Deep Reinforcement Learning and Transfer Learning with Flappy Bird

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Motivation

Reinforcement learning is a technique for solving certain decision tasks where an agent learns how to act in a real world environment. In recent years, major breakthroughs in RL have come from common video games. Since we grew up playing tons of video games, we wanted to explore the applicability of RL to the games Flappy Bird and Pixel Copter.

Problem

- We wish to use reinforcement learning to play the games Flappy Bird and Pixel Copter, determining whether RL can beat us and/or an expert in score.
- Q-learning does not generalize well to large state spaces, since many states would be left unexplored. We can use **deep Q-learning**, which uses a neural network to approximate the Q-value function and allows us to generalize to unseen states.
- Instead of using the game's screen as input, we use **feature engineering**, which allows us to achieve the same level of performance without having to train a CNN to learn features for each game.
- We also aim to explore the impact of **transfer learning** to our task. In our case, transfer learning would be starting an instance of Pixel Copter training with weights already trained on Flappy Bird.

Challenges

- Training required extensive time and compute
  - Opted to forgo image input and use feature engineering instead
- Difficult to pull together several packages for this task
  - Used ALE, PLE, Keras-rl, OpenAI Gym, tensorflow
- Transfer learning was traditionally used for CNNs
  - Changed observation spaces of both games to be as similar as possible
- Couldn't use lots of data we collected since we changed our training and testing process several times

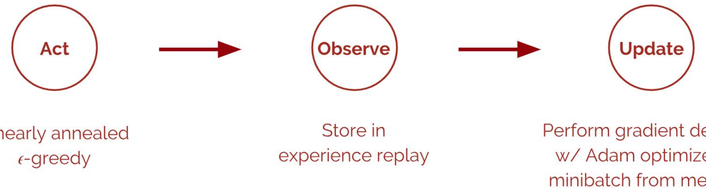
References

- Mnih, Volodymyr, et al. "Playing atari with deep reinforcement learning." *Neural Information Processing Systems*. (2013).
- Taylor, Matthew E., and Peter Stone. "Transfer learning for reinforcement learning domains: A survey." *Journal of Machine Learning Research* 10.Jul (2009): 1633-1685.
- Watkins, Christopher JCH, and Peter Dayan. "Q-learning." *Machine learning* 8.3-4 (1992): 279-292.

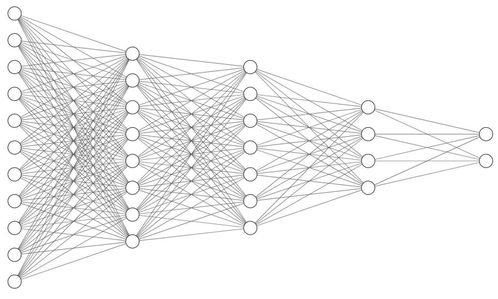
Methods and Models

Deep Q Learning with experience replay
We use a neural network to approximate the Q function, and perform weight updates based on mini batches drawn from a cache of (s, a, r, s') tuples.

For each episode, we do:



Neural Network Architecture
- Input in R^{11} and output in R^2, which are the Q-values for the two actions, **jump or not jump**.
- Each hidden layer pictured here has dimensionality of $2^{\text{num nodes pictured}}$
- The input layers and hidden layers are followed by **ReLU layers**, while the last layer is followed by a **linear activation layer**.



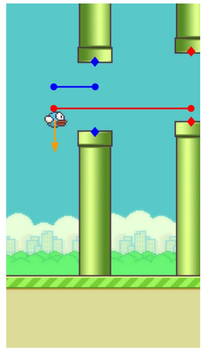
Feature Engineering
We had to come up with a way to make the state spaces similar to facilitate transfer learning, but didn't want to use images as input.

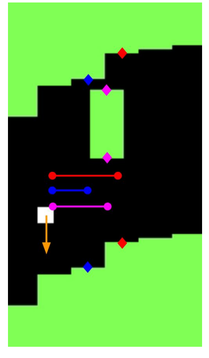
We used the following features for **both** games:
- y position and velocity (orange arrow)
- distance to next terrain (blue line) and next next terrain (red line)
- absolute y positions of the next terrain (blue dot) and next next terrain (red dot)

Additionally, Pixel Copter had obstacles that had no analogue in Flappy Bird:
- distance to next block obstacle (purple line)
- absolute y positions of the next block obstacle (purple dots)

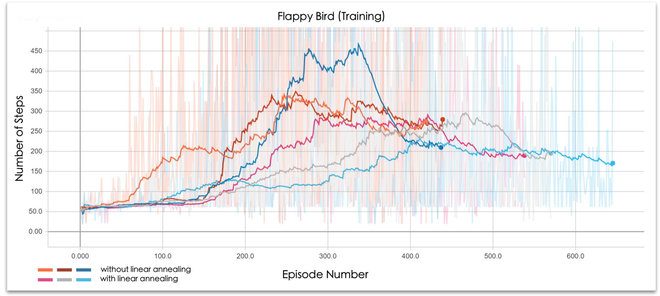
Table for hyperparameters
- For our DQN, we tested several hyperparameters through trial and error to optimize the performance of both games.
- If not noted here, the hyperparameters were left as their default values.

	Flappy Bird	Pixel Copter
Hyperparameters		
Target Model Update	1e-2	1e-2
Learning Rate	1e-3	4e-4
γ	0.99	0.99
Exploration Policy	Linearly annealed ϵ-greedy	
Annealed ϵ	0.2 → 0.05	
Annealing Steps	50,000	150,000
Warm Up Steps	50	100
Training Steps	100,000	300,000
Reward Profile		
Tick	0.1	0.1
Passed Obstacle	1.0	1.0
Collided	-10.0	-10.0

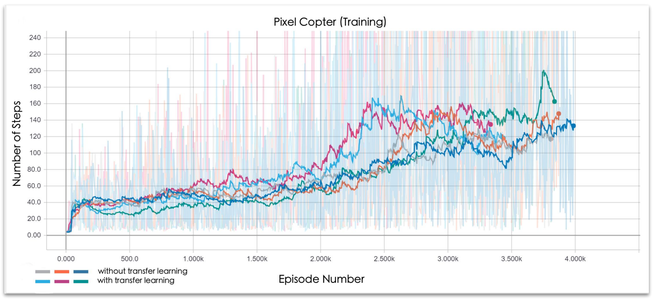




Results



6 runs of Flappy Bird training with the hyperparams to the left. We don't show testing data here since each model can run indefinitely.



6 runs of Pixel Copter training with the hyperparams to the left. Test data is shown below, demonstrating little to no improvement for average ability of the agent when using transfer learning, but improvement in the best performance for each agent.

Pixel Copter	w/o Transfer Learning	w/ Transfer Learning
Average # Steps / Episode	518.5	519
Average Top # Steps / Episode	1939	2544

Conclusion and Future Work

- Deep reinforcement learning was able to play both Pixel Copter and Flappy Bird better than we could, and for Flappy Bird in particular our agent reached **superhuman levels of ability**.
- We did see transfer learning improve training times for Pixel Copter and absolute performance slightly, but only after we used some tricks to ease the process.
- We expect that transfer learning when **using images as input** would be much more impactful, since we wouldn't need to relearn as much to interpret the game's screen.
- In the future, we'd like to play around with **games that have higher dimensionality** in terms of observation and action spaces. There are many cool things in RL right now, like OpenAI's Dota bot and DeepMind's AlphaGo Zero!

Motivation / Intro

Problem

Challenges

Approaches / Methods

- DQN
- Neural net
- Model
- Transfer Learning

Results / Analysis

Conclusion and Future Work

Deep Reinforcement Learning and Transfer Learning with Flappy Bird

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Motivation

Here at Demo2Tutor, we seek to **democratize** the fine arts, combining recent advancements in **AI** with a beautiful **user interface** to spread music to all.

Process

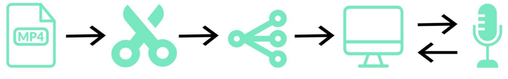


Fig. 1: Flow of Demo2Tutor system

- The input .mp4 file is **segmented** into learnable chunks.
- The chunks are then arranged into a sensible **curriculum tree**.
- The curriculum is presented to the user via the **interface**.
- Users record themselves for instant **feedback**, and may be given autonomy.

Visualizing the User Experience

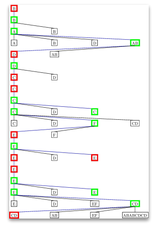


Fig. 2: Tree of student's path

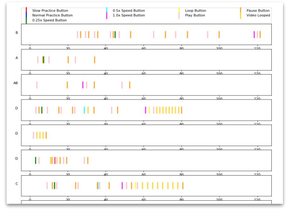


Fig 3: Timeline of student's activity

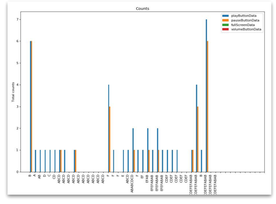


Fig. 4: Button Clicks Per Segment

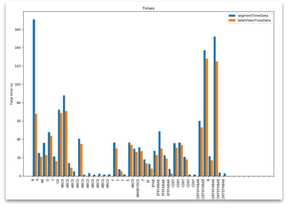


Fig. 5: Time Spent Per Segment

Interface Model

Our interface model consisted of several core features, including a video player, progress visualization, speed/loop buttons, and a feedback button, which records the user playing, compares them against an expert, and suggests which segment the user should try next.

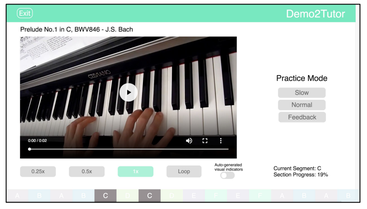


Fig. 6: Interface v1 (Progress Bar)

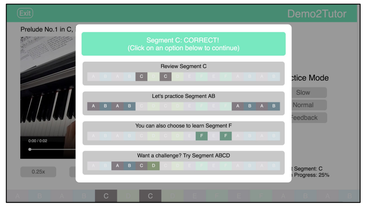


Fig. 7: Interface v1 (Feedback Mode)

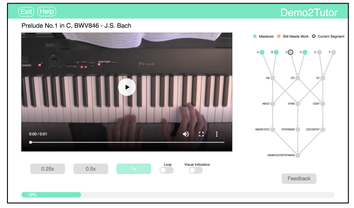


Fig. 8: Interface v2 (Tree Visualization)

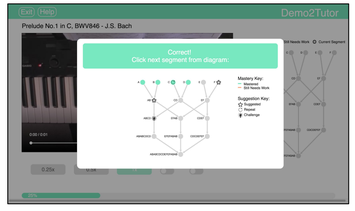


Fig. 9: Interface v2 (Feedback Mode)

Mistake Detection

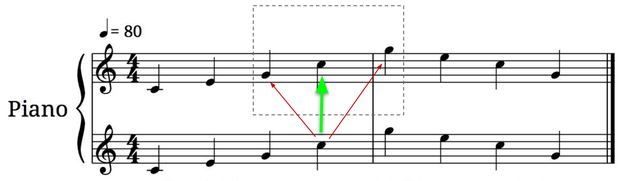


Fig. 10: Mistake detection V1.0 (Direct correlation)

- Directly compares **spectral signal** of each time-step to spectra in a window of time-steps.
- Reasonably accurate; 16/26 examples classified correctly.

- Uses techniques from signal processing to detect **onsets**.
- Onsets are pruned for noise and repeats.
- **Dynamic Time Warping** used to match student onsets to experts'.
- Improvement - 21/26 correctly classified.

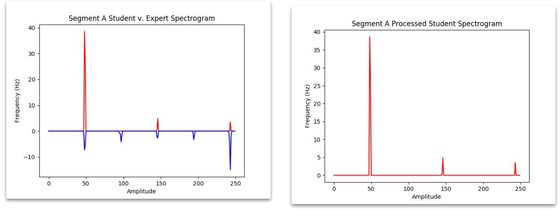


Fig. 11: Mistake detection V2.0 (onset detection)

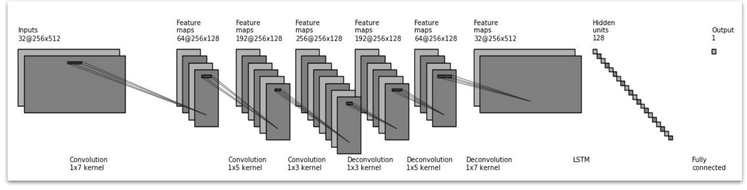


Fig. 12: Mistake detection V3.0 (midi + CNN)

- **Midi** examples pulled and mistakes randomly added.
- **CNN** trained on spectrograms to classify mistakes at each time step.

User Studies

Throughout the project, several user studies were piloted in order to improve our design and functionality:

- **Tree** visualization vs. progress bar
- Speed vs. mode **buttons** and distinction of buttons
- Button **persistence** across sections
- Top-down vs side view video **perspective**

Figs. 8, 9 showcase the changes we made from Figs. 6, 7 in response to the findings made in our studies.

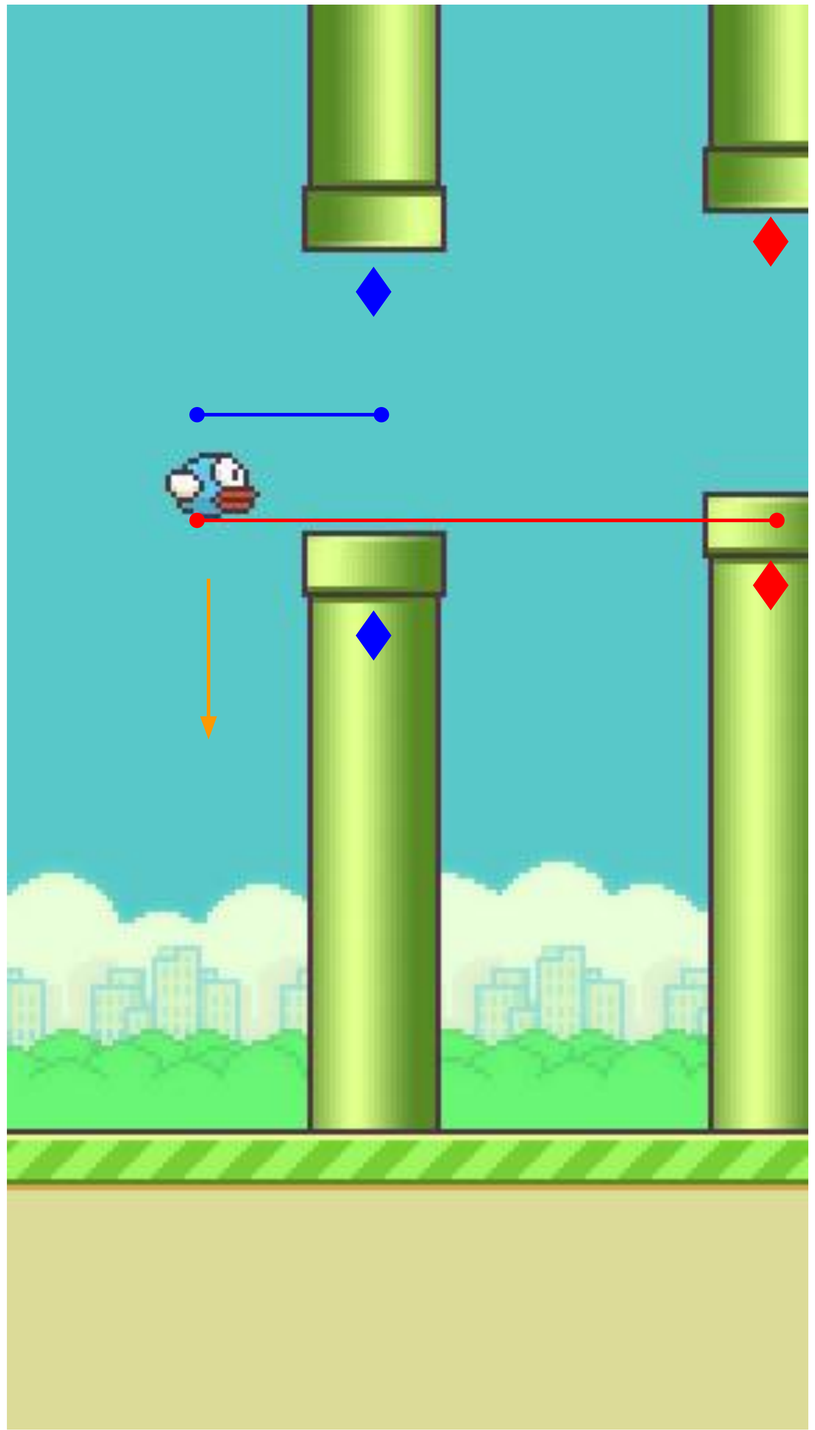
Future Plans

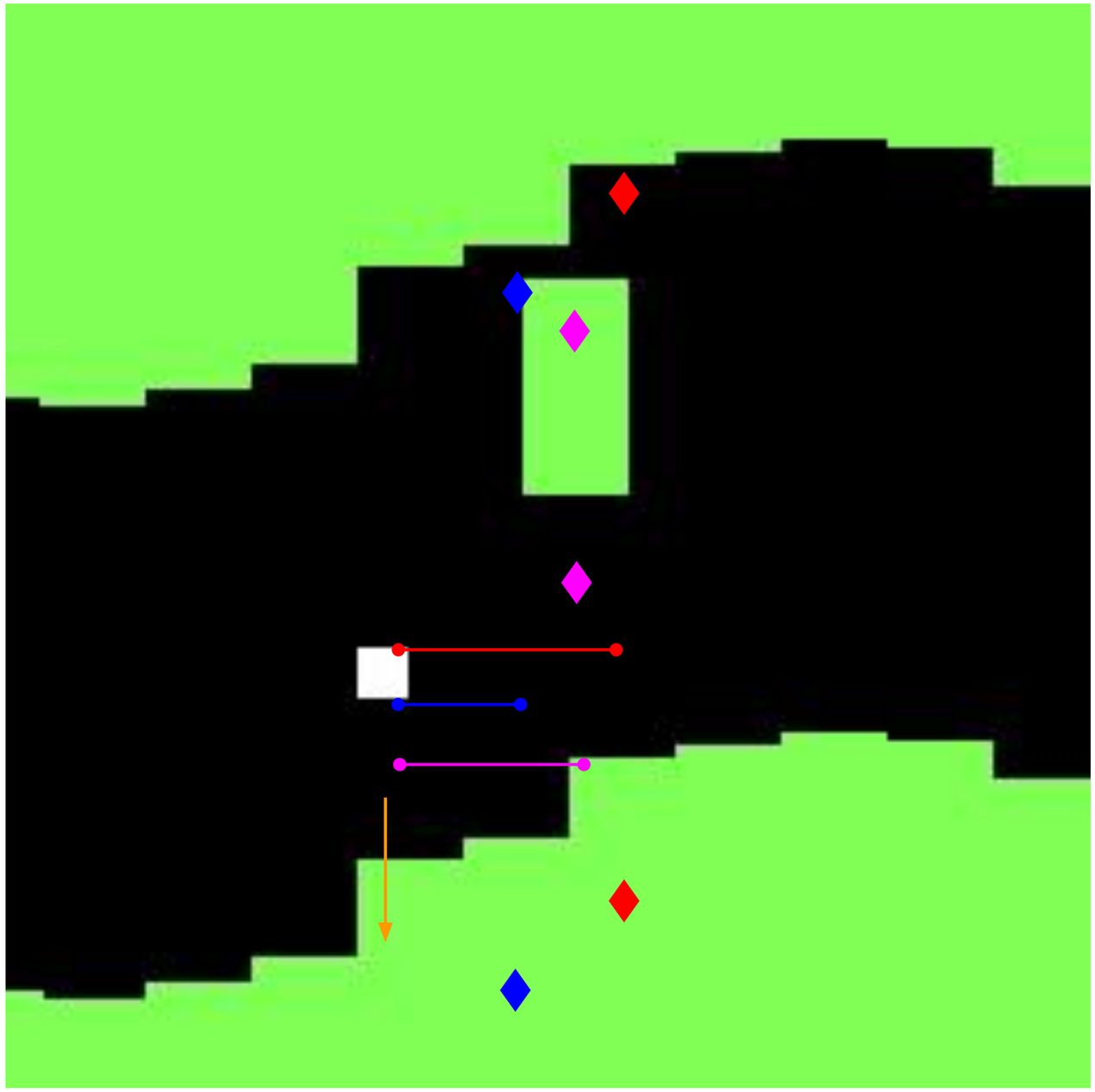
Our future plans consist of:

- Promoting further **engagement** (e.g. including breaks in the curriculum and studying the effects).
- Creating an **account** option for saving user progress.
- Training the CNN model on **all segments** and mistake types.
- Formally **experimenting** with different autonomy levels (full vs. shared vs. none).

Acknowledgements

We wish to give special thanks to **Karan Goel**, **Tong Mu**, and **Dr. Emma Brunskill**. We could not have accomplished and learned as much as we did without all of your wisdom and guidance!






Act
Observe
Update
Linearly annealed
ϵ-greedy
Store in
experience replay
Perform gradient descent
w/ Adam optimizer on
minibatch from memory