Introduction

This document has as purpose to serve as an exercise for you to try out some things within IATEX for each level individually. At the end there are also some challenges if you think you got what it takes. Good luck in recreating this document!

Beginner

$$\left((\neg A \Rightarrow B) \lor (C \land D) \right) \leftrightarrow E$$

$$\begin{vmatrix} 1 & 2 & 3 \\ \hline 4 & 5 \\ \hline 6 & 7 & \alpha \end{vmatrix}$$

Question! Is dark mode better than light mode?

- a) Yes
- b) No

Maybe I want to create a ${\bf table} \cdot \cdot \cdot$

$$f(x) = \frac{1}{2} \cdot \begin{pmatrix} 4\\1 \end{pmatrix}$$

$$f_2(x) = \int_a^b x^2$$

A nice J perhaps? Please visit youtube.com

Intermediate

Lët's gó;

Hello...

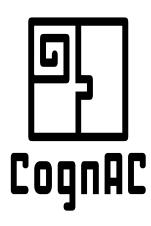
Is it me you're looking for?

$$\alpha(z_1, z_2) = \left(\frac{\partial \beta(z_1, z_2)}{\partial z_1}, \frac{\partial \beta(z_1, z_2)}{\partial z_2}\right) \qquad \qquad \vec{v} = \begin{pmatrix} \lambda & 0 \\ 0 & \lambda \end{pmatrix} \\ = \lambda \cdot \mathbf{I}$$

Clearly the complexity of this algorithm is $\mathcal{O}(n \log n)$, as is given by the following:

```
private void smartMethod() {
    Operator op = new Operator(nr_of_questions, input);
    if (input.size() < 3) {
        op.low_students();
        answers = op.getAnswers();
    } else if (op.correct_input()) {
        op.smartSolution();
        answers = op.getAnswers();
} else {
        answers.add((long) 0);
        answers.add((long) 0);
    }
}</pre>
```

Given is that $\forall \eta, \exists \pi \in \mathbb{C}$ such that $\gamma(\eta) \stackrel{?}{=} \begin{cases} 0 & \text{if } \eta = 0 \\ \max_{i \geq 5} \left[\frac{\pi}{\lambda}\right] & \text{if } \eta > 0 \end{cases}$



Little bit wrong

Figure 1: This is COGNAC!

Advanced

_

Expert

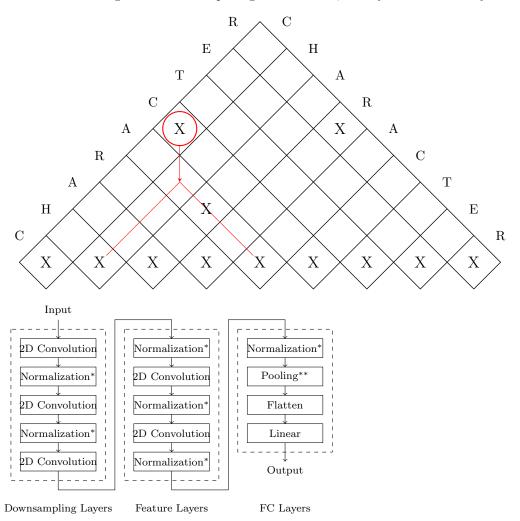
-

Godlike

-

Challenges

Tip: I created these images with the Tikz package from scratch, so they are created solely in LATEX!



^{*}Group Normalization

^{**2}D Adaptive Average Pooling

Algorithm 1 Deep Q-Network with replay buffer

```
1: Initialize replay memory \mathcal{D} to capacity N
 2: Initialize action-value function Q with random weights
     for episode=1,M do
 3:
          Initialize sequence s_1 = \{x_1\} and preprocessed sequenced \phi_1 = \phi(s_1)
 4:
 5:
          for t=1,T do
               With probability \epsilon select a random action a_t
 6:
               otherwise select a_t = \max_a Q^*(\phi(s_t), a; \theta)
 7:
 8:
               Execute action a_t in emulator and observe reward r_t and image x_{t+1}
               Set s_{t+1} = s_t, a_t, x_{t+1} and preprocess \phi_{t+1} = \phi(s_{t+1})
 9:
               Store transition (\phi_j, a_j, r_j, \phi_{j+1}) in \mathcal{D}
10:
               Sample random minibatch of transitions (\phi_j, a_j, r_j, \phi_{j+1}) from \mathcal{D}
11:
              Set y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}
Perform a gradient descent step on (y_j - Q(\phi_j, a_j; \theta)) with respect to weights \theta
12:
13:
               Every C steps reset \hat{Q} = Q
14:
          end for
15:
16: end for
```