

Machine Learning – Lecture 22

Wrapping Up

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Bastian Leibe

RWTH Aachen

<http://www.vision.rwth-aachen.de>

leibe@vision.rwth-aachen.de

Announcements

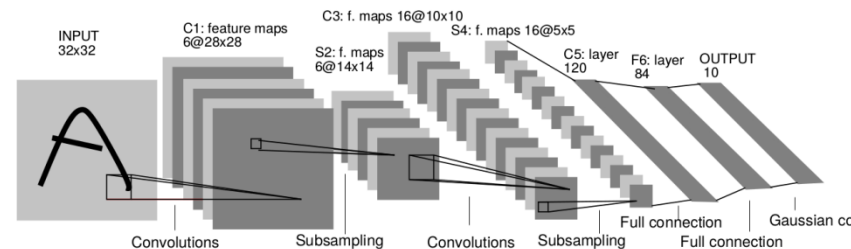
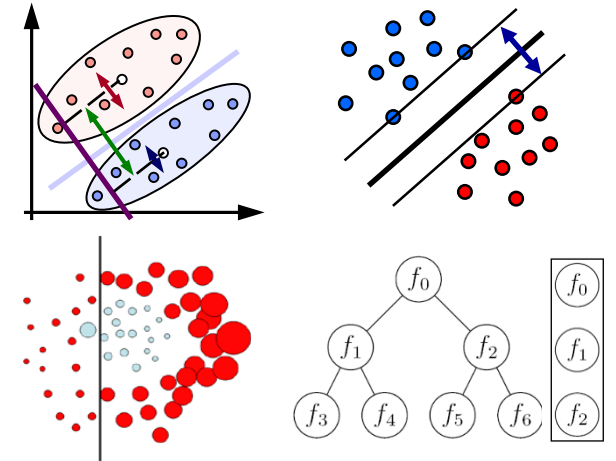
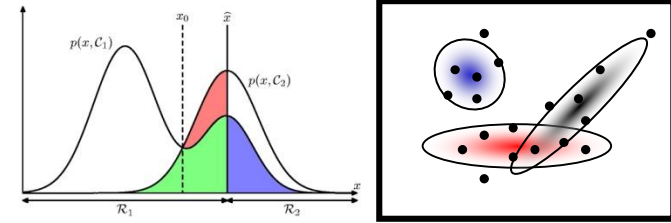
- Exam details
 - For everybody registered, we will send around detailed information (precise starting time, room assignments) about 1 week before the exam.
- For those who could not register for technical reasons
 - You may participate in the exam conditioned on approval by your degree program's examination board.
 - It is your responsibility to ask your examination board what conditions they impose
 - Most boards demand that you file a written request before the exam date
 - We have created a registration poll on the moodle, where you can sign up for the 1st or 2nd exam date to participate in the exam.
 - *We need this information in order to allocate sufficient space!*

Announcements (2)

- For exchange students only
 - For those of you who need to leave Aachen before the date of the first exam, we will offer several special oral exam slots.
 - An announcement has been sent by email, please sign up on the corresponding Doodle poll.
 - *We will send around an assignment to exam slots by middle of next week.*

Course Outline

- Fundamentals
 - Bayes Decision Theory
 - Probability Density Estimation
- Classification Approaches
 - Linear Discriminants
 - Support Vector Machines
 - Ensemble Methods & Boosting
 - Random Forests
- Deep Learning
 - Foundations
 - Convolutional Neural Networks
 - Recurrent Neural Networks
 - **Current Research Directions**

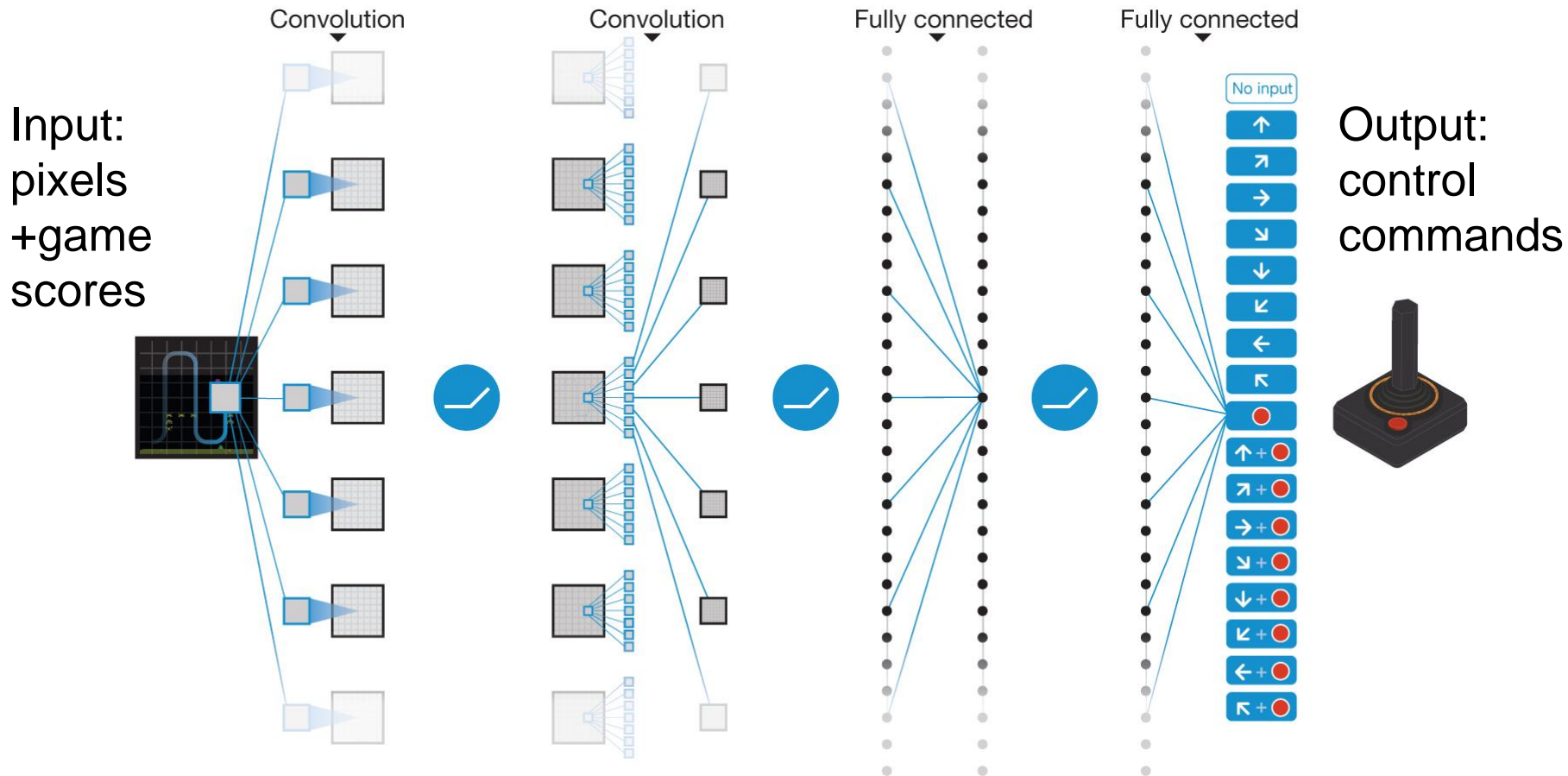


Currently Hot Research Directions

- Generative Models
 - Networks for image generation
 - Generative Adversarial Networks (GAN)
- Towards General Models of Computation
 - Memory Networks
 - Neural Turing Machines
- Deep Reinforcement Learning

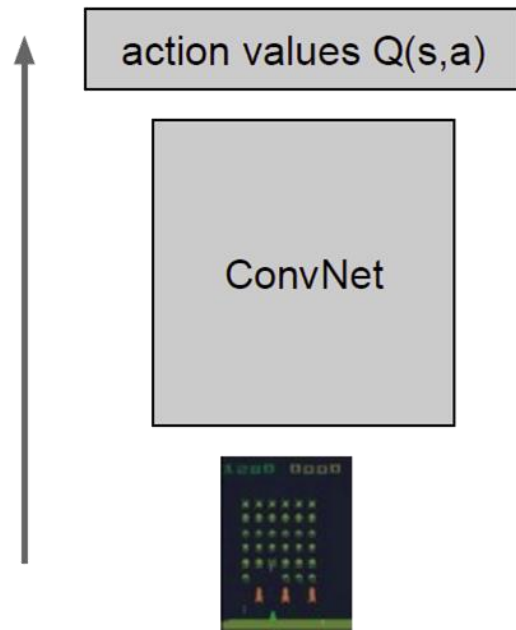
Deep Reinforcement Learning

- Example application: Learning to play Atari games



V. Mnih et al., [Human-level control through deep reinforcement learning](#), Nature Vol. 518, pp. 529-533, 2015

Idea Behind the Model



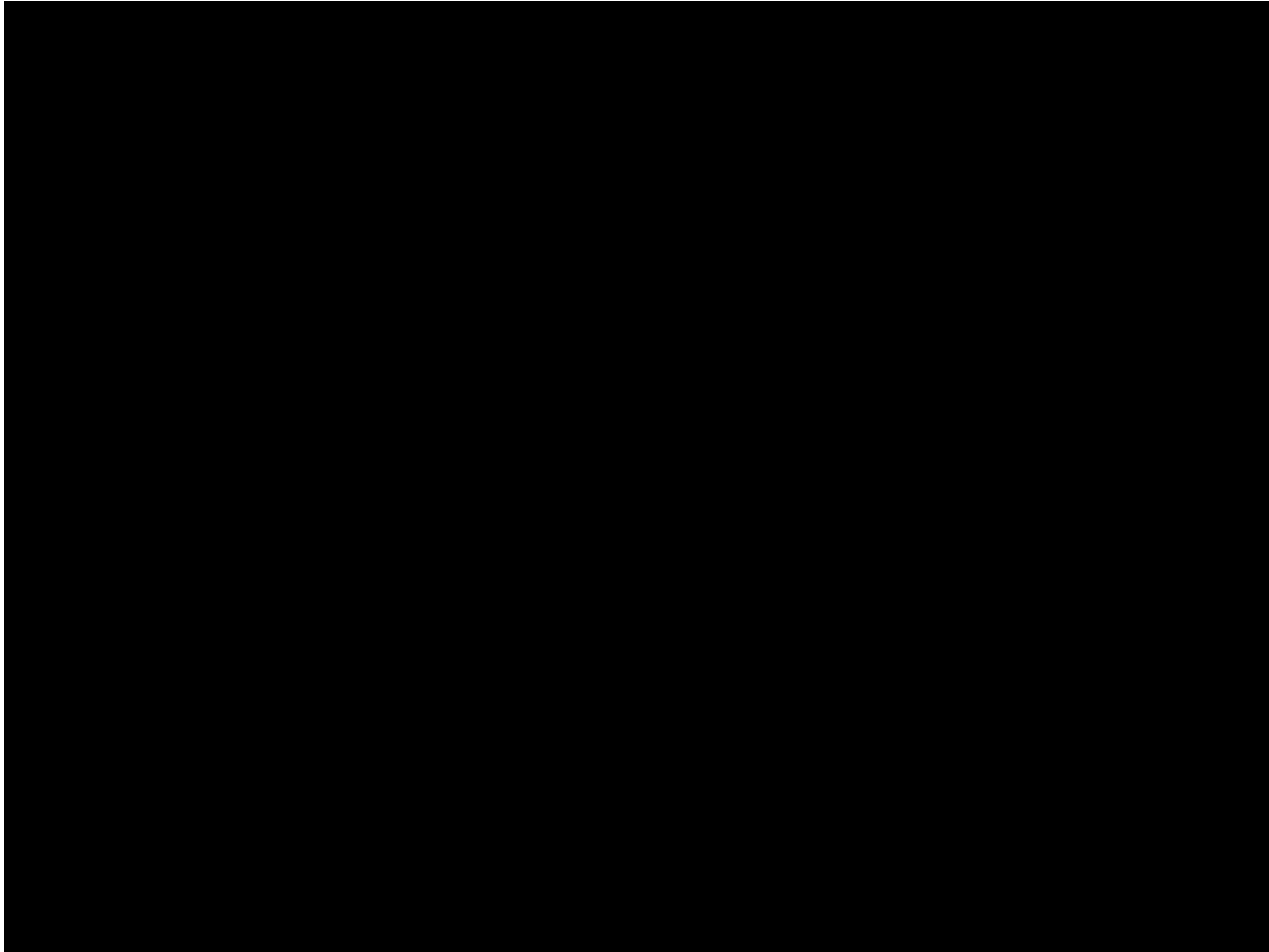
- Interpretation
 - Assume finite number of actions
 - Each number here is a real-valued quantity that represents the **Q function** in Reinforcement Learning
- Collect experience dataset:
 - Set of tuples $\{(s,a,s',r), \dots\}$
 - (State, Action taken, New state, Reward received)

• L2 Regression Loss

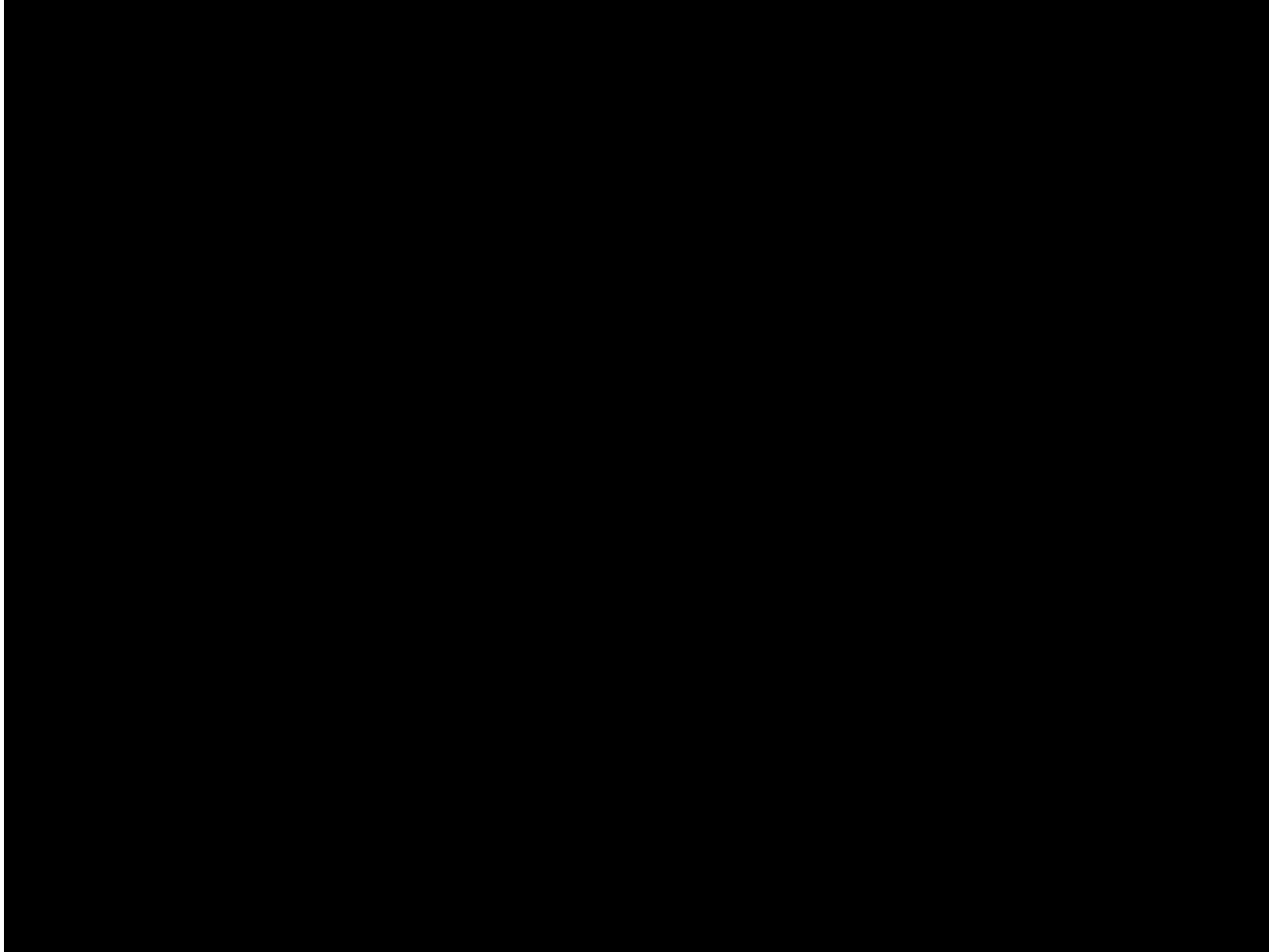
$$L_i(\theta_i) = \mathbb{E}_{(s,a,r,s') \sim \mathcal{U}(D)} \left[\left(\overset{\text{target value}}{\boxed{r + \gamma \max_{a'} Q(s', a'; \theta_i^-)}} - \overset{\text{predicted value}}{\boxed{Q(s, a; \theta_i)}} \right)^2 \right]$$

Current reward + estimate of future reward, discounted by γ

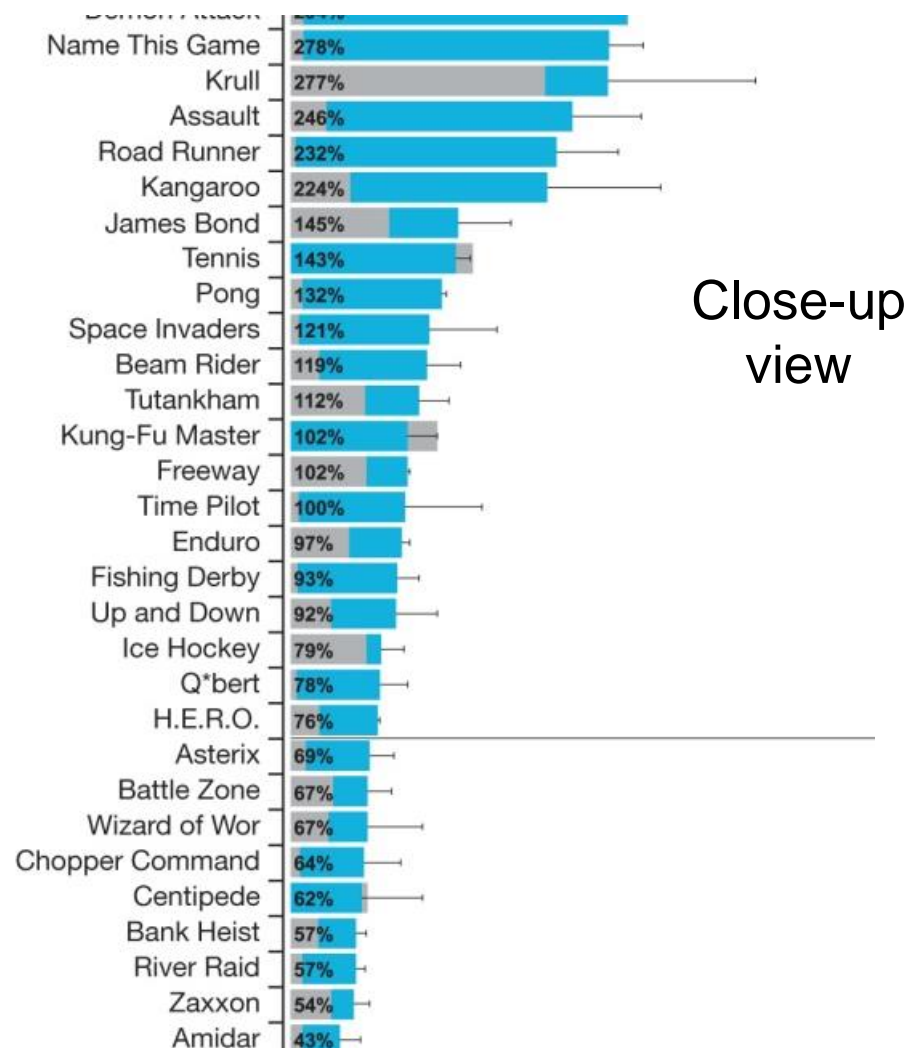
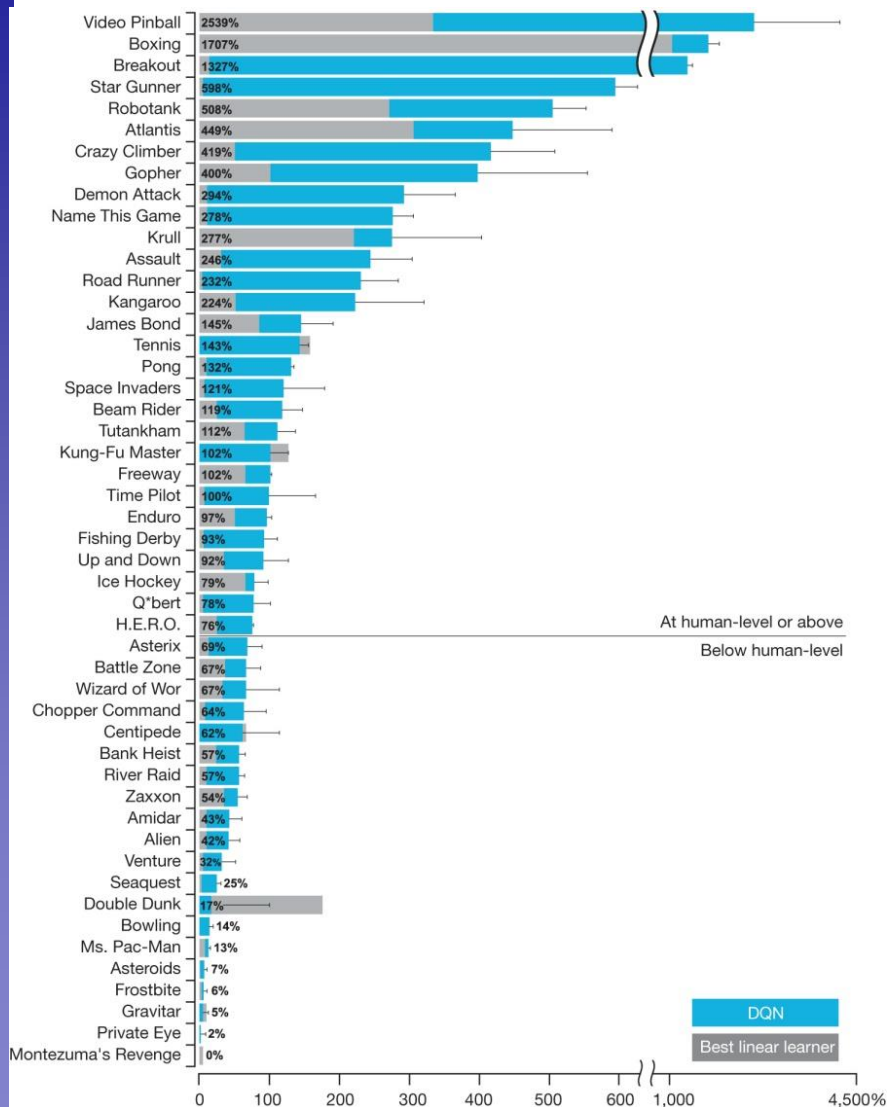
Results: Space Invaders



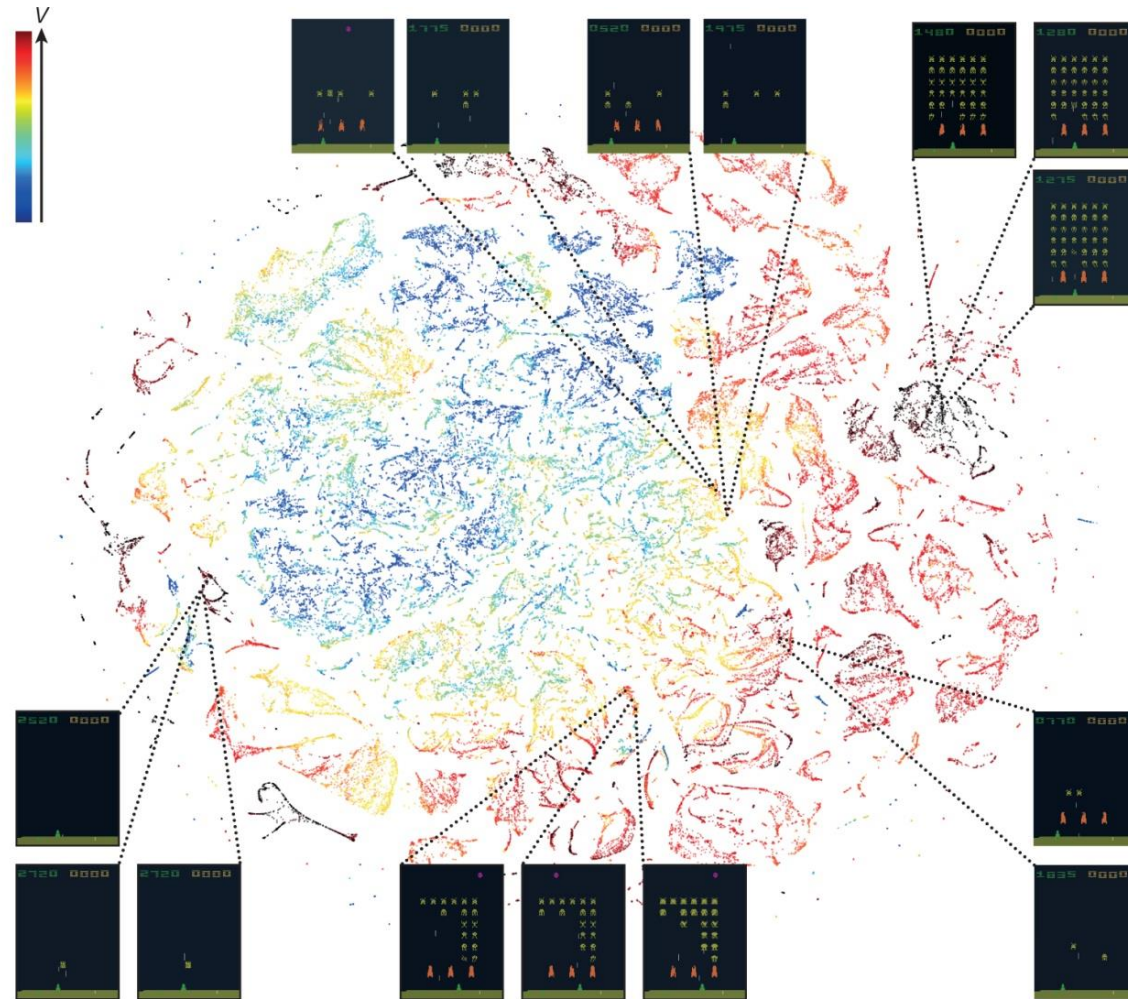
Results: Breakout



Comparison with Human Performance



Learned Representation



- t-SNE embedding of DQN last hidden layer (Space Inv.)

Success Story: Alpha Go



Applications: Autonomous Driving

- Reinforcement Learning

- Learning to drive purely by RL is actually not such a good idea...
- ...at least not in real traffic.



- Working in a simulated environment can help keep down the cost, but...

- The environment needs to be realistic enough and needs to include realistic behaviors by other traffic participants.
- *If we already have good models for such realistic driving behavior, what do we then actually need RL for?*
- RL will only teach us acceptable driving behavior (within the bounds of the reward function), it will not teach us good driving.
- *Better: Learning from humans*

Example Driving Simulator: CARLA



A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, V. Koltun, [CARLA: An Open Urban Driving Simulator](#), CoRL 2017.

Imitation Learning



(a) Aerial view of test environment



(b) Vision-based driving, view from onboard camera



(c) Side view of vehicle

- Imitation Learning
 - Learn from demonstrations of human driving
 - But... we cannot fully imitate the human behavior, since we may want to drive to a different location
- Conditional Imitation Learning
 - Learn driving behaviors directed by high-level commands

F. Codevilla, M. Mueller, A. Lopez, V. Koltun, A. Dosovitskiy, [End-to-end Driving via Conditional Imitation Learning](#), ICRA 2018.

Imitation Learning

End-to-end Driving via Conditional Imitation Learning

Felipe Codevilla, Matthias Mueller, Antonio Lopez, Vladlen Koltun, Alexey Dosovitskiy

ICRA 2018

F. Codevilla, M. Mueller, A. Lopez, V. Koltun, A. Dosovitskiy, [End-to-end Driving via Conditional Imitation Learning](#), ICRA 2018.

References and Further Reading

- DQN paper
 - www.nature.com/articles/nature14236
- AlphaGo paper
 - www.nature.com/articles/nature16961

