AI For Chrome Offline Dinosaur Game

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Abstract

- **Goal:** AI for T-rex game without knowing the underlying dynamics
- **Input:** Raw game image, Reward
- **Output:** Jump or not
- **Two Difficulty Levels:**
  1. Constant Speed
  2. With Acceleration: game velocity increase overtime
- **Different ML Algorithm:**
  - Pixel Level Feature Based Model
  - Multi Layered Perceptron
  - Deep Reinforcement Learning

Methods and Materials

- **Pixel-based feature Extraction**
  - Preprocessing
  - Getting Bounding Box and classifying object
  - Calculating Speed and object status
- **Pixel Level Feature Based Algorithm**
  - Jump when obstacles are close enough
- **Multi-layered Perceptron**
  - Features:
    - Distance between Cactus and T-rex
    - Height of the obstacles
    - Width of the obstacles
    - Speed of T-rex
  - MLP Architecture diagram can be shown as Figure 4
- **Deep Reinforcement Learning**
  - Deep Q-Learning Framework, using only raw pixel and reward as input.
  - Deep Q-Network Architecture diagram can be shown as Figure 2.
  - Different training methods are used in different training phases, which can be shown in our discussion part.

Figure 3. Pixel-based feature extraction

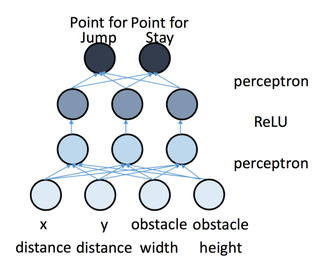

Figure 4. MLP architecture diagram

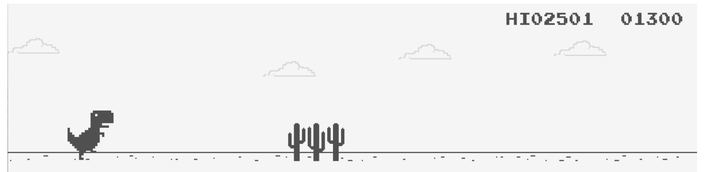

Figure 1. Highest score for the T-rex game with acceleration.

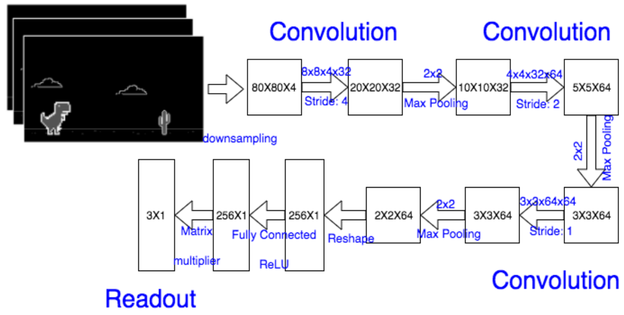

Figure 2. Deep Q-Network architecture diagram

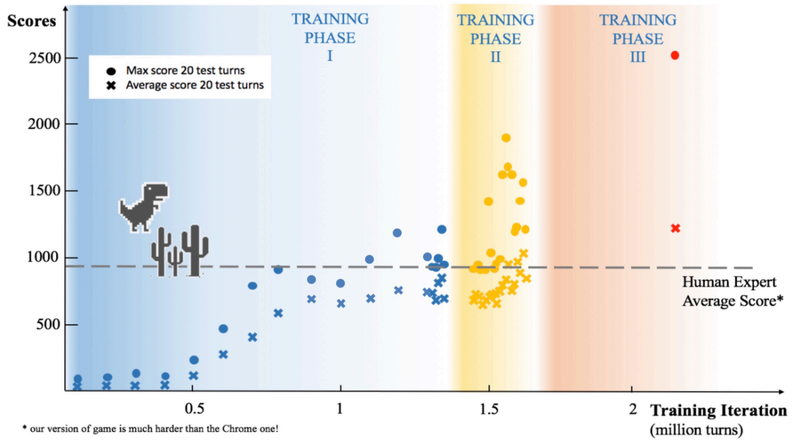

Figure 5. Learning curve for Deep Q-Learning in T-rex game with acceleration.

Results

Table 1. Final scores for different algorithm in T-rex game with acceleration.

Algorithm	AVG20	MAX	STD
Keep Jumping (Baseline)	41	111	23
Human Expert	910	1500	420
Feature-based	196	467	133.7
MLP	232	458	115
Deep Q-Learning	1216	2501	678.1

- Deep Q-Learning out-performs other methods and achieves super-human performance.
- The STDs of different methods are large because obstacles appears randomly and some are hard to pass

Discussion

- **Q-Learning in Two Different Difficulty levels:**
  - **Constant Speed:**
    - Easily achieve super-human performance.
  - **With Acceleration:**
    - Need to use different training phases in order to adapt to speed change.
- **3 Training Phase** of Deep Q Network in the Game With Acceleration
  - **PHASE I** (1.35 million iterations):
    Training with normal acceleration under high exploration probability (starting from 0.1 and decreases linearly)
  - **PHASE II** (0.2 million iterations):
    Training with normal acceleration and no exploration, so that our AI can see more examples of high speed.
  - **PHASE III** (0.5 million iterations):
    Training under higher acceleration and exploration, so that our AI can adapt to higher speed.
    Finally model is retrained on the game with normal acceleration

Conclusions

Our algorithms successfully learn to play the T-rex game straightly from the pixels and reward, achieving super-human results in both constant speed and acceleration scenarios. However, in game with acceleration, the model has a hard time capturing velocity change because of the relatively small state space. Future work could attempt to explore and resolve this issue.