DEEP REINFORCEMENT LEARNING APPLIED TO GENERATE TRADING SIGNALS FOR FINANCIAL MARKETS

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Outline

1. Motivation
   - Deep Learning
   - Reinforcement Learning
   - Direct Reinforcement
2. The model
   - The Simple Trader Agent
   - The optimization problem
3. Results
   - The model implementation
   - SPX500 Examples

Outline

Deep Learning

- It is an emerging technique based on neuron conectivities.
- Used for feature learning.
- Difficult to understand the output.

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Reinforcement Learning

- Learning comes from the interactions with the environment.
- Solves dynamic control problems like trading decision.
- The agent "understands" the Deep Feature Learning.

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Direct Reinforcement

The policy is learned directly from observation to action.

Advantages:

- Avoids the Bellman's *curse of dimensionality*.
- Allows to implement recurrences (RRL)
- Can learn stochastic policies.

Disadvantages:

- Usually converge to a local instead of a global optimum.
- High variance on the results.

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The algorithm

Recurrent Reinforcement Learning

Input: $\mathcal{O}_t$
Output: π_θ policy.
Initialize θ randomly
for each episode **do**
    for each time t **do**
        apply deep learning $g_t(o_t, \theta)$
        take action a_{t+1} from $f(g_t, a_t)$
    end for
    $u(a;\theta) = U_T(R_1, R_2, ...R_T)$
    π_θ: improved from a local approximation of the u gradient
end for
return u, π_θ

The recurrent model

Trader action

$$F_t = F(O_{t-1}^{(n)}, F_{t-1}^{(m)}; \theta_t)$$

Rewards

$$R_t = F_{t-1} r_t - c|F_t - F_{t-1}|$$

Utility, Sharpe ratio

$$S_t = \frac{\mu(R_t)}{\sigma(R_t)}$$

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The optimization

The maximization problem

$$\begin{aligned}
\underset{\theta=\{W,W_a\}}{\text{maximize}} \quad & U_T(R_1, ..., R_T) \\
\text{subject to} \quad & R_t = F_{t-1} - c|F_t - F_{t-1}| \\
& F_t = f(< W, g_t > +b + W_a F_{t-1}) \\
& g_t = \varphi(o_t)
\end{aligned}$$

Vanishing gradient

Problem

- The model has a deep timed-based structure.
- The magnitude of the transition weight has a large impact on the learning process.

Solution

- Evolutionary algorithms, for instance particle swarm optimization.
- LSTM networks.

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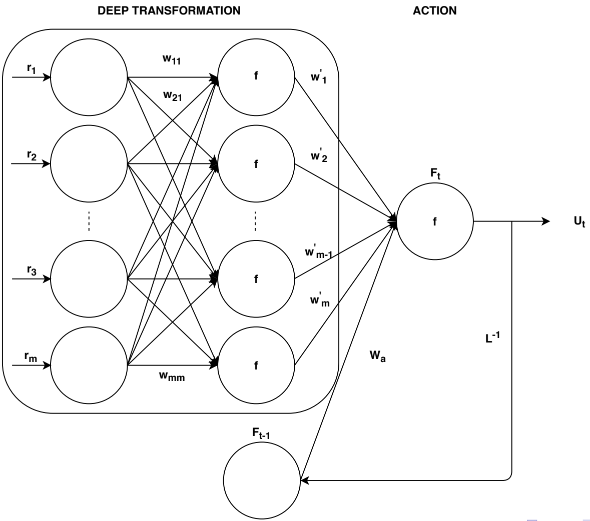
Two layer model



Side data model

- Adding new features reduce bias (but increase variance).
- Helps the trader to take "better" decisions.
- Highest / Lowest price, moving averages, ...

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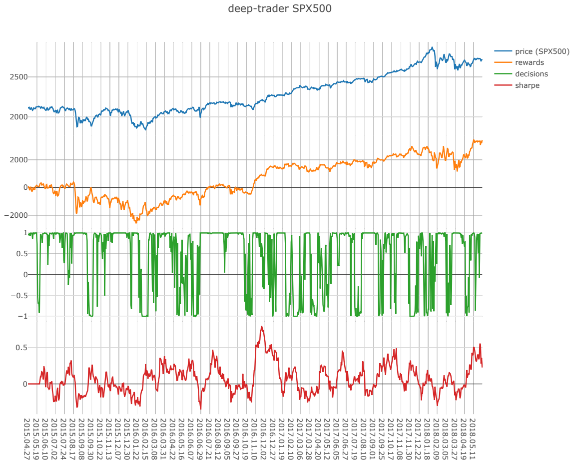

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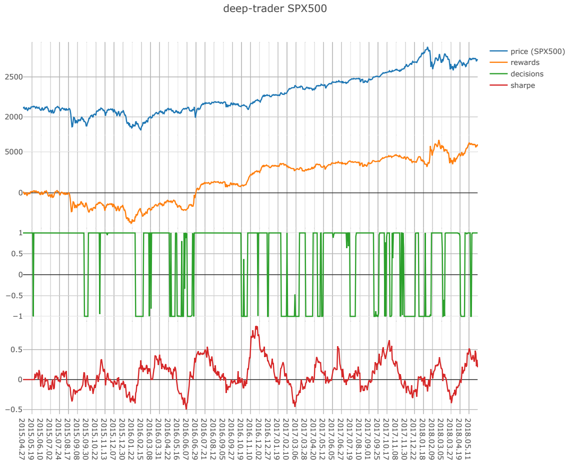

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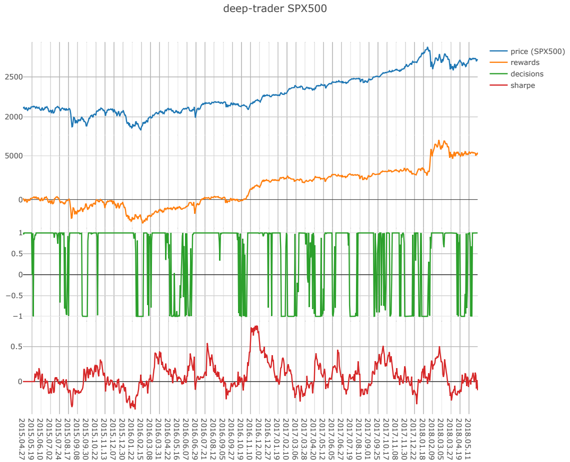
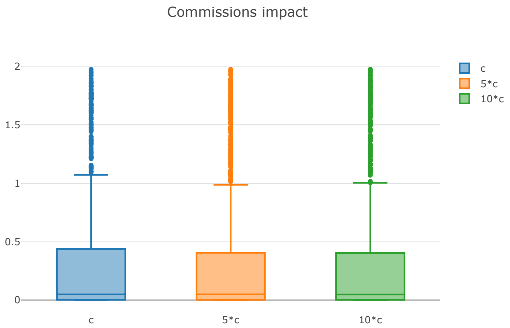


Commission analysis



Conclusions

- The simple agent trader is a trend follower algorithm.
- The side data augmented model improves the results of the simpler case with one hidden layer.
- The two hidden layer model improves the results of the model with one hidden layer.
- Future work lines
  - To implement a LSTM model, trade multiple assets, new utility functions,...

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Thank You!
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