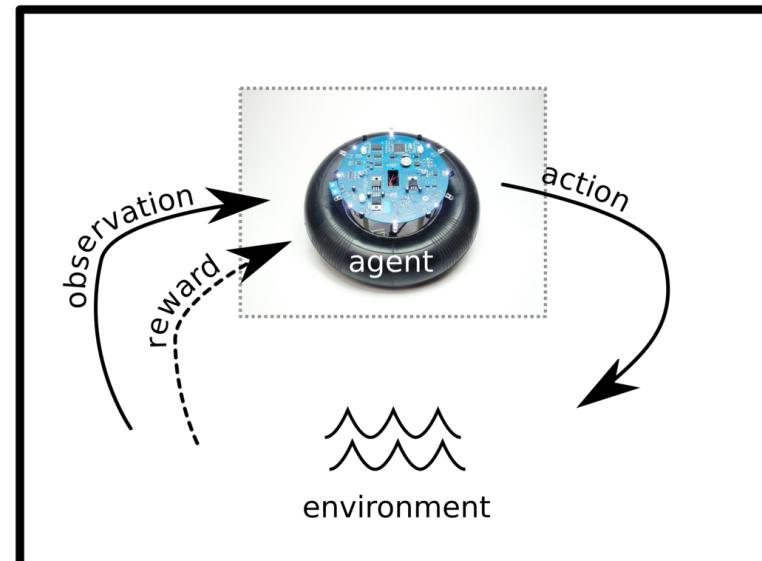
- Security: Agent can learn dynamic/evolving behavior of adversary
- DevOPs: Agent can learn workflow automation (e.g. Openstack Mistral)
- Orchestration: Agent can learn dynamic behavior of VNFs/system
- Deep policy net,  $\pi(s) = a, s \in S, a \in A(s)$ , can capture human intuition



# Static vs. Reinforcement Learning Architectures



- Today's Static ML Architectures
  - ML doesn't have "agency"
  - Hard-coded or open loop control
- Learns prediction
- **Doesn't learn control**
- Assumes stationary DGD
- Largely off-line



- Reinforcement Learning Architecture
  - Agent architecture
  - **Agent learns control/action selection**
- Adapts to evolving environment
- Non-stationary distributions
- *Network gamification*

# Summary

- Lots of Network Data
  - Standardized and labeled datasets still scarce
  - However, most network data sources (e.g., netflow) not designed for ML
  - Arbitrary data might be over-valued
- Lots of open source ML frameworks, Cloud APIs, Examples, ...
  - Google -- Tensorflow ([tensorflow.org](https://tensorflow.org))
  - Facebook -- Torch ([torch.ch](https://pytorch.org))
  - Microsoft -- CNTK (<https://github.com/Microsoft/CNTK>)
  - Amazon -- MXNET (<https://aws.amazon.com/mxnet>)
  - Other popular frameworks
    - Keras (<https://keras.io/>)
    - Theano (<https://github.com/Theano>)
    - ...
- However, networking industry still dominated by MLwashing, platforms, clustering, ...
- Skills gap persists and it still requires skill/experience to
  - Build DNN architectures/models
  - Find "good" settings for hyper-parameters
  - Prevent overfitting
  - But again, be careful: SOTA LSTMs+RLs are starting to be able to build neural networks
    - <https://openreview.net/pdf?id=r1Ue8Hcxg>, <http://papers.nips.cc/paper/6461-learning-to-learn-by-gradient-descent-by-gradient-descent.pdf>, ...
  - ...
- All of this said, you *will* be seeing ML in all facets of networking
  - And everything else for that matter

# So Call To Action

## Where Do We Need To Focus?

- Find a Useful Theory of Networking
  - As opposed to ad-hoc approaches
  - Again, consider the success of convolutional neural networks
  - What is the “interlingua” for networking?
- Public Data Sets
- Skill Sets
- State of the art machine learning algorithms
- ML platforms and associated automation
- Explainable end-to-end systems
- Learn control not just prediction
  - Reinforcement Learning
  - Evolution Strategies (<https://blog.openai.com/evolution-strategies>)
  - Others?

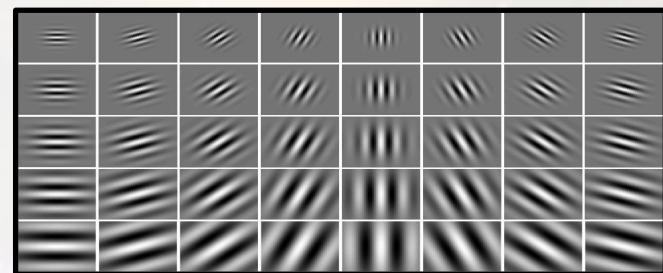
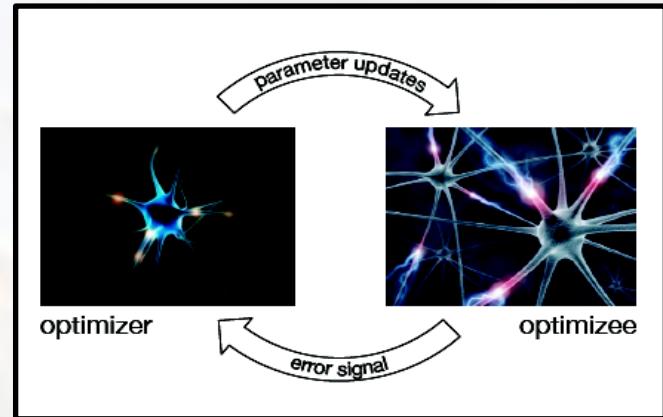
# Finally...Many Beautiful Mysteries Remain

- Back-propagation
  - Gradient-based optimization/back-propagation
  - Why is such a simple algorithm so powerful?
  - New optimizer/optimizee paradigms
    - AlphaGo
      - <https://deepmind.com/research/alphago>
    - Adversarial Images/Generative Adversarial Nets (GANs)
      - <https://arxiv.org/abs/1412.6572>
    - Learning to learn by gradient descent by gradient descent
      - <https://arxiv.org/abs/1606.04474>
    - Neural Architecture Search With Reinforcement Learning
      - <https://openreview.net/pdf?id=r1Ue8Hcxg>
- Neural Nets
  - What are the units (artificial neurons) actually doing?
    - <https://arxiv.org/pdf/1509.06321.pdf>
- Why does deep and cheap learning work so well?
  - Physics perspective
  - <http://arxiv.org/pdf/1608.08225v1.pdf>

$x$   
"panda"  
57.7% confidence

$\text{sign}(\nabla_x J(\theta, x, y))$   
"nematode"  
8.2% confidence

$x + \epsilon \text{sign}(\nabla_x J(\theta, x, y))$   
"gibbon"  
99.3 % confidence



- So how many 28x28 grayscale images are there?
- Say there are 8 bits of grayscale  $\rightarrow 256^{784}$  possible images
- Our autoencoder had 156800 parameters and  $156800/256^{784} \approx 0$
- So how can a simple autoencoder find the MNIST subspace?