## **Apple Picker Project**

AI & Robotics components



Guntis Bārzdiņš 05/10/2017

### ApplePickerProject: Parallel Tracks

- SW/hw: Find the apples
- HW/sw: Pick the apples
- Bridge the gap HW/SW

#### ApplePickerProject: Parallel Tracks

- SW/hw: Find the apples
  - Didzis, Renars, Guntis (DeepMind/OpenAl, Pytorch, +)
- HW/sw: Pick the apples
  - Gunars&Co (Amazon@RoboCup2017, 250K\$ prize)
- Bridge the gap HW/SW
  - Nauris (Mag.thesis, Autopilot, TensorFlow RT)

#### **Grounded Language Learning**

GROUNDED LANGUAGE LEARNING

#### Grounded Language Learning in a Simulated 3D World

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Deepmind London, UK

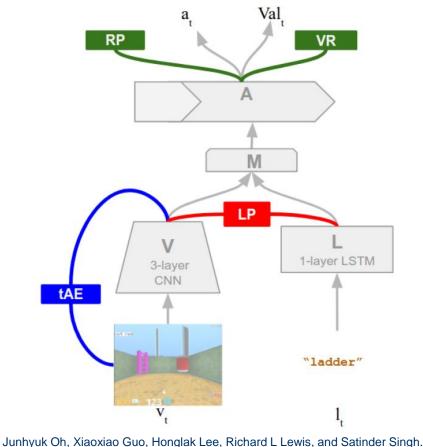
#### Abstract

We are increasingly surrounded by artificially intelligent technology that takes decisions and executes actions on our behalf. This creates a pressing need for general means to communicate with, instruct and guide artificial agents, with human language the most compelling means for such communication. To achieve this in a scalable fashion, agents must be able to relate language to the world and to actions; that is, their understanding of language must be grounded and embodied. However, learning grounded language is a notoriously challenging problem in artificial intelligence research. Here we present an agent that learns to interpret language in a simulated 3D environment where it is rewarded for the successful execution of written instructions. Trained via a combination of reinforcement and unsupervised learning, and beginning with minimal prior knowledge, the agent learns to relate linguistic symbols to emergent perceptual representations of its physical surroundings and to pertinent sequences of actions. The agent's comprehension of language extends beyond its prior experience, enabling it to apply familiar language to unfamiliar situations and to interpret entirely novel instructions. Moreover, the speed with which this agent learns new words increases as its semantic knowledge grows. This facility for generalising and bootstrapping semantic knowledge indicates the potential of the present approach for reconciling ambiguous natural language with the complexity of the physical world.

#### 1. Introduction

Endowing machines with the ability to relate language to the physical world is a longstanding challenge for the development of Artificial Intelligence. As situated intelligent

Neural Information Processing Systems 28, 2015. (https://arxiv.org/abs/1507.08750) https://sites.google.com/a/umich.edu/iunhvuk-oh/action-conditional-video-prediction https://github.com/iunhvukoh/nips2015-action-conditional-video-prediction



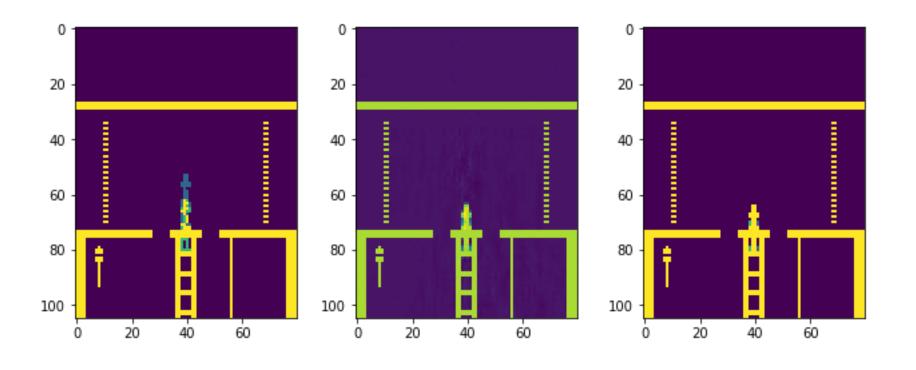
Actionconditional video prediction using deep networks in Atari games. In Advances in

https://arxiv.org/abs/1706.06551

https://github.com/dai-dao/Grounded-Language-Learning-in-Pytorch

## tAE: temporal AutoEncoder (2M)

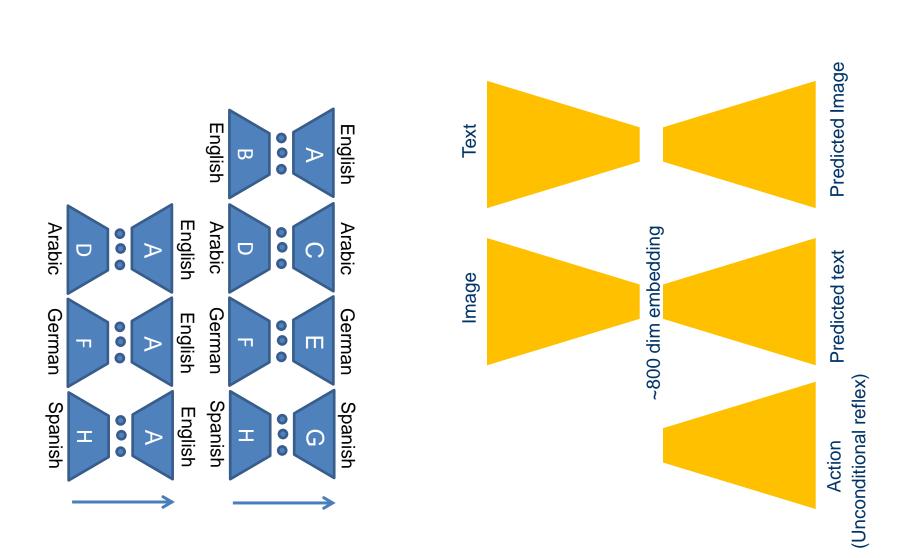
Imagine/Predict



State\_A → Action\_17→ Guess\_B

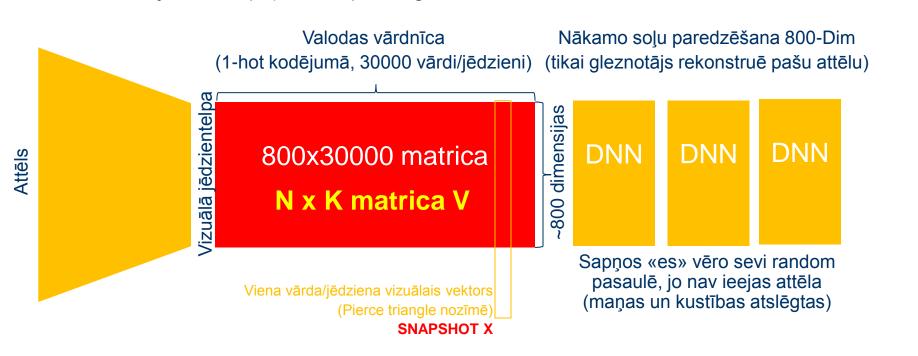
State\_B

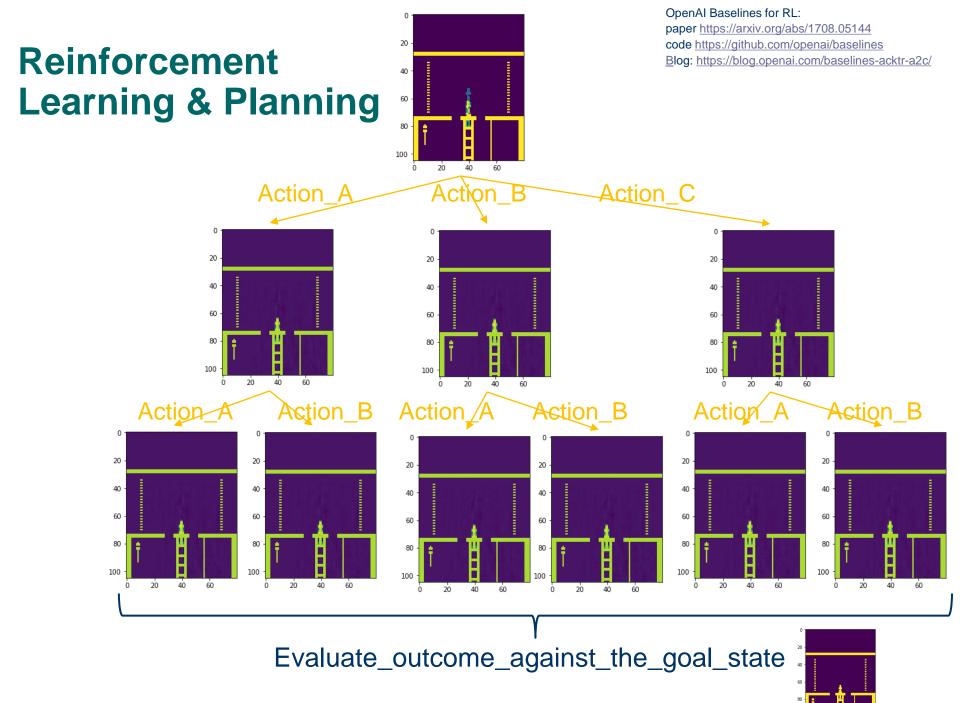
#### Multimodal inputs/outputs of tAE



## Low-Dimensional Representation of High-Dimensional Input (Vispārināšana)

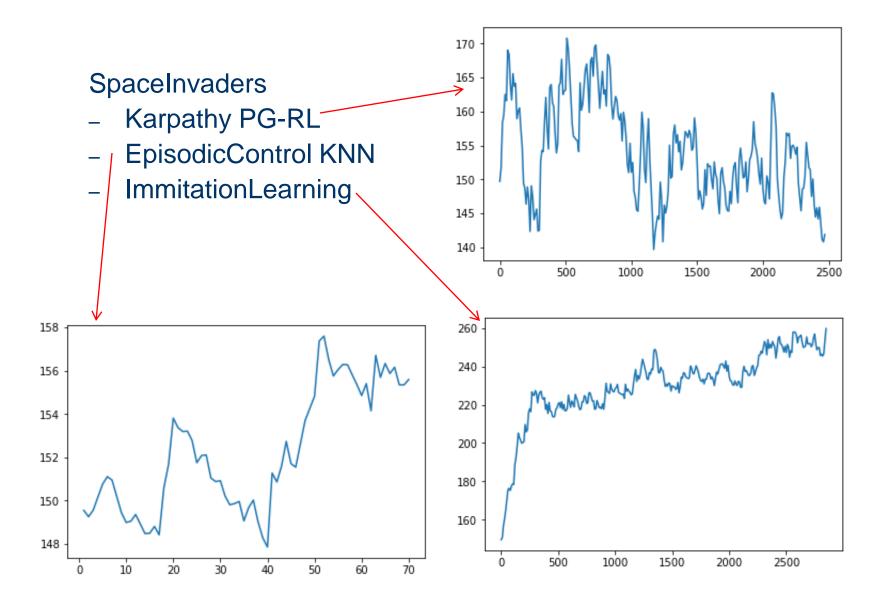
- Vizuālā jēdzientelpa pastāvēja pirms valodas (dzīvniekiem)
  - Jedzientelpu atklāja caur Word Embeddings
  - Tad pamanīja, ka tā izomorfa vizuālās realitātes jēdzientelpai
- Teorēma #1
  - N-Dim Jēdzientelpas aritmētika (King Man + Woman = Queen) saglabājas to reizinot ar NxM dimensionalitātes patvaļīgu matricu (projicējot to M-Dim jēdzientelpā), kur M patvaļīgs skaitlis







### **ImmitationLearning (1M)**



# MemoryNeuron: Aktivācijas→Svari (3M) (1-Shot Learning)

#### Teorēma #2

- N-Dim jēdzientelpas aktivācijas vērtību normēts vektors X (snapshot, |X|=1), tādu <u>saglabāti</u> K gabali un tie veido NxK matricu V.
  - Matrica V reizināta ar patvaļīgu citu šīs jēdzientelpas normētu aktivācijas vērtību vektory Y dod K-Dim vektoru Q tādu, ka KNN2=2-2Q (KNN2 ir N-Dim Eiklīda telpas attālumu kvadrāti no Y līdz K gabaliem <u>saglabāto</u> snapshot vektoru)
    - Pierādījums: KNN2= $(x_1-x_2)^2 + (y_1-y_2)^2 = x_1^2-2x_1x_2+x_2^2+y_1^2-2y_1y_2+y_2^2 = 2-2(x_1x_2+y_1y_2) = 2-2Q$  (Cosine similarity)
    - Sekas: Pārdzīvojums <u>aktivācijas</u> vērtības X saglabā kā <u>svarus</u> matricā V (veidojojas instinkts). Matrica V ir neironu tīkls ar ieeju Y un izeju Q. KNN ir aktivācijas funkcija no Q.

#### MemoryNeuron code (3M)

- Failā raksta tikai, ja DiscREW>0 (vai <0)</li>
  - {IMG\_A, ACTION, IMG\_B} virknes
- Immitation for Karpathy (1M) no faila lieto
  - {IMG\_A, ACTION}
- tAE (2M) no faila lieto
  - {IMG\_A+ACTION, IMG\_B} ← reāla AutoEncoder Bootstraping
- Conditional STM Memory (3M)
  - Nem 2M satrenēto tAE un tā 800-Dim lieto RandomProjekcijas vietā iekš 1M (AutoEncoder Bootstraping)
  - Tālāk Karpathy HelfResolution arī vietā lieto 800-Dim
  - Šī daļa 1M un 2M un Karpathy kodos jāpārveido (Pytorch)



### Pytorch priekšrocības (3M)

- T :Neironu tīkla ģeometrija bez svariem
- T(S) :Neironu tīkls T piepildīts ar svariem S
- f(T,S) → T(S) :Neironu tīkla piepildīšanas funkcija
- F(T,S,[input,output],LossFunction,LearningRate) → S'
  :Neironu tīkla pietjūnēšanas funkcija
- Rand(T) → S :Sākuma svaru random uzstādīšana
- <T,Rand,F> :Neironu tīkla situācija (species, evolūcijas rez)
- T1+T2 → T3 :T1 izeju ar T2 ieeju saštepselēšana rada T3
- G(T,S,input) → output, hidden :Rēķina (super ātri, paralēli)
- f(T,input) →T(S) :MemoryNeuron, rēķina similarity (dim jāsakrīt)
- Max(list1,list2) → element
  :element ir list2 vertiba pozīcijā, kur list1 sasniedz max vērtību

#### ToDo

- Datori ar Nvidia Titan GPU
- iRobot + Raspbery PI + video + power + interface + steering wheel + ...
- Accenture e-mail pw, IDs for Ethics etc.
- JIRA