

Distributional Robust Kelly Gambling

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Abstract

In classic Kelly gambling, bets are chosen to maximize the expected log growth, under a known probability distribution. In this note we consider the distributional robust version of the Kelly gambling problem, in which the probability distribution is not known, but lies in a given set of possible distributions. The bet is chosen to maximize the worst-case (smallest) log growth among the distributions in the given set. This distributional robust Kelly gambling problem is convex, but in general need not be tractable. We show that it can be tractably solved in the case of a finite number of outcomes, and some useful sets of distributions.

1 Introduction

Gambling. We consider a setting where a gambler repeatedly allocates a fraction of her wealth (assumed positive) across n different bets in multiple rounds. We assume there are n bets available to the gambler, who can bet any nonnegative amount on each of the bets. We let $b \in \mathbf{R}^n$ denote the bet allocation, so $b \geq 0$ and $\mathbf{1}^T b = 1$, where $\mathbf{1}$ is the vector with all entries one. Letting S_n denote the probability simplex in \mathbf{R}^n , we have $b \in S_n$. With bet allocation b , the gambler is betting Wb_i (in dollars) on outcome i , where $W > 0$ is the gambler's wealth (in dollars).

We let $r \in \mathbf{R}_+^n$ denote the random returns on the n bets, with $r_i \geq 0$ the amount won by the gambler for each dollar she puts on bet i . With allocation b , the total she wins is $r^T b W$, which means her wealth increases by the (random) factor $r^T b$. We assume that the returns r in different rounds are IID. We will assume that $r_n = 1$ almost surely, so b_n corresponds to the fraction of wealth the gambler holds in cash; the allocation $b = e_n$ corresponds to not betting at all. Since her wealth is multiplied in each round by the IID random factor $r^T b$, the log of the wealth over time is therefore a random walk, with increment distribution given by $\log(r^T b)$.

Finite outcome case. We consider here the case where one of K events occurs, *i.e.*, r is supported on only K points. We let r_1, \dots, r_K denote the return vectors, and $\pi = (\pi_1, \dots, \pi_K) \in S_K$ the corresponding probabilities. We collect the K payoff vectors into a

matrix $R \in \mathbf{R}^{n \times K}$, with columns r_1, \dots, r_K . The vector $R^T b \in \mathbf{R}^K$ gives the wealth growth factor in the K possible outcomes. The mean log growth rate is

$$G_\pi(b) = \mathbf{E} \log(r^T b) = \pi^T \log(R^T b) = \sum_{k=1}^K \pi_k \log(r_k^T b),$$

where the log in the middle term is applied to the vector elementwise. This is the mean drift in the log wealth random walk.

Kelly gambling. In a 1956 classic paper [1], John Kelly proposed to choose the allocation vector b so as to maximize the mean log growth rate $G_\pi(b)$, subject to $b \geq 0$, $\mathbf{1}^T b = 1$. This method was called the Kelly criterion; since then, much work has been done on this topic [2, 3, 4, 5, 6, 7]. The mean log growth rate $G_\pi(b)$ is a concave function of b , so choosing b is a convex optimization problem [8, 9]. It can be solved analytically in simple cases, such as when there are $K = 2$ possible outcomes. It is easily solved in other cases using standard methods and algorithms, and readily expressed in various domain specific languages (DSLs) for convex optimization such as CVX [10], CVXPY [11], Convex.jl [12], or CVXR [13]. We can add additional convex constraints on b , which we denote as $b \in B$, with $B \subseteq S_K$ a convex set. These additional constraints while preserve convexity, and therefore tractability, of the optimization problem. While Kelly did not consider additional constraints, or indeed the use of a numerical optimizer to find the optimal bet allocation vector, we still refer to the problem of maximizing $G_\pi(b)$ subject to $b \in B$ as the Kelly (gambling) problem (KP).

There have been many papers exploring and extending the Kelly framework; for example, a drawdown risk constraint, that preserves convexity (hence, tractability) is described in [14]. The Bayesian version of Kelly optimal betting is described in [15]. In [16], Kelly gambling is generalized to maximize the proportion of wealth relative to the total wealth in the population.

Distributional robust Kelly gambling. In this note we study a distributional robust version of Kelly gambling, in which the probability distribution π is not known. Rather, it is known that $\pi \in \Pi$, a set of possible distributions. We define the worst-case log growth rate (under Π) as

$$G_\Pi(b) = \inf_{\pi \in \Pi} G_\pi(b).$$

This is evidently a concave function of b , since it is an infimum of a family of concave functions of b , *i.e.*, $G_\pi(b)$ for $\pi \in \Pi$. The *distributional robust Kelly problem* (DRKP) is to choose $b \in B$ to maximize $G_\Pi(b)$. This is in principle a convex optimization problem, specifically a distributional robust problem; but such problems in general need not be tractable, as discussed in [17, 18, 19] The purpose of this note is to show how the DRKP can be tractably solved for some useful probability sets Π .

Related work on distributional robust optimization. Distributional robust optimization is a well studied topic. Previous work to distribution robust optimization studied finite-

dimensional parametrization for probability set like moments, support or directional deviations constraints in [20, 21, 22, 23, 24, 25]. Beyond finite-dimensional parametrization for probability set, people have also studied non-parametric distances for probability measure, like f -divergences (*e.g.*, Kullback-Leibler divergences) [26, 27, 28, 29, 30] and Wasserstein distances [31, 32, 33, 34].

2 Tractable distributional robust Kelly gambling

In this section we show how to formulate DRKP as a tractable convex optimization problem for a variety of distribution set Π . The key is to derive a tractable description of the worst-case log growth $G_\Pi(b)$. We use duality to express $G_\Pi(b)$ as the value of a convex maximization problem, which allows us to solve DRKP as one convex problem.

2.1 Polyhedral distribution sets

Here we consider the case when Π is a polyhedron.

Convex hull of finite set. We start with the simplest example, when Π is a polyhedron defined as the convex hull of a finite set of points, $\Pi = \mathbf{conv}(\pi, \dots, \pi_s)$. The infimum of the log growth over $\pi \in \Pi$ is the same as the minimum over the vertices:

$$G_\Pi(b) = \min_i G_{\pi_i}(b) = \min_i \pi_i^T \log(R^T b).$$

Then the DRKP becomes

$$\begin{aligned} & \text{maximize} && \min_i \pi_i^T \log(R^T b) \\ & \text{subject to} && b \in B, \end{aligned}$$

with variable b . This problem is tractable, and indeed in modern domain specific languages for convex optimization, can be specified in just a few lines of simple code.

Polyhedron defined by linear inequalities and equalities. Here we consider the case when Π is given by a finite set of linear inequalities and equalities,

$$\Pi = \{\pi \in S_K \mid A_0 \pi = d_0, A_1 \pi \leq d_1\},$$

where $A_0 \in \mathbf{R}^{m_0 \times K}$, $b_0 \in \mathbf{R}^{m_0}$, $A_1 \in \mathbf{R}^{m_1 \times K}$, $b_1 \in \mathbf{R}^{m_1}$. The worst-case log growth rate $G_\Pi(b)$ is given by the optimal value of the linear program (LP)

$$\begin{aligned} & \text{minimize} && \pi^T \log(R^T b) \\ & \text{subject to} && \mathbf{1}^T \pi = 1, \quad \pi \geq 0, \\ & && A_0 \pi = d_0, \quad A_1 \pi \leq d_1, \end{aligned} \tag{1}$$

with variable π .

We form a dual of this problem, working with the constraints $A_0\pi = d_0$, $A_1\pi \leq d_1$; we keep the simplex constraints $\pi \geq 0$, $\mathbf{1}^T\pi = 1$ as an indicator function $I_S(\pi)$ in the objective. The Lagrangian is

$$L(\nu, \lambda, \pi) = \pi^T \log(R^T b) + \nu^T (A_0\pi - d_0) + \lambda^T (A_1\pi - d_1) + I_S(\pi),$$

where $\nu \in \mathbf{R}^{m_0}$ and $\lambda \in \mathbf{R}^{m_1}$ are the dual variables, with $\lambda \geq 0$. Minimizing over π we obtain the dual function,

$$g(\nu, \lambda) = \inf_{\pi \in S_K} L(\nu, \lambda, \pi) = \min(\log(R^T b) + A_0^T \nu + A_1^T \lambda) - d_0^T \nu - d_1^T \lambda,$$

where the min of a vector is the minimum of its entries. The dual problem associated with (1) is then

$$\begin{aligned} & \text{maximize} && \min(\log(R^T b) + A_0^T \mu + A_1^T \lambda) - d_0^T \mu - d_1^T \lambda \\ & \text{subject to} && \lambda \geq 0, \end{aligned}$$

with variables μ, λ . This problem has the same optimal value as (1), *i.e.*,

$$G_{\Pi}(b) = \sup_{\nu, \lambda \geq 0} (\min(\log(R^T b) + A_0^T \mu + A_1^T \lambda) - d_0^T \mu - d_1^T \lambda).$$

Using this expression for $G_{\Pi}(b)$, the DRKP becomes

$$\begin{aligned} & \text{maximize} && \min(\log(R^T b) + A_0^T \mu + A_1^T \lambda) - d_0^T \mu - d_1^T \lambda \\ & \text{subject to} && b \in B, \quad \lambda \geq 0, \end{aligned}$$

with variables b, μ, λ . This is a tractable convex optimization problem, readily expressed in domain specific languages for convex optimization.

Box distribution set. We consider a special case of a polyhedral distribution set, with lower and upper bounds for each π_k :

$$\Pi = \{\pi \in S_K \mid |\pi - \pi^{\text{nom}}| \leq \rho\},$$

where $\pi^{\text{nom}} \in S_K$ is the nominal distribution, and $\rho \in \mathbf{R}_+^n$ is a vector of radii. (The inequality $|\pi - \pi^{\text{nom}}| \leq \rho$ is interpreted elementwise.)

Using the general method above, expressing the limits as $A_1\pi \leq d_1$ with

$$A_1 = \begin{bmatrix} I \\ -I \end{bmatrix}, \quad d_1 = \begin{bmatrix} \pi^{\text{nom}} + \rho \\ \rho - \pi^{\text{nom}} \end{bmatrix},$$

the DRKP problem becomes

$$\begin{aligned} & \text{maximize} && (\min(\log(R^T b) + \lambda_+ - \lambda_-)) - (\pi^{\text{nom}})^T (\lambda_+ - \lambda_-) - \rho^T (\lambda_+ + \lambda_-) \\ & \text{subject to} && b \in B, \quad \lambda_+ \geq 0, \quad \lambda_- \geq 0, \end{aligned}$$

with variables b, λ_+, λ_- . Defining $\lambda = \lambda_+ - \lambda_-$, we have $|\lambda| = \lambda_+ + \lambda_-$, so the DRKP becomes

$$\begin{aligned} & \text{maximize} && \min(\log(R^T b) + \lambda) - (\pi^{\text{nom}})^T \lambda - \rho^T |\lambda| \\ & \text{subject to} && b \in B, \end{aligned}$$

with variables b, λ .

2.2 Ellipsoidal distribution set

Here we consider the case when Π is the inverse image of a p -norm ball, with $p \geq 1$, under an affine mapping. This includes an ellipsoid (and indeed the box set described above) as a special case. We take

$$\Pi = \{\pi \in S_K \mid \|W^{-1}(\pi - \pi^{\text{nom}})\|_p \leq 1\},$$

where W is a nonsingular matrix. As usual we define q by $1/p + 1/q = 1$.

We define $x = -\log(R^T b)$, $z = W^{-1}(\pi - \pi^{\text{nom}})$, and $D_{p,W} = \{z \mid \|z\|_p \leq 1, \mathbf{1}^T W z = 0, \pi^{\text{nom}} + W z \geq 0\}$. Then we have

$$\begin{aligned} G_\Pi(b) &= -\sup_{\pi \in \Pi} ((\pi - \pi^{\text{nom}})^T x + (\pi^{\text{nom}})^T x) \\ &= -\sup_{z \in D_{p,W}} z^T W x + (\pi^{\text{nom}})^T x \\ &= \sup_{\mu, \lambda \geq 0} (-\sup_{\|z\|_p \leq 1} z^T W(x + \lambda - \mu \mathbf{1}) + (\pi^{\text{nom}})^T(\lambda + x)) \\ &= \sup_{\mu, \lambda \geq 0} (-\|W(x + \lambda - \mu \mathbf{1})\|_q + (\pi^{\text{nom}})^T(\lambda + x)). \end{aligned}$$

Here the second last equation is the Lagrangian form where we keep the p -norm constraint as a convex indicator, and the last equation is based on the Hölder equality

$$\sup_{\|z\|_p \leq 1} z^T W(x + \lambda - \mu \mathbf{1}) = \|W(x + \lambda - \mu \mathbf{1})\|_q,$$

Using this expression for $G_\Pi(b)$, DRKP becomes

$$\begin{aligned} &\text{maximize} && -\|W(\lambda - \log(R^T b) - \mu \mathbf{1})\|_q - (\pi^{\text{nom}})^T \lambda + (\pi^{\text{nom}})^T \log(R^T b) \\ &\text{subject to} && \lambda \geq 0, \quad b \in B, \end{aligned}$$

with variables b, λ, μ .

2.3 Divergence based distribution set

Let $\pi_1, \pi_2 \in S_K$ be two distributions. For a convex function $f : \mathbf{R}_+ \rightarrow \mathbf{R}$ with $f(1) = 0$, the f -divergence of π_1 from π_2 is defined as

$$D_f(\pi_1 \parallel \pi_2) = \pi_2^T f(\pi_1 / \pi_2),$$

where the ratio is meant elementwise. Recall that the Fenchel conjugate of f is $f^*(s) = \sup_{t \geq 0} (ts - f(t))$.

We can use the f -divergence from a nominal distribution to define a set of distributions. We take

$$\Pi = \{\pi \in S_K \mid D_f(\pi \parallel \pi^{\text{nom}}) \leq \epsilon\},$$

where $\epsilon > 0$ is a given value. In other words, our set of distributions is those with ϵ of the distribution π^{nom} , as measured by the f -divergence. (Such sets arise naturally when π^{nom} is the empirical distribution of a set of samples from a distribution.)

We define $x = -\log(R^T b)$ again. Our goal is to minimize $-G_\Pi(b) = \sup_{\pi \in \Pi} \pi^T x$. We form a dual of this problem, working with the constraints $D_f(\pi \parallel \pi_0) \leq \epsilon$ and $\mathbf{1}^T \pi = 1$; we

keep the constraint $\pi \geq 0$ implicit. With dual variables $\lambda \in \mathbf{R}_+$, $\gamma \in \mathbf{R}$, then for $\pi \geq 0$, the Lagrangian is

$$L(\gamma, \lambda, \pi) = \pi^T x + \lambda(-(\pi^{\text{nom}})^T f(\frac{\pi}{\pi^{\text{nom}}}) + \epsilon) - \gamma(e^T \pi - 1) + I_+(\pi),$$

where I_+ is the indicator function of \mathbf{R}_+^K . The dual objective function is

$$\begin{aligned} \sup_{\pi \geq 0} L(\gamma, \lambda, \pi) &= \sup_{\pi \geq 0} (\sum_{i=1}^K \pi_i^{\text{nom}} (\frac{\pi_i}{\pi_i^{\text{nom}}} x_i - \frac{\pi_i}{\pi_i^{\text{nom}}} \gamma - \lambda f(\frac{\pi_i}{\pi_i^{\text{nom}}})) + \lambda \epsilon + \gamma) \\ &= \sum_{i=1}^K \pi_{0,i} \sup_{t_i \geq 0} (t_i (x_i - \gamma) - \lambda f(t_i)) + \lambda \epsilon + \gamma \\ &= \sum_{i=1}^K \pi_{0,i} \lambda f^*(\frac{x_i - \gamma}{\lambda}) + \lambda \epsilon + \gamma, \end{aligned}$$

so the DRKP becomes

$$\begin{aligned} &\text{maximize} && -(\pi^{\text{nom}})^T \lambda f^*(\frac{-\log(R^T b) - \gamma}{\lambda}) - \lambda \epsilon - \gamma \\ &\text{subject to} && \lambda \geq 0, \quad b \in B, \end{aligned}$$

with variables b, γ, λ .

We now show some more specific examples of f -divergences; for a more detailed discussion see [29].

- *Reverse KL-divergence.* With $f(t) = -\log(t) + t - 1$, the f -divergence is the reverse KL-divergence. We have $f^*(s) = -\log(1 - s)$ for $s < 1$.
- *KL-divergence.* With $f(t) = t \log(t) - t + 1$, we obtain the KL-divergence. We have $f^*(s) = \exp(s) - 1$.
- χ^2 -divergence. With $f(t) = (t - 1)^2/t$, we obtain the χ^2 -divergence. We have $f^*(s) = 2 - 2\sqrt{1 - s}$, $s < 1$.
- *Total variation distance.* With $f(t) = |t - 1|$, the f -divergence is the total variation distance. We have $f^*(s) = -1$ for $s \leq -1$ and $f^*(s) = s$ for $-1 \leq s \leq 1$.

2.4 Wasserstein distance distribution set

The Wasserstein distance $D_c(\pi, \pi^{\text{nom}})$ with cost $c \in \mathbf{R}_+^{K \times K}$ is defined as the optimal value of the problem

$$\begin{aligned} &\text{minimize} && \sum_{i,j} Q_{i,j} c_{i,j} \\ &\text{subject to} && Q \mathbf{1} = \pi, \quad Q^T \mathbf{1} = \pi^{\text{nom}}, \quad Q \geq 0, \end{aligned}$$

with variable Q . The Wasserstein distance distribution set is

$$\Pi = \{\pi \in S_K \mid D_c(\pi, \pi^{\text{nom}}) \leq \epsilon\},$$

with $\epsilon > 0$. The Wasserstein distance has several other names, including Monge-Kantorovich, earth-mover's, or optimal transport distance [31, 32, 33, 34].

The worst-case log growth $G_{\Pi}(b)$ is given by the value of the following LP,

$$\begin{aligned} & \text{minimize} && \pi^T \log(R^T b) \\ & \text{subject to} && Q\mathbf{1} = \pi, \quad Q^T \mathbf{1} = \pi^{\text{nom}}, \quad Q \geq 0, \\ & && \sum_{i,j} Q_{i,j} c_{i,j} \leq s, \end{aligned}$$

with variable Q . Using strong duality for LP, the DRKP becomes

$$\begin{aligned} & \text{maximize} && \left(\sum_j \pi_j^{\text{nom}} \min_i (\log(R^T b)_i + \lambda c_{ij}) - s\lambda \right) \\ & \text{subject to} && b \in B, \lambda \geq 0. \end{aligned}$$

where $\lambda \in \mathbf{R}_+$ is the dual variable.

3 Numerical example

In this section we illustrate distributional robust Kelly gambling with an example. Our example is a simple horse race with n horses, with bets placed on each horse placing, *i.e.*, coming in first or second. There are thus $K = n(n-1)/2$ outcomes (indexed as j, k with $j < k \leq n$), and n bets (one for each horse to place).

We first describe the nominal distribution of outcomes π^{nom} . We model the speed of the horses as independent random variables, with the fastest and second fastest horses placing. With this model, π^{nom} is entirely described by the probability that horse i comes in first, which denote β_i . For $j < k$, we have

$$\begin{aligned} \pi_{jk}^{\text{nom}} &= P(\text{horse } j \text{ and horse } k \text{ are the first and second fastest}) \\ &= P(j \text{ is 1st, } k \text{ is 2nd}) + P(k \text{ is 1st, } j \text{ is 2nd}) \\ &= P(j \text{ is 1st})P(k \text{ is 2nd} \mid j \text{ is 1st}) + P(k \text{ is 1st})P(j \text{ is 2nd} \mid k \text{ is 1st}) \\ &= \beta_j(\beta_k/(1-\beta_j)) + \beta_k(\beta_j/(1-\beta_k)) \\ &= \beta_j\beta_k\left(\frac{1}{1-\beta_i} + \frac{1}{1-\beta_j}\right). \end{aligned}$$

The fourth line uses $P(k \text{ is 2nd} \mid j \text{ is 1st}) = \beta_k/(1-\beta_j)$.

Our set of possible distributions is the box

$$\Pi = \{\pi \mid |\pi - \pi^{\text{nom}}| \leq \eta\pi^{\text{nom}}, \mathbf{1}^T \pi = 1, \pi \geq 0\},$$

where $\eta \in (0, 1)$. Roughly speaking, each probability can vary by up to the factor η from its nominal value.

For the return matrix, we use parimutuel betting, with the fraction of bets on each horse equal to β_i , the probability that it will win (under the nominal probability distribution). The return matrix $R \in \mathbf{R}^{n \times K}$ then has the form

$$R_{i,jk} = \begin{cases} \frac{n}{1+\beta_j/\beta_k} & i = j \\ \frac{n}{1+\beta_k/\beta_j} & i = k \\ 0 & i \notin \{j, k\}, \end{cases}$$

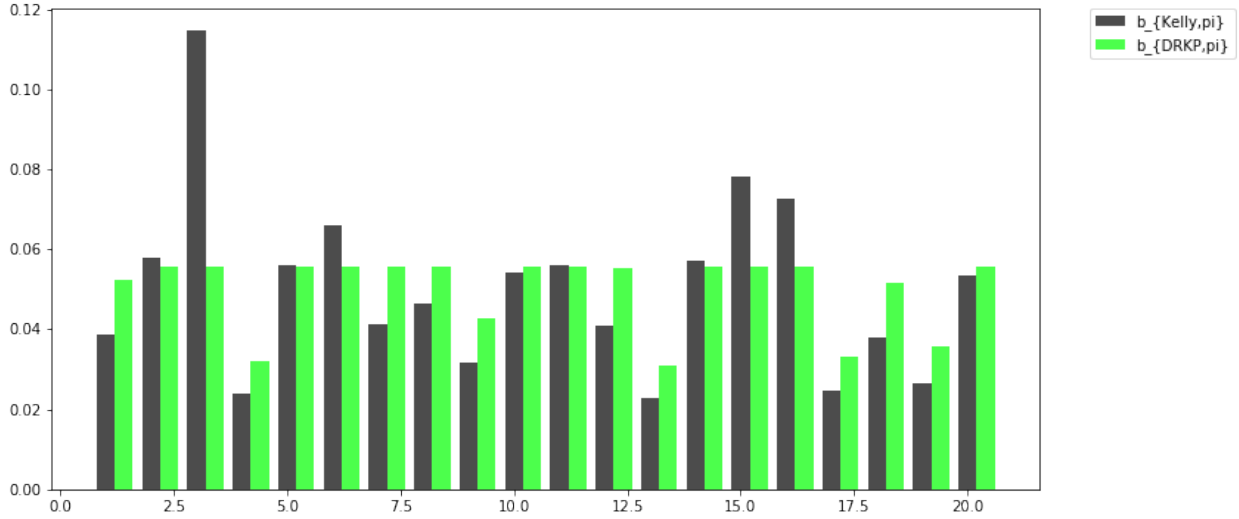


Figure 1: The Kelly optimal bets for the nominal distribution, and the distributional robust optimal bets.

	b^K	b^{RK}
$G(b)$	4.28%	2.38%
$G_{\Pi}(b)$	0.75%	1.15%

Table 1: Growth rate and worst-case growth rate for the Kelly optimal and the distributional robust Kelly optimal bets.

where we index the columns (outcomes) by the pair jk , with $j < k$.

For our specific example instance, we take $n = 20$ horses, so there are $K = 190$ outcomes. We choose β_i , the probability distribution of the winning horse, proportional to $\exp z_i$, where we sample independently $z_i \sim \mathcal{N}(0, 1/4)$. This results in β_i ranging from around 20% (the fastest horse) to around 1% (the slowest horse). For the set of distributions, we take $\eta = 0.15$, *i.e.*, each probability can vary by $\pm 15\%$ from its nominal value.

We find the nominal Kelly optimal bet b^K and the distributional robust Kelly bet b^{RK} , which are shown in figure 1. The corresponding growth rate and worst-case growth rates are shown in table 1. We can see that, as expected, the Kelly optimal bet has higher log growth under the nominal distribution, and the distributional robust Kelly bet has better worst-case log growth. We see that the worst-case growth of the distributional robust Kelly bet is more than 1.5 times the worst-case growth of the nominal Kelly optimal bet.

For each of our bets b^K and b^{RK} we find a corresponding worst case distribution, denoted $\pi^{\text{wc},K}$ and $\pi^{\text{wc},RK}$, which minimize $G_{\pi}(b)$ over $\pi \in \Pi$. These distributions, shown in figure 2, achieve the corresponding worst-case log growth for the two bet vectors. The worst-case distributions are generally, but not always, at the limit of $\pm 15\%$ deviation from the nominal

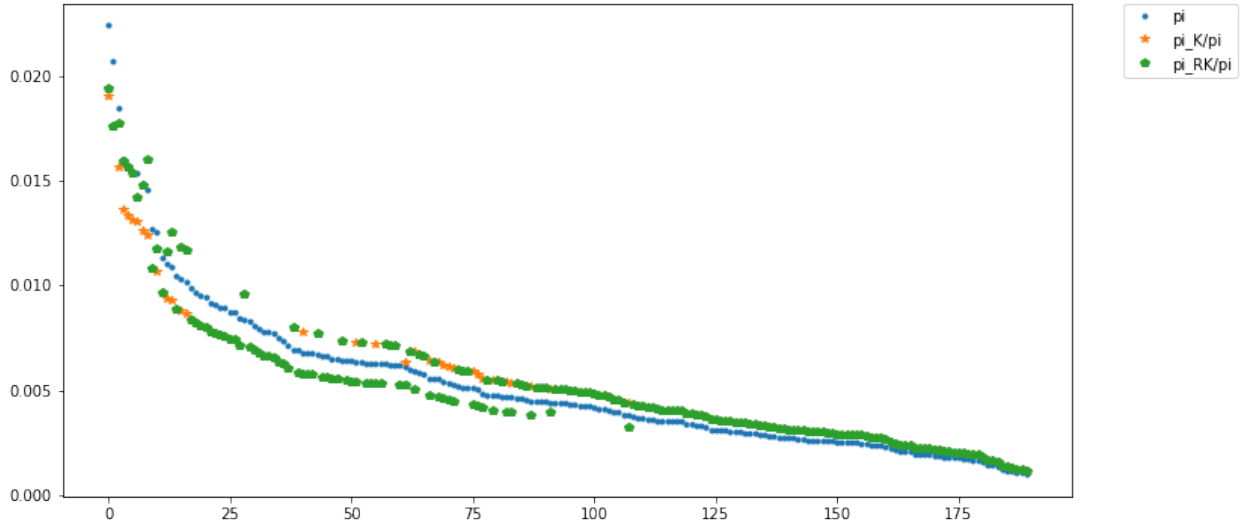


Figure 2: The nominal distribution π^{nom} (sorted) and the two worst-case distributions $\pi^{\text{wc},K}$ and $\pi^{\text{wc},RK}$.

distribution.

Appendix

All of the formulations of DRKP are not only tractable, but easily expressed in DSLs for convex optimization. The CVXPY code to specify and solve the DRKP for box constraints, for example, is given below.

```

pi_nom = Parameter(K, nonneg=True)
rho = Parameter(K, nonneg=True)
b = Variable(n)
mu = Variable(K)
wc_growth_rate = min(log(R.T*b) + mu) - pi_nom.T*abs(mu) - rho.T*mu
constraints = [sum(b) == 1, b >= 0]
DRKP = Problem(Maximize(wc_growth_rate), constraints)
DRKP.solve()

```

Here R is the matrix whose columns are the return vectors, pi_nom is the vector of nominal probabilities, and rho is K dimensional box constraint. The second to last line forms the problem, and in the last line the problem is solved. The robust optimal bet is written into b.value . The code for this example can be found at

<https://github.com/QingyunSun/Distributional-Robust-Kelly-Gambling>.

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