PokerPrime

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Problem Description

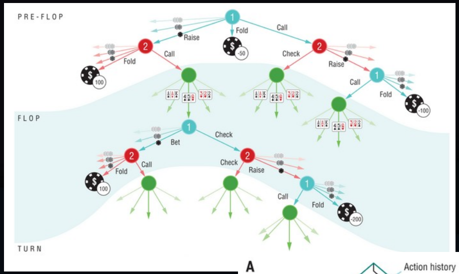
- In order to build a agent capable playing poker we need to first solve the problem of card classification. It provides the basic information about the current stage of the game.
- Thus the main goal is to design a neural network that can accurately predict highest card hand.

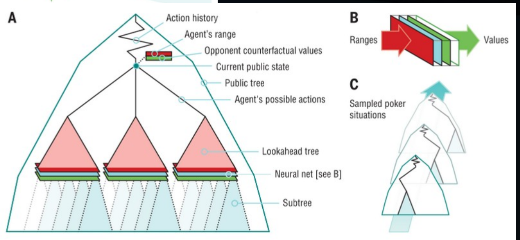
Related Work

COMPUTER SCIENCE

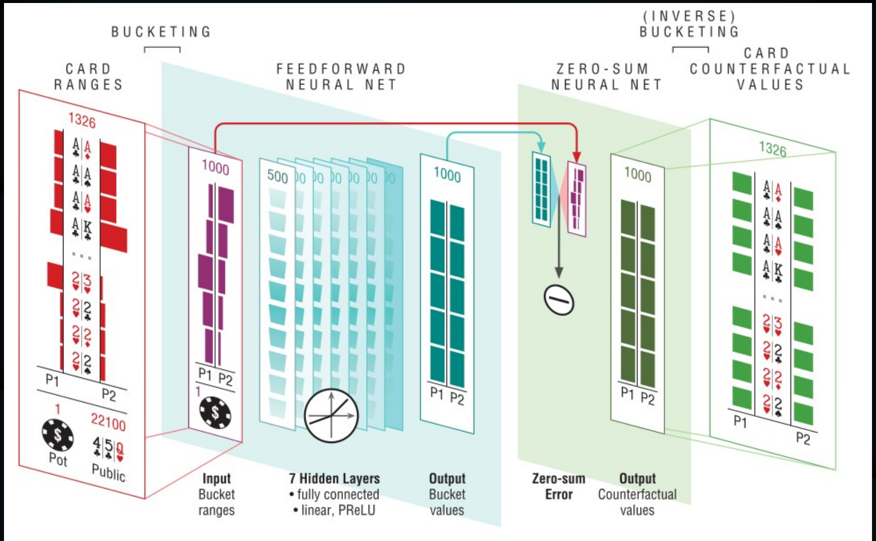
DeepStack: Expert-level artificial intelligence in heads-up no-limit poker

Matej Moravčík,[1,2]* Martin Schmid,[1,2]* Neil Burch,[1] Viliam Lisý,[1,3] Dustin Morrill,[1] Nolan Bard,[1] Trevor Davis,[1] Kevin Waugh,[1] Michael Johanson,[1] Michael Bowling[1]†





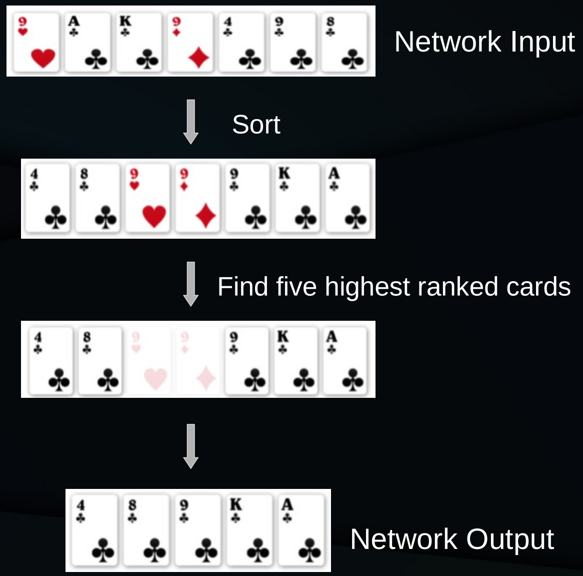
Deep Counterfactual Value Network

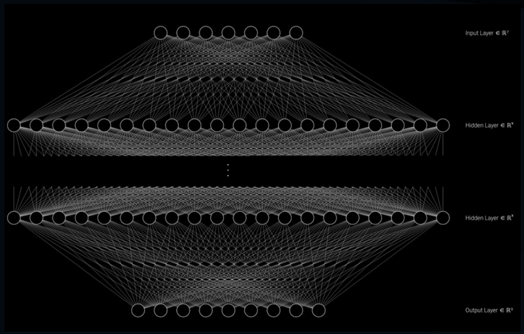


Approach

Networks tested:

- -Feedforward Neural Network
- -Regularized Residual Neural Network
- -Recurrent Neural Network





Rationale

Feedforward Neural Network

Advantage

- Simple
- Fast to train

Disadvantage

- Not complex
- Vanishing gradient

Regularized Residual Neural Network

Advantage

- Helps with vanishing gradient
- Semi complex

Disadvantage

- Slower than FNN

Recurrent Neural Network

Advantage

- Models sequences (time series)

Disadvantage

- Vanishing gradient (a LSTM used to overcome)
- Difficult to train

Parameters: Categorical Crossentropy loss function, Adam optimizer, 120 epochs

Data

Hand probabilities in unbalanced training data:

High card probability:	17.4424 %
Pair probability:	43.8591 %
Two paris probability:	23.4389 %
Three cards probability:	4.8403 %
Straight probability:	4.5965 %
Flush probability:	3.0368 %
Full house probability:	2.5804 %
Four cards probability:	0.1787 %
Straight flush probability:	0.0269 %

Hand probabilities in balanced training data:

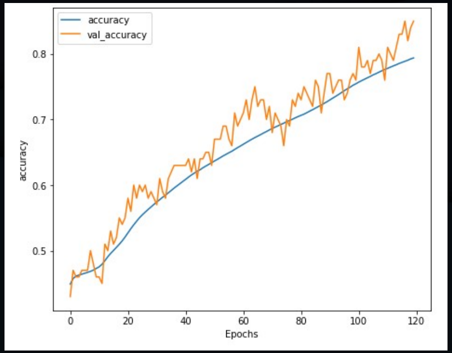
High card probability:	11.276 %
Pair probability:	11.276 %
Two paris probability:	11.276 %
Three cards probability:	10.916 %
Straight probability:	10.366 %
Flush probability:	10.273 %
Full house probability:	11.639 %
Four cards probability:	11.687 %
Straight flush probability:	11.284 %

Evaluation

Accuracy was the main metric used for the evaluation. Since standard card classification algorithms already exist our target accuracy was 100%.

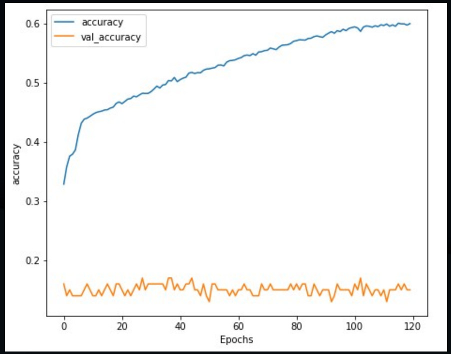
Feedforward Neural Network

Unbalanced Data



Max Accuracy: 79.6%

Balanced Data

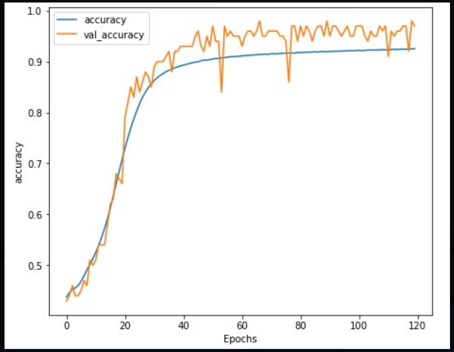


Max Accuracy: 19.7%

Evaluation

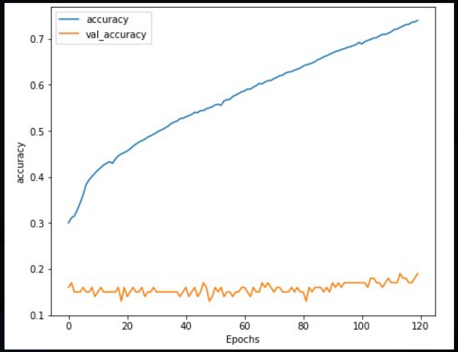
Regularized Residual Neural Network

Unbalanced Data



Max Accuracy: 93.0%

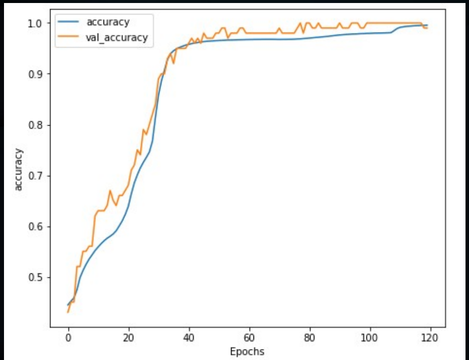
Balanced Data



Max Accuracy: 21.5%

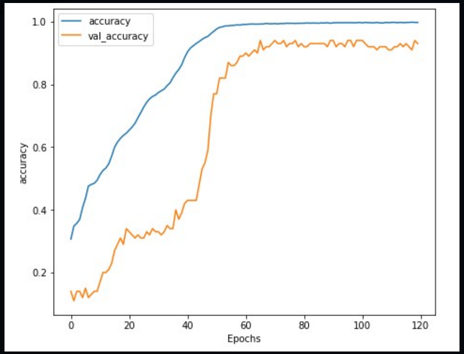
Recurrent Neural Network

Unbalanced Data



Max Accuracy: 99.6%

Balanced Data



Max Accuracy: 87.9%

Topics Learned

Scope of the project:

- Data preprocessing
- Feedforward Neural Network
- Regularized Residual Neural Network
- Recurrent Neural Network

Libraries used:

- TensorFlow
- RL Card
- pypoks

Challenges

Main issues during development:

- Long training times (25 min to 2 hours)
- Lack of support for RNN training in AMD GPU
- Lack of time for a working agent

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Questions