World Models

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How do we experience the world?

- Humans build spatial and temporal models of the environment we experience
  - Sometimes actions occur so fast we work instinctively from these models
  - Predicting rather than processing
- Can we build neural networks which operate similarly?

Figure 1: Art by Scott McCloud$^a$.

$^a$McCloud and Martin, *Understanding comics: The invisible art.*
1990: RNN model-controllers (right)$^a$
2012: AlexNet and deep neural networks$^b$
2013: Variational auto-encoders$^c$
2018: World models$^d$

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$^a$Schmidhuber, Making the world differentiable: on using self supervised fully recurrent neural networks for dynamic reinforcement learning and planning in non-stationary environments, Figure 2.

$^b$Krizhevsky, Sutskever, and Hinton, “ImageNet Classification with Deep Convolutional Neural Networks”.

$^c$Kingma and Welling, Auto-Encoding Variational Bayes.

$^d$Ha and Schmidhuber, World Models.

Figure 2: A controller with internal RNN model of the world.
“Can agents learn inside of their own dreams?”\(^1\)

- Combine existing approaches (model-controller RNNs, DNNs, variational auto-encoders) into state-of-the-art generative models for game environments
- Show that agents can be trained through the lens of their own generative models (their dreams)

\(^1\)Ha and Schmidhuber, *World Models*. 
Components

**Figure 3**: A diagram of a variational auto-encoder\(^a\).

\(^a\)EugenioTL, *Variational Autoencoder structure*.

**Figure 4**: A diagram of an RNN with a mixture density network output layer\(^a\).

\(^a\)Ha and Schmidhuber, *World Models*, Figure 6.
Three components to model

- **V**: Learns to represent spatial component of the environment as latent representation $z$
- **M**: Learns to predict temporal component of the environment
- **C**: Learns to maximise reward from world model only

- $V + M$ are the world model – large, but can be trained unsupervised from environment
- $C$ adds agency – small (single-layer), takes features from world model as input

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*Figure 5: Flow diagram of the agent model*\(^a\)

\(^a\) Ha and Schmidhuber, *World Models*, Figure 8.
Training cars to race

1. Collect 10,000 rollouts from a random policy
2. Train VAE (V) to encode frames into $z \in \mathbb{R}^{32}$.
3. Train MDN-RNN (M) to model $P(z_{t+1} | a_t, z_t, h_t)$.
4. Define Controller (C) as $a_t = W_c [z_t, h_t] + b_c$.
5. Use CMA-ES\textsuperscript{a} to solve for $W_c$ and $b_c$ that maximizes the expected cumulative reward

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**Figure 6:** A photo\textsuperscript{a} of CarRacing-v0 from OpenAI's gym\textsuperscript{b}

\textsuperscript{a}Ha and Schmidhuber, World Models, Figure 11.
\textsuperscript{b}Car Racing - Gym Documentation.

\textsuperscript{a}Loshchilov and Hutter, CMA-ES for Hyperparameter Optimization of Deep Neural Networks.
Winning races

Figure 7: CarRacing-v0 scores achieved using various methods\(^2\).

| Method                                                      | Avg. Score |
|--------------------------------------------------------------|------------|
| DQN (Prieur, 2017)                                          | 343 ± 18   |
| A3C (continuous) (Jang et al., 2017)                        | 591 ± 45   |
| A3C (discrete) (Khan & Elibol, 2016)                        | 652 ± 10   |
| CEOBillionaire (Gym Leaderboard)                            | 838 ± 11   |
| V model                                                     | 632 ± 251  |
| V model with hidden layer                                   | 788 ± 141  |
| **Full World Model**                                        | **906 ± 21** |

\(^2\)Ha and Schmidhuber, *World Models*, Table 1.

- Spatial only \((V + C)\) model is fairly effective, albeit with unstable driving
- Full world \((V + M + C)\) model is best-in-class, “attacking” sharp corners
Do agents dream of electric cars?

Figure 8: Car racing observation and reconstruction from autoencoder – interactive demo available: https://worldmodels.github.io/

- With the trained MDN-RNN, we can predict the next state $z_{t+1}$ from $z_t$ and the action.
- What if we used this prediction instead of an empirical observation?
Learning from dreams

Figure 9: Flow diagram of the agent model\textsuperscript{a}.

\textsuperscript{a}Ha and Schmidhuber, World Models, Figure 8.

Figure 10: Modified agent model, “learning inside a dream”.
VizDoom experiment

- Similar setup to the Car Racing experiment, but this time all learning is done in dreams

- This works! Agents can learn inside their own dreams, with this learnt policy being effective in the actual environment

- There are a few issues:
  - Model doesn’t perfectly represent environment, so agent can “cheat”, resolved by leveraging temperature
  - Complex environments are hard to search comprehensively, resolved by iteratively training

Figure 11: Screenshot of the “VizDoom: Take Cover” environment\(^a\).

\(^a\) Ha and Schmidhuber, World Models, Figure 14.
• Influential in the ongoing development of foundation models
  • “The first work that proposes to learn a compressed spatial and temporal representation of the environment in an unsupervised manner using a simple Variational Autoencoder”\(^3\).

• Resulted in the “Dreamer” series of papers by Google DeepMind:
  1. Dreamer solves long-horizon tasks using latent imagination of reinforcement learning\(^4\)
  2. DreamerV2 then uses this approach to successfully play Atari games\(^5\)
  3. DreamerV3 further extends this approach to generally solve tasks without human input\(^6\)

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\(^3\) Zhou et al., *A Comprehensive Survey on Pretrained Foundation Models*, Appendix E.
\(^4\) Hafner, Lillicrap, Ba, et al., *Dream to Control*.
\(^5\) Hafner, Lillicrap, Norouzi, et al., *Mastering Atari with Discrete World Models*.
\(^6\) Hafner, Pasukonis, et al., *Mastering Diverse Domains through World Models*. 
Criticism and future work

Strengths:

+ Proposes architecture which outperforms existing work on competitive benchmarks
+ Demonstrates that training in dreams learns effective policies

Weaknesses:

– Motivations for training in dreams only mentioned briefly – demonstrations of how it facilitates training without expensive simulation would be helpful
– Reward function separated from spatial/temporal feature extraction, causing unnecessary artefacts
– Approach is “instinctive” – no mechanism for planning far ahead

Future work:

⇒ Including reward function in spatial and temporal models
⇒ Hierarchical models to support planning and strategy
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