

RISK-AVERSE DISTRIBUTIONAL REINFORCEMENT LEARNING

A CVAR OPTIMIZATION APPROACH

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ABSTRACT

Short summary of the contents in English. . . a great guide by Kent Beck how to write good abstracts can be found here:

<https://plg.uwaterloo.ca/~migod/research/beckOOPSLA.html>

ABSTRAKT

Český abstrakt

*We have seen that computer programming is an art,
because it applies accumulated knowledge to the world,
because it requires skill and ingenuity, and especially
because it produces objects of beauty.*

— **knuth:1974** [**knuth:1974**]

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Put your acknowledgments here.

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¹ Members of GuIT (Gruppo Italiano Utilizzatori di T_EX e L^AT_EX)

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INTRODUCTION

A staple of an intelligent agent is the ability to reason and act in an environment over time, while working towards a desirable goal. This is the setting explored in reinforcement learning (RL), a branch of machine learning that focuses on dynamic decision making in an unknown environment.

Recent advances in artificial intelligence (AI) are encouraging governments and corporations to deploy AI in high-stakes settings including driving cars autonomously, managing the power grid, trading on stock exchanges, and controlling autonomous weapon systems. As the industry steps away from specialized AI systems towards more general solutions, the demand for safe approaches to artificial intelligence increases.

In this thesis, we tackle one aspect of safe reinforcement learning, robustness, by considering the risk involved in acting in a nondeterministic, noisy environment.

1.1 MOTIVATION

Lately, there has been a surge of successes in machine learning research and applications, ranging from visual object detection [14] to machine translation [3]. Reinforcement learning has also been a part of this success, with excellent results regarding human-level control in computer games [17] or beating the best human players in the game of Go [24]. While these successes are certainly respectable and of great importance, reinforcement learning still has a long way to go before being applied on critical real-world decision-making tasks. This is partially caused by concerns of safety, as mistakes caused by can be costly in the real world.

One of the problems encountered when training a reinforcement learning agent is sample efficiency, or the large amount of training time needed for the agent to successfully learn new and correct behaviors. The solution used by many is to train the agent in simulation - it is indeed faster (as the simulation can run in parallel or faster than real-time), safer (we do not face any real danger in simulations) and cheaper than to train the agent in the real world. This approach then raises the question if an agent trained in simulation would perform well outside of the simulation.

Robustness, or distributional shift, is one of the identified issues of AI safety [15][1] directly tied to the discrepancies between the environment the agent trains on and is tested on. Chow et al. [8] have shown that risk, a measure of uncertainty of the potential loss/reward, can be seen as equal to robustness, taking into account the differences during train- and test-time. This point is discussed in more detail in chapter 2.

While the term risk is a general one, we will focus on a concrete notion of risk - a particular risk metric called Conditional Value-at-Risk (CVaR). Due to its favorable computational properties, CVaR has been recognized as the industry standard for measuring risk in finance, as in 2014 the Basel Committee on Banking Supervision changed its guidelines for banks to replace VaR (a previously used metric) with CVaR for assessing market risk Committee [9]. The metric has also been identified as one of the metrics satisfying axioms of risk in robotics [16].

Another motivational point, aside from robustness, might be one of general decision-making. Commonly encountered in finance, decision makers face the problem of maximizing profits while keeping the risks to a minimum. The solutions to problems encountered in this thesis can therefore be seen as ones of general time-dependent risk-averse decision making.

The aim of this thesis is to consider reinforcement learning agents that maximize Conditional Value-at-Risk instead of the usual expected value, hereby learning a robust, risk-averse policy. The word *distributional* in the title emphasizes that our approach takes inspirations from, or directly uses, recent advances in distributional reinforcement learning [5].

1.2 THESIS OUTLINE

1.3 CONTRIBUTIONS

PRELIMINARIES

The goal of this chapter is to provide a formal background on the covered material, together with a unified notation (which differs quite a lot from publication to publication). The described topics include reinforcement learning, risk-averse measures and others. The interested reader is welcome to explore the books and publications referenced throughout this chapter and in section 2.6. An informed reader may choose to skip to section 2.5 where we formalize the problems tackled in this thesis.

2.1 PROBABILITY ESSENTIALS

2.2 REINFORCEMENT LEARNING

todo: RL intro

2.2.1 Markov Decision Processes

An MDP is a 5-tuple $\mathcal{M} = (\mathcal{X}, \mathcal{A}, R, P, \gamma)$, where \mathcal{X} and \mathcal{A} are the finite state and action spaces; $R(x, a) \in [R_{\min}, R_{\max}]$ is a random variable representing the reward generated by being in state x and selecting action a ; $P(\cdot|x, a)$ is the transition probability distribution; $\gamma \in [0, 1)$ is a discount factor. We also assume we are given a starting state x_0 .

todo: policies

A stationary (or markovian) policy is a mapping from states to actions $\pi : \mathcal{X} \rightarrow \mathcal{A}$.

We define the return $Z^\pi(x_t)$ as a random variable representing the discounted reward along a trajectory generated by the MDP by following the policy π , starting at state x_t

$$Z^\pi(x_t) = \sum_{t=0}^{\infty} \gamma^t R(x_t, \pi(x_t)) \quad (2.1)$$

We will sometimes omit the π superscript when the policy is clear from context.

2.2.2 Bellman equation

The Bellman equation is a recursive equation that defines the action-value function Q :

$$Q^\pi(x, a) = \mathbb{E} [Z^\pi(x, a)] = \mathbb{E} [R(x, a) + \gamma \sum_{x'} P(x'|x, a) V^\pi(x')] \quad (2.2)$$

where the next state X' is sampled according to the MDP's transition probabilities.

2.3 DISTRIBUTIONAL REINFORCEMENT LEARNING

2.4 RISK-SENSITIVITY

2.4.1 *general*

2.4.2 *var*

2.4.3 *cvar*

Let Z be a bounded-mean random variable, i.e. $\mathbb{E}[|Z|] < \infty$, with cumulative distribution function (c.d.f.) $F(z) = \mathbb{P}(Z \leq z)$. In this paper we interpret Z as a reward¹. The value-at-risk (VaR) at confidence level $\alpha \in (0, 1)$ is the α quantile of Z , i.e.

$$\text{VaR}_\alpha(Z) = F^{-1}(\alpha) = \max \{z | F(z) \leq \alpha\} \quad (2.3)$$

We will use the notation $\text{VaR}_\alpha(Z)$, $F^{-1}(\alpha)$ interchangeably, often explicitly denoting the random variable of inverse c.d.f. as $F_Z^{-1}(\alpha)$.

2.4.4 *Conditional Value-at-Risk*

The conditional value-at-risk (CVaR) at confidence level $\alpha \in (0, 1)$ is defined as:

$$\text{CVaR}_\alpha(Z) = \frac{1}{\alpha} \int_0^\alpha F_Z^{-1}(\beta) d\beta = \frac{1}{\alpha} \int_0^\alpha \text{VaR}_\beta(Z) d\beta \quad (2.4)$$

We will also use the following equivalent formulation from [21]:

$$\text{CVaR}_\alpha(Z) = \max_s \left\{ \frac{1}{\alpha} \mathbb{E}[(Z - s)^-] + s \right\} \quad (2.5)$$

where $(x)^- = \min(x, 0)$ represents the negative part of x .

2.4.5 *Time-consistency*

An important property of CVaR MDPs is that of time-consistency. ***Choose one definition, describe*** The notion of time consistency varies from author to author; in Shapiro [XXX] it is shown ***.

*** Policy gradient literature ignores the time consistency-issue, leading to locally optimal policies *** show that they can be worse than EXP ***.

¹ This is in accordance with reinforcement learning literature and opposed to risk-related literature.

2.5 PROBLEM FORMULATION

The risk-sensitive problem we wish to adress for a given confidence level α is as follows:

$$\max_{\pi} \text{CVaR}_{\alpha}(Z^{\pi}(x_0)) \quad (2.6)$$

2.6 LITERATURE SURVEY

VALUE ITERATION WITH CVAR

Value iteration is a standard algorithm for maximizing expected discounted reward used in reinforcement learning. In this chapter we extend the results of Chow et al. [8], who have recently proposed an approximate value iteration algorithm for CVaR MDPs.

The original algorithm requires the computation of a linear program in each step of the value iteration procedure. Utilizing a connection between the used αCVaR_α function and the quantile function, we sidestep the need for this computation and propose a linear-time version of the algorithm, making CVaR value iteration feasible for much larger MDPs.

We first present the original algorithm in section 3.1. The improved algorithm is presented in section 3.2. In section 3.3, we test the algorithm on selected environments.

3.1 CVAR VALUE ITERATION

Chow et al. [8] present a dynamic programming formulation for the CVaR MDP problem (see section 2.5). **todo: more** We repeat their key ideas and results bellow, as they form a basis for our contributions presented in later sections. The results are presented with our notation introduced in chapter 2, which differs slightly from the paper, but the core ideas remain the same.

3.1.1 Bellman Equation for CVaR

The results of Chow et al. [8] heavily rely on the CVaR decomposition theorem [decomp]:

unclear: repeat the original theorems in full?

$$CVaR_\alpha(Z^\pi(x, a)) = \min_{\xi \in \mathcal{U}_{\text{CVaR}}(\alpha, P(\cdot|x, a))} \sum_{x'} p(x'|x, a) \xi(x') CVaR_{\xi(x')\alpha}(Z^\pi(x')) \quad (3.1)$$

where the risk envelope $\mathcal{U}_{\text{CVaR}}(\alpha, P(\cdot|x, a))$ coincides with the dual definition of CVaR ??.

The theorem states that we can compute the $CVaR_\alpha(Z^\pi(x, a))$ as the minimal (or worst-case) weighted combination of $CVaR_\alpha(Z^\pi(x'))$ under a probability distribution perturbed by $\xi(x')$.

Note that the decomposition requires only the representation of CVaR at different (or all) confidence levels and not the whole distribution. **todo: make the distinction clear, maybe in prelim?**

Chow et al. [8] extend these results by defining the *CVaR value-function* $V(x, y)$ with an augmented state-space $\mathcal{X} \times \mathcal{Y}$ where $\mathcal{Y} = (0, 1]$ is an additional continuous state.

$$V(x, y) = \max_{\pi \in \Pi} \text{CVaR}_y(Z^\pi(x)) \quad (3.2)$$

Similar to standard DP, it is convenient to work with operators defined on the space of value functions. This leads to the following definition of the CVaR Bellman operator $\mathbf{T} : \mathcal{X} \times \mathcal{Y} \rightarrow \mathcal{X} \times \mathcal{Y}$:

$$\mathbf{T}V(x, y) = \max_a \left[R(x, a) + \gamma \min_{\xi \in \mathcal{U}_{\text{CVaR}}(\alpha, P(\cdot|x, a))} \sum_{x'} p(x'|x, a) \xi(x') V(x', y\xi(x')) \right] \quad (3.3)$$

or in our simplified notation:

$$\mathbf{T}CVaR_y(Z(x)) = \max_a [R(x, a) + \gamma CVaR_y(Z(x, a))] \quad (3.4)$$

[8](lemma 3) showed that the operator \mathbf{T} is a contraction and also preserves the convexity of $yCVaR_t$. The maximization problem 3.1 is a convex one and therefore has a unique solution. Additionally, the fixed point of this contraction is the optimal $V^*(x, y) = \max_{\pi \in \Pi} CVaR_y(Z^\pi(x, y))$ (Theorem 4).

The value-function V^* can then be used to extract the optimal policy π^* of the original problem ??, using the following theorem

Theorem 1 (Optimal Policies, Theorem 5 in [8]). *Let $\pi_H^* = \{\mu_0, \mu_1, \dots\} \in \Pi_H$ be a history-dependent policy recursively defined as:*

$$\mu_k(h_k) = u^*(x_k, y_k), \quad \forall k \geq 0, \quad (3.5)$$

with initial conditions x_0 and $y_0 = \alpha$, and state transitions

$$x_k \sim P(\cdot | x_{k-1}, u^*(x_{k-1}, y_{k-1})), \quad y_k = y_{k-1} \xi_{x_{k-1}, y_{k-1}, u^*}^*(x_k), \quad \forall k \geq 1, \quad (3.6)$$

where the stationary Markovian policy $u^*(x, y)$ and risk factor $\xi_{x, y, u^*}^*(\cdot)$ are solution to the min-max optimization problem in the CVaR Bellman operator $\mathbf{T}[V^*](x, y)$. Then, π_H^* is an optimal policy for problem (??) with initial state x_0 and CVaR confidence level α .

This algorithm is unfortunately unusable in practice, as the state-space is continuous in y . The solution proposed in [8] is then to represent the convex $yCVaR_y$ as a piecewise linear function.

3.1.2 Value Iteration with Linear Interpolation

Given a set of $N(x)$ interpolation points $\mathbf{Y}(x) = \{y_1, \dots, y_{N(x)}\}$, we can interpolate the $yV(x, y)$ function on these points, i.e.

$$\mathcal{I}_x[V](y) = y_i V(x, y_i) + \frac{y_{i+1} V(x, y_{i+1}) - y_i V(x, y_i)}{y_{i+1} - y_i} (y - y_i),$$

where $y_i = \max\{y' \in \mathbf{Y}(x) : y' \leq y\}$. The interpolated Bellman operator is then also a contraction and has a bounded error (Theorem 7).

todo: bounded \rightarrow linear in θ

$$\mathbf{T}_{\mathcal{I}}V(x, y) = \max_a \left[R(x, a) + \gamma \min_{\xi \in \mathcal{U}_{\text{CVaR}}(\alpha, P(\cdot|x, a))} \sum_{x'} p(x'|x, a) \frac{\mathcal{I}_{x'}[V](y\xi(x'))}{y} \right] \quad (3.7)$$

The full value iteration procedure is presented in algorithm 1

Algorithm 1 CVaR Value Iteration with Linear Interpolation

1: **Given:**

- $N(x)$ interpolation points $\mathbf{Y}(x) = \{y_1, \dots, y_{N(x)}\} \in [0, 1]^{N(x)}$ for every $x \in \mathcal{X}$ with $y_i < y_{i+1}$, $y_1 = 0$ and $y_{N(x)} = 1$.
- Initial value function $V_0(x, y)$ that satisfies Assumption ??.

2: For $t = 1, 2, \dots$

- For each $x \in \mathcal{X}$ and each $y_i \in \mathbf{Y}(x)$, update the value function estimate as follows:

$$V_t(x, y_i) = \mathbf{T}_{\mathcal{I}}[V_{t-1}](x, y_i),$$

3: Set the converged value iteration estimate as $\hat{V}^*(x, y_i)$, for any $x \in \mathcal{X}$, and $y_i \in \mathbf{Y}(x)$.

This algorithm can be used to find an approximate global optimum in any MDP. There is however the issue of computational complexity. As the algorithm stands, the straightforward approach is to solve each iteration of 3.7 as a linear program, since the problem is convex and piecewise linear. This however is not practical, as the LP computation can be demanding and is therefore not suitable for large state-spaces.

unclear: maybe formulate the LP exactly?

In the next section we aim to find a different way of computing the optimization problem presented in 3.1.

3.2 EFFICIENT COMPUTATION USING QUANTILE REPRESENTATION

We note several important facts regarding the CVaR computation. Firstly, it is unimportant *how* we arrive at the $\text{CVaR}_y(Z(x, a))$ present in the CVaR Bellman operator

3.4. Secondly, note that any discrete distribution has a piecewise linear $y\text{CVaR}_y$ function [22], and this statement is twosided: any a piecewise linear $y\text{CVaR}_y$ function can be seen as representing a certain discrete distribution.

The relation between $y\text{CVaR}_y$ and the underlying distribution is best described in the following equation:

$$\frac{\partial}{\partial \alpha} \alpha \text{CVaR}_\alpha(Z) = \frac{\partial}{\partial \alpha} \int_0^\alpha \text{VaR}_\beta(Z) d\beta = \text{VaR}_\alpha(Z) \quad (3.8)$$

We see that the quantile function of Z is extractable from the $y\text{CVaR}_y$ function by differentiating over y **todo: unify y, α** . The opposite direction also holds:

$$\alpha \text{CVaR}_\alpha(Z) = \int_0^\alpha \text{VaR}_\beta(Z) d\beta + c \quad (3.9)$$

where we have $c = 0$ because of a starting condition $y\text{CVaR}_y \Big|_{y=0} = 0$.

3.2.1 CVaR Computation via Quantile Representation

We propose the following procedure: instead of using linear programming for the CVaR computation, we use the underlying distributions represented by the $\alpha \text{CVaR}_\alpha$ function to compute CVaR.

The computation of CVaR of a discrete probability mixture is a linear-time process as we show bellow. The general steps of the computation are as follows

1. transform $y\text{CVaR}_y$ of each possible state transition to a discrete probability distribution function using 3.8
2. combine these to to a distribution representing the full state-action distribution
3. compute $y\text{CVaR}_y$ for all atoms using 3.9

todo: pretty pictures

unclear: proof necessary? also, maybe it is already in the ξ proof

3.2.2 ξ -computation

Similarly to theorem 1, we need a way to compute the $y_{k+1} = y_k \xi^*(x_k)$ to extract the optimal policy. Again, we can skip the LP computation by using the following intuition: y_{k+1} is the portion of $Z(x_{k+1})$ that is present in $\text{CVaR}_{y_k}(Z(x_k))$. In the continuous case, it is the probability in $Z(x_{k+1})$ before the $\text{VaR}_{y_k}(Z(x_k))$ as we show bellow.

todo: proof for discrete distributions

Theorem 2. *Solution to minimization problem 3.1 can be computed without optimization by setting*

$$\xi(x') = \frac{F_{x'}(F_x^{-1}(\alpha))}{\alpha} \quad (3.10)$$

Proof. For simplification, we work only with two states: x' the actual sampled state and \bar{x}' representing the other states. The equation then simplifies to

$$\begin{aligned} CVaR_\alpha(x, a) &= \min_{\xi} p\xi CVaR_{\xi\alpha}(x') + (1-p) \frac{1-p\xi}{1-p} CVaR_{\frac{1-p\xi}{1-p}\alpha}(\bar{x}') \\ &= \min_{\xi} p\xi CVaR_{\xi\alpha}(x') + (1-p\xi) CVaR_{\frac{1-p\xi}{1-p}\alpha}(\bar{x}') \end{aligned} \quad (3.11)$$

To find the min we first find the first derivative¹ w.r.t. ξ

$$\begin{aligned} \frac{\partial CVaR_\alpha}{\partial \xi} &= pCVaR_{\xi\alpha} + p\xi \frac{\partial CVaR_{\xi\alpha}}{\partial \xi} - pCVaR_{\frac{1-p\xi}{1-p}\alpha} + (1-p\xi) \frac{\partial CVaR_{\frac{1-p\xi}{1-p}\alpha}}{\partial \xi} \\ &= pCVaR_{\xi\alpha} + p\xi \left[\frac{1}{\xi} VaR_{\xi\alpha} - \frac{1}{\xi} CVaR_{\xi\alpha} \right] - pCVaR_{\frac{1-p\xi}{1-p}\alpha} \\ &\quad + (1-p\xi) \left[\frac{p}{1-p\xi} CVaR_{\frac{1-p\xi}{1-p}\alpha} - \frac{p}{1-p\xi} VaR_{\frac{1-p\xi}{1-p}\alpha} \right] \\ &= pCVaR_{\xi\alpha} + pVaR_{\xi\alpha} - pCVaR_{\xi\alpha} - pCVaR_{\xi\alpha} - pCVaR_{\frac{1-p\xi}{1-p}\alpha} \\ &\quad + CVaR_{\frac{1-p\xi}{1-p}\alpha} - pVaR_{\frac{1-p\xi}{1-p}\alpha} \\ &= pVaR_{\xi\alpha} - pVaR_{\frac{1-p\xi}{1-p}\alpha} \end{aligned} \quad (3.12)$$

By setting the derivative to 0 (to find the min), we get

$$VaR_{\xi\alpha}(x') = VaR_{\frac{1-p\xi}{1-p}\alpha}(\bar{x}') \quad (3.13)$$

By inserting claim 3.10 into ?? we get the symmetrical claim

$$\frac{1-p\xi}{1-p} = \xi(\bar{x}') = \frac{F_{\bar{x}'}(F_x^{-1}(\alpha))}{\alpha} \quad (3.14)$$

We rewrite 3.11 as (assuming ξ is the minimum point)

$$\begin{aligned} \frac{1}{\alpha} \int_0^\alpha F_x^{-1}(t) dt &= p\xi \frac{1}{\xi\alpha} \int_0^{\xi\alpha} F_{x'}^{-1}(t) dt + (1-p\xi) \frac{1-p}{(1-p\xi)\alpha} \int_0^{\frac{1-p\xi}{1-p}\alpha} F_{\bar{x}'}^{-1}(t) dt \\ &= p \frac{1}{\alpha} \int_0^{\xi\alpha} F_{x'}^{-1}(t) dt + (1-p) \frac{1}{\alpha} \int_0^{\frac{1-p\xi}{1-p}\alpha} F_{\bar{x}'}^{-1}(t) dt \end{aligned} \quad (3.15)$$

This must also hold if we multiply both sides by α

$$\int_0^\alpha F_x^{-1}(t) dt = p \int_0^{\xi\alpha} F_{x'}^{-1}(t) dt + (1-p) \int_0^{\frac{1-p\xi}{1-p}\alpha} F_{\bar{x}'}^{-1}(t) dt \quad (3.16)$$

¹ We used the following identities:

$$\frac{\partial CVaR_{\xi\alpha}}{\partial \xi} = \frac{1}{\xi} VaR_{\xi\alpha} - \frac{1}{\xi} CVaR_{\xi\alpha} \quad \frac{\partial CVaR_{\frac{1-p\xi}{1-p}\alpha}}{\partial \xi} = \frac{p}{1-p\xi} CVaR_{\frac{1-p\xi}{1-p}\alpha} - \frac{p}{1-p\xi} VaR_{\frac{1-p\xi}{1-p}\alpha}$$

And we take derivations w.r.t. α of both sides

$$F_x^{-1}(\alpha) = p\xi F_{x'}^{-1}(\xi\alpha) + (1-p\xi)F_{\bar{x}'}^{-1}\left(\frac{1-p\xi}{1-p}\alpha\right) \quad (3.17)$$

By inserting 3.10 we get

$$\begin{aligned} p\xi F_{x'}^{-1}(\xi\alpha) + (1-p)\xi_2 F_{\bar{x}'}^{-1}(\xi_2\alpha) &= p\xi F_{x'}^{-1}(F_{x'}(F_x^{-1}(\alpha))) + (1-p\xi)F_{\bar{x}'}^{-1}\left(F_{\bar{x}'}(F_x^{-1}(\alpha))\right) \\ &= p\xi F_x^{-1}(\alpha) + (1-p\xi)F_x^{-1}(\alpha) = F_x^{-1}(\alpha) \end{aligned} \quad (3.18)$$

We've shown that the proposed solution 3.10 satisfies the minimization constraint 3.13 (= is a minimal point) and satisfies the dual decomposition 3.1. (This has been shown only in the differentiated form)

□

3.3 EXPERIMENTS

todo: $|\mathcal{X}| \sim 1M$ tabular environment

todo: get matlab code from tamar

3.3.1 *Cliffworld*

3.4 SUMMARY

Q-LEARNING WITH CVAR

4.1 VAR-BASED POLICY IMPROVEMENT

4.1.1 Policy Improvement

Recall the primal definition of CVaR (***). Our goal can then be rewritten as

$$\max_{\pi} CVaR_{\alpha}^{\pi}(Z) = \max_{\pi} \max_s \frac{1}{\alpha} \mathbb{E} [(Z^{\pi} - s)^{-}] + s \quad (4.1)$$

It also holds [XXX] that for the maximum, it holds $s^* = VaR_{\alpha}$

$$CVaR_{\alpha}(Z) = \max_s \left\{ \frac{1}{\alpha} \mathbb{E} [(Z - s)^{-}] + s \right\} = \frac{1}{\alpha} \mathbb{E} [(Z - VaR_{\alpha}(Z))^{-}] + VaR_{\alpha}(Z) \quad (4.2)$$

The main idea of the algorithm 2, partially explored in [4], is as follows: If we knew the value s^* in the solution to equation (***), we could simplify the problem to maximize only

$$\max_{\pi} CVaR_{\alpha}(Z) = \max_{\pi} \frac{1}{\alpha} \mathbb{E} [(Z^{\pi} - s^*)^{-}] + s^* \quad (4.3)$$

Given that we have access to the return distributions, we can improve the policy by simply choosing an action that maximizes CVaR in the first state $a_0 = \arg \max_{\pi} CVaR_{\alpha}(Z^{\pi}(x_0))$. We can then, as an approximation, set $s = VaR_{\alpha}(Z(x_0))$ and then only maximize the simpler criterion

$$\max_{\pi} CVaR_{\alpha}(Z) = \max_{\pi} \frac{1}{\alpha} \mathbb{E} [(Z^{\pi} - s^*)^{-}] + s^* \quad (4.4)$$

The algorithm can be seen as coordinate ascent; in the first phase (when we compute CVaR) we maximize w.r.t. s while keeping π fixed; in the second phase we fix s and maximize w.r.t. π .

In the following theorem, we show that this indeed leads to a monotonic improvement over the previous policy.

Theorem 3. *Let π be a fixed policy, $\alpha \in (0, 1]$. By following policy π' from algorithm 2, we will improve $CVaR_{\alpha}(Z)$ in expectation:*

$$CVaR_{\alpha}(Z^{\pi}) \leq CVaR_{\alpha}(Z^{\pi'})$$

Proof. Let s^* be a solution to eq 2.5. Then by optimizing $\max_{\pi} \frac{1}{\alpha} \mathbb{E} [(Z - s^*)^-]$, we will monotonely improve the optimization criterion 4.3.

$$CVaR_{\alpha}(Z^{\pi}) = \frac{1}{\alpha} \mathbb{E} [(Z^{\pi} - s^*)^-] + s^* \leq \max_{\pi'} \frac{1}{\alpha} \mathbb{E} [(Z^{\pi'} - s^*)^-] + s^*$$

Note the following facts:

$$Z_t = R_t + \gamma Z_{t+1} \tag{4.5}$$

$$\mathbb{E} [(Z_t - s)^-] = \mathbb{E} [(Z_t - s) \mathbf{1}(Z_t \leq s)] \tag{4.6}$$

$$\mathbb{E}[H(Z)] = \sum_i p_i \mathbb{E}[H(Z_i)] \tag{4.7}$$

The last equation holds if $Z \sim p_i$ is a probability mixture for any function H . We can rewrite the criterion as

$$\begin{aligned} \mathbb{E} [(Z_t - s)^-] &= \mathbb{E} [(Z_t - s) \mathbf{1}(Z_t \leq s)] = \mathbb{E} \left[(R_t + \gamma Z_{t+1} - s) \mathbf{1}(Z_{t+1} \leq \frac{s - R_t}{\gamma}) \right] \\ &= \sum_{x_{t+1}, r_t} P(x_{t+1}, r_t | x_t, a) \mathbb{E} \left[(r_t + \gamma Z(x_{t+1}) - s) \mathbf{1}(Z(x_{t+1}) \leq \frac{s - r_t}{\gamma}) \right] \\ &= \sum_{x_{t+1}, r_t} P(x_{t+1}, r_t | x_t, a) \mathbb{E} \left[\gamma \left(Z(x_{t+1}) - \frac{s - r_t}{\gamma} \right) \mathbf{1}(Z(x_{t+1}) \leq \frac{s - r_t}{\gamma}) \right] \\ &= \gamma \sum_{x_{t+1}, r_t} P(x_{t+1}, r_t | x_t, a) \mathbb{E} \left[\left(Z(x_{t+1}) - \frac{s - r_t}{\gamma} \right) \mathbf{1}(Z(x_{t+1}) \leq \frac{s - r_t}{\gamma}) \right] \\ &= \gamma \sum_{x_{t+1}, r_t} P(x_{t+1}, r_t | x_t, a) \mathbb{E} \left[\left(Z(x_{t+1}) - \frac{s - r_t}{\gamma} \right)^- \right] \end{aligned} \tag{4.8}$$

Now let's say we sampled reward \hat{r}_t and state \hat{x}_{t+1} , we are still trying to find a policy π^* that maximizes

$$\begin{aligned} \pi^* &= \arg \max_{\pi} \mathbb{E} [(Z_t - s)^- | \hat{x}_{t+1}, \hat{r}] \\ &= \arg \max_{\pi} \mathbb{E} \left[\left(Z(\hat{x}_{t+1}) - \frac{s - \hat{r}_t}{\gamma} \right)^- \right] \end{aligned} \tag{4.9}$$

Where we ignored the unsampled states (since these are not a function of \hat{x}_{t+1}) and the multiplicative constant γ that will not affect the maximum argument.

At the starting state, we set $s = s^*$. At each following state we select an action according to equation 4.9. By induction we maximize the criterion ?? in each step. \square

Note that the resulting policy is nonstationary, however we do not need an extended state-space to follow this policy, it is only necessary to remember our previous s .

Algorithm 2 VaR-based policy improvement

```

input  $\alpha, x_0, \gamma$ 
 $a = \arg \max_a CVaR_\alpha(Z(x_0, a))$ 
 $s = VaR_\alpha(Z(x_0, a))$ 
 $x_t, r_t = \text{envTransition}(x_0, a)$ 
while  $x_t$  is not terminal do
   $s = \frac{s - r_t}{\gamma}$ 
   $a = \arg \max_a \mathbb{E} [(Z(x_t, a) - s)^-]$ 
   $x_t, r_t = \text{envTransition}(x_t, a)$ 
end while

```

4.1.2 *Repeated policy improvement*

This policy then could be evaluated again by the distributional Q-learning procedures, however we

4.2 TODO

4.3 TODO

4.4 TODO

4.5 EXPERIMENTS

todo: ai safety gridworld

APPROXIMATE Q-LEARNING WITH CVAR

5.1 TODO

5.2 TODO

5.3 TODO

5.4 EXPERIMENTS

CONCLUSION

Bäuerle and Ott [4] Bellemare, Dabney, and Munos [5] Chow et al. [8] Dabney et al. [10] Garcia and Fernández [11] Majumdar and Pavone [16] Morimura et al. [18] Morimura et al. [19] Pflug and Pichler [20] Rockafellar and Uryasev [21] Rockafellar and Uryasev [22] Majumdar and Pavone [16] Leike et al. [15] Amodei et al. [1] Shapiro [23] Artzner et al. [2] Tamar et al. [26] Sutton and Barto [25] Watkins and Dayan [28] Bellman [6] Tsitsiklis [27] Boyd and Vandenberghe [7] Kreyszig [13] Koenker and Hallock [12] Committee [9] Mnih et al. [17] Silver et al. [24] **rajpurkar2017cardiologist** Krizhevsky, Sutskever, and Hinton [14]



INTRODUCTION

This bundle for L^AT_EX has two goals:

1. Provide students with an easy-to-use template for their Master's or PhD thesis. (Though it might also be used by other types of authors for reports, books, etc.)
2. Provide a classic, high-quality typographic style that is inspired by **bringhurst:2002**'s "*The Elements of Typographic Style*" [bringhurst:2002].

*Risk-Averse
Distributional
Reinforcement
Learning
version 0.0*

The bundle is configured to run with a *full* MiK_TE_X or T_EXLive¹ installation right away and, therefore, it uses only freely available fonts. (Minion fans can easily adjust the style to their needs.)

People interested only in the nice style and not the whole bundle can now use the style stand-alone via the file `classicthesis.sty`. This works now also with "plain" L^AT_EX.

As of version 3.0, `classicthesis` can also be easily used with L_YX² thanks to Nicholas Mariette and Ivo Pletikosić. The L_YX version of this manual will contain more information on the details.

This should enable anyone with a basic knowledge of L^AT_EX 2_ε or L_YX to produce beautiful documents without too much effort. In the end, this is my overall goal: more beautiful documents, especially theses, as I am tired of seeing so many ugly ones.

The whole template and the used style is released under the GNU General Public License.

If you like the style then I would appreciate a postcard:

André Miede
Detmolder Straße 32
31737 Rinteln
Germany

The postcards I received so far are available at:

<http://postcards.miede.de>

So far, many theses, some books, and several other publications have been typeset successfully with it. If you are interested in some typographic details behind it, enjoy Robert Bringhurst's wonderful book.

*A
well-balanced
line width
improves the
legibility of the
text. That's
what
typography is
all about,
right?*

¹ See the file `LISTOFFILES` for needed packages. Furthermore, `classicthesis` works with most other distributions and, thus, with most systems L^AT_EX is available for.

² <http://www.lyx.org>

IMPORTANT NOTE: Some things of this style might look unusual at first glance, many people feel so in the beginning. However, all things are intentionally designed to be as they are, especially these:

- No bold fonts are used. Italics or spaced small caps do the job quite well.
- The size of the text body is intentionally shaped like it is. It supports both legibility and allows a reasonable amount of information to be on a page. And, no: the lines are not too short.
- The tables intentionally do not use vertical or double rules. See the documentation for the `booktabs` package for a nice discussion of this topic.³
- And last but not least, to provide the reader with a way easier access to page numbers in the table of contents, the page numbers are right behind the titles. Yes, they are *not* neatly aligned at the right side and they are *not* connected with dots that help the eye to bridge a distance that is not necessary. If you are still not convinced: is your reader interested in the page number or does she want to sum the numbers up?

Therefore, please do not break the beauty of the style by changing these things unless you really know what you are doing! Please.

YET ANOTHER IMPORTANT NOTE: Since `classicthesis`' first release in 2006, many things have changed in the \LaTeX world. Trying to keep up-to-date, `classicthesis` grew and evolved into many directions, trying to stay (some kind of) stable and be compatible with its port to \LyX . However, there are still many remains from older times in the code, many dirty workarounds here and there, and several other things I am absolutely not proud of (for example my unwise combination of KOMA and `titlesec` etc.).

Currently, I am looking into how to completely re-design and re-implement `classicthesis` making it easier to maintain and to use. As a general idea, `classicthesis.sty` should be developed and distributed separately from the template bundle itself. Excellent spin-offs such as `arsclassica` could also be integrated (with permission by their authors) as format configurations. Also, current trends of `microtype`, `fontspec`, etc. should be included as well. As I am not really into deep \LaTeX programming, I will reach out to the \LaTeX community for their expertise and help.

*An outlook
into the future
of
classicthesis.*

A.1 ORGANIZATION

A very important factor for successful thesis writing is the organization of the material. This template suggests a structure as the following:

- **Chapters/** is where all the “real” content goes in separate files such as **Chapter01.tex** etc.
- **FrontBackMatter/** is where all the stuff goes that surrounds the “real” content, such as the acknowledgments, dedication, etc.

*You can use
these margins
for summaries
of the text
body...*

³ To be found online at <http://mirror.ctan.org/macros/latex/contrib/booktabs/>.

- `gfx/` is where you put all the graphics you use in the thesis. Maybe they should be organized into subfolders depending on the chapter they are used in, if you have a lot of graphics.
- `Bibliography.bib`: the BibTeX database to organize all the references you might want to cite.
- `classicthesis.sty`: the style definition to get this awesome look and feel. Does not only work with this thesis template but also on its own (see folder `Examples`). Bonus: works with both L^AT_EX and PDFL^AT_EX...and L^YX. Great tool and it's free!
- `ClassicThesis.tex`: the main file of your thesis where all gets bundled together.
- `classicthesis-config.tex`: a central place to load all nifty packages that are used.

Make your changes and adjustments here. This means that you specify here the options you want to load `classicthesis.sty` with. You also adjust the title of your thesis, your name, and all similar information here. Refer to [Section A.3](#) for more information.

This had to change as of version 3.0 in order to enable an easy transition from the “basic” style to L^YX.

In total, this should get you started in no time.

A.2 STYLE OPTIONS

There are a couple of options for `classicthesis.sty` that allow for a bit of freedom concerning the layout:

- General:
 - **drafting**: prints the date and time at the bottom of each page, so you always know which version you are dealing with. Might come in handy not to give your Prof. that old draft.
- Parts and Chapters:
 - **parts**: if you use Part divisions for your document, you should choose this option. (Cannot be used together with **nochapters**.)
 - **linedheaders**: changes the look of the chapter headings a bit by adding a horizontal line above the chapter title. The chapter number will also be moved to the top of the page, above the chapter title.
- Typography:
 - **eulerchapternumbers**: use figures from Hermann Zapf’s Euler math font for the chapter numbers. By default, old style figures from the Palatino font are used.
 - **beramono**: loads Bera Mono as typewriter font. (Default setting is using the standard CM typewriter font.)
 - **eulermath**: loads the awesome Euler fonts for math. Palatino is used as default font.
- Table of Contents:
 - **totaligned**: aligns the whole table of contents on the left side. Some people like that, some don’t.
 - **dottedtoc**: sets pagenumbers flushed right in the table of contents.
 - **many chapters**: if you need more than nine chapters for your document, you might not be happy with the spacing between the chapter number and the chapter title in the Table of Contents. This option allows for additional space in this context. However, it does not look as “perfect” if you use `\parts` for structuring your document.
- Floats:
 - **listings**: loads the `listings` package (if not already done) and configures the List of Listings accordingly.
 - **floatperchapter**: activates numbering per chapter for all floats such as figures, tables, and listings (if used).

... or your supervisor might use the margins for some comments of her own while reading.

Options are enabled via `option=true`

Furthermore, pre-defined margins for different paper sizes are available, e. g., **a4paper**, **a5paper**, and **letterpaper**. These are based on your chosen option of `\documentclass`.

The best way to figure these options out is to try the different possibilities and see what you and your supervisor like best.

In order to make things easier, `classicthesis-config.tex` contains some useful commands that might help you.

A.3 CUSTOMIZATION

This section will show you some hints how to adapt `classicthesis` to your needs.

The file `classicthesis.sty` contains the core functionality of the style and in most cases will be left intact, whereas the file `classicthesis-config.tex` is used for some common user customizations.

The first customization you are about to make is to alter the document title, author name, and other thesis details. In order to do this, replace the data in the following lines of `classicthesis-config.tex`:

*Modifications
in classic-
thesis-config.tex*

```
% *****
% 2. Personal data and user ad-hoc commands
% *****
\newcommand{\myTitle}{A Classic Thesis Style\xspace}
\newcommand{\mySubtitle}{An Homage to...\xspace}
```

Further customization can be made in `classicthesis-config.tex` by choosing the options to `classicthesis.sty` (see [Section A.2](#)) in a line that looks like this:

```
\PassOptionsToPackage{
  drafting=true,      % print version information on the bottom
                      % of the pages
  totaligned=false,   % the left column of the toc will be
                      % aligned (no indentation)
  dottedtoc=false,    % page numbers in ToC flushed right
  parts=true,         % use part division
  eulerchapternumbers=true, % use AMS Euler for chapter font
                      % (otherwise Palatino)
  linedheaders=false, % chapter headers will have line
                      % above and beneath
  floatperchapter=true, % numbering per chapter for all
                      % floats (i.e., Figure 1.1)
  listings=true,      % load listings package and setup LoL
  subfig=true,        % setup for preloaded subfig package
  eulermath=false,    % use awesome Euler fonts for
                      % mathematical formulae (only with pdfLaTeX)
  beramono=true,      % toggle a nice monospaced font (w/ bold)
  minionpro=false     % setup for minion pro font; use minion
                      % pro small caps as well (only with pdfLaTeX)
}{classicthesis}
```

Many other customizations in `classicthesis-config.tex` are possible, but you should be careful making changes there, since some changes could cause errors.

A.4 ISSUES

This section will list some information about problems using `classicthesis` in general or using it with other packages.

Beta versions of `classicthesis` can be found at Bitbucket:

<https://bitbucket.org/amiede/classicthesis/>

There, you can also post serious bugs and problems you encounter.

A.5 FUTURE WORK

So far, this is a quite stable version that served a couple of people well during their thesis time. However, some things are still not as they should be. Proper documentation in the standard format is still missing. In the long run, the style should probably be published separately, with the template bundle being only an application of the style. Alas, there is no time for that at the moment... it could be a nice task for a small group of L^AT_EXnicians.

Please do not send me email with questions concerning L^AT_EX or the template, as I do not have time for an answer. But if you have comments, suggestions, or improvements for the style or the template in general, do not hesitate to write them on that postcard of yours.

A.6 BEYOND A THESIS

The layout of `classicthesis.sty` can be easily used without the framework of this template. A few examples where it was used to typeset an article, a book or a curriculum vitae can be found in the folder **Examples**. The examples have been tested with `latex` and `pdflatex` and are easy to compile. To encourage you even more, PDFs built from the sources can be found in the same folder.

A.7 LICENSE

GNU GENERAL PUBLIC LICENSE: This program is free software; you can redistribute it and/or modify it under the terms of the GNU General Public License as published by the Free Software Foundation; either version 2 of the License, or (at your option) any later version.

This program is distributed in the hope that it will be useful, but *without any warranty*; without even the implied warranty of *merchantability* or *fitness for a particular purpose*. See the GNU General Public License for more details.

You should have received a copy of the GNU General Public License along with this program; see the file **COPYING**. If not, write to the Free Software Foundation, Inc., 59 Temple Place - Suite 330, Boston, MA 02111-1307, USA.

CLASSICTHESIS AUTHORS' NOTE: There have been some discussions about the GPL's implications on using `classicthesis` for theses etc. Details can be found here:

<https://bitbucket.org/amiede/classicthesis/issues/123/>

We chose (and currently stick with) the GPL because we would not like to compete with proprietary modified versions of our own work. However, the whole template is free as free beer and free speech. We will not demand the sources for theses, books, CVs, etc. that were created using `classicthesis`.

Postcards are still highly appreciated.

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DECLARATION

Put your declaration here.

Prague, February, 2018

Silvestr Stanko

COLOPHON

This document was typeset using the typographical look-and-feel `classicthesis` developed by André Miede and Ivo Pletikosić. The style was inspired by Robert Bringhurst’s seminal book on typography “*The Elements of Typographic Style*”. `classicthesis` is available for both L^AT_EX and L^YX:

<https://bitbucket.org/amiede/classicthesis/>

Happy users of `classicthesis` usually send a real postcard to the author, a collection of postcards received so far is featured here:

<http://postcards.miede.de/>

Thank you very much for your feedback and contribution.