A Proof of Proposition 1

We provide here a detailed proof of Proposition 1.

A.1 Forward Propagation

The optimization problem can be written as

$$\begin{split} \mathsf{csparsemax}(\boldsymbol{z},\boldsymbol{u}) &= \mathsf{arg\,min} \quad \frac{1}{2} \|\boldsymbol{\alpha}\|^2 - \boldsymbol{z}^\top \boldsymbol{\alpha} \\ \mathsf{s.t.} \quad \begin{cases} \mathbf{1}^\top \boldsymbol{\alpha} = 1 \\ \mathbf{0} \leq \boldsymbol{\alpha} \leq \boldsymbol{u}. \end{cases} \end{split}$$

The Lagrangian function is:

$$\mathcal{L}(\boldsymbol{\alpha},\tau,\boldsymbol{\mu},\boldsymbol{\nu}) = -\frac{1}{2} \|\boldsymbol{\alpha}\|^2 - \boldsymbol{z}^\top \boldsymbol{\alpha} + \tau (\boldsymbol{1}^\top \boldsymbol{\alpha} - 1) - \boldsymbol{\mu}^\top \boldsymbol{\alpha} + \boldsymbol{\nu}^\top (\boldsymbol{\alpha} - \boldsymbol{u}).$$
(9)

To obtain the solution, we invoke the Karush-Kuhn-Tucker conditions. From the stationarity condition, we have $\mathbf{0} = \boldsymbol{\alpha} - \boldsymbol{z} + \tau \mathbf{1} - \boldsymbol{\mu} + \boldsymbol{\nu}$, which due to the primal feasibility condition implies that the solution is of the form:

$$\alpha = z - \tau \mathbf{1} + \boldsymbol{\mu} - \boldsymbol{\nu}. \tag{10}$$

From the complementarity slackness condition, we have that $0 < \alpha_j < u_j$ implies that $\mu_j = \nu_j = 0$ and therefore $\alpha_j = z_j - \tau$. On the other hand, $\mu_j > 0$ implies $\alpha_j = 0$, and $\nu_j > 0$ implies $\alpha_j = u_j$. Hence the solution can be written as $\alpha_j = \max\{0, \min\{u_j, z_j - \tau\}$, where τ is determined such that the distribution normalizes:

$$\tau = \frac{\sum_{j \in \mathcal{A}} z_j + \sum_{j \in \mathcal{A}_R} u_j - 1}{|\mathcal{A}|},\tag{11}$$

with $\mathcal{A} = \{j \in [J] \mid 0 < \alpha_j < u_j\}$ and $\mathcal{A}_R = \{j \in [J] \mid \alpha_j = u_j\}$. Note that τ depends itself on the set \mathcal{A} , a function of the solution. In §A.3, we describe an algorithm that searches the value of τ efficiently.

A.2 Gradient Backpropagation

We now turn to the problem of backpropagating the gradients through the constrained sparsemax transformation. For that, we need to compute its Jacobian matrix, i.e., the derivatives $\frac{\partial \alpha_i}{\partial z_j}$ and $\frac{\partial \alpha_i}{\partial u_j}$ for $i, j \in [J]$. Let us first express α as

$$\alpha_i = \begin{cases} 0, & i \in \mathcal{A}_L, \\ z_i - \tau, & i \in \mathcal{A}, \\ u_i, & i \in \mathcal{A}_R, \end{cases}$$
(12)

with τ as in Eq. 11. Note that we have $\partial \tau / \partial z_j = \mathbb{1}(j \in \mathcal{A}) / |\mathcal{A}|$ and $\partial \tau / \partial u_j = \mathbb{1}(j \in \mathcal{A}_R) / |\mathcal{A}|$. Thus, we have the following:

$$\frac{\partial \alpha_i}{\partial z_j} = \begin{cases} 1 - 1/|\mathcal{A}|, & \text{if } j \in \mathcal{A} \text{ and } i = j \\ -1/|\mathcal{A}|, & \text{if } i, j \in \mathcal{A} \text{ and } i \neq j \\ 0, & \text{otherwise,} \end{cases}$$
(13)

and

$$\frac{\partial \alpha_i}{\partial u_j} = \begin{cases} 1, & \text{if } j \in \mathcal{A}_R \text{ and } i = j \\ -1/|\mathcal{A}|, & \text{if } j \in \mathcal{A}_R \text{ and } i \in \mathcal{A} \\ 0, & \text{otherwise.} \end{cases}$$
(14)

Finally, we obtain:

$$dz_{j} = \sum_{i} \frac{\partial \alpha_{i}}{\partial z_{j}} d\alpha_{i}$$

= $\mathbb{1}(j \in \mathcal{A}) \left(d\alpha_{j} - \frac{\sum_{i \in \mathcal{A}} d\alpha_{i}}{|\mathcal{A}|} \right)$
= $\mathbb{1}(j \in \mathcal{A}) (d\alpha_{j} - m),$ (15)

Algorithm 1 Pardalos and Kovoor's Algorithm

1: input: *a*, *b*, *c*, *d*

- 2: Initialize working set $\mathcal{W} \leftarrow \{1, \ldots, J\}$
- 3: Initialize set of split points:

$$\mathcal{P} \leftarrow \{a_j, b_j\}_{j=1}^J \cup \{\pm \infty\}$$

4: Initialize $\tau_{\rm L} \leftarrow -\infty, \tau_{\rm R} \leftarrow \infty, s_{\rm tight} \leftarrow 0, \xi \leftarrow 0.$ 5: while $\mathcal{W} \neq \emptyset$ do Compute $\tau \leftarrow \text{Median}(\mathcal{P})$ 6: Set $s \leftarrow s_{\text{tight}} + \sum_{j \in \mathcal{W} \mid b_i < \tau} c_j b_j + \sum_{j \in \mathcal{W} \mid a_j > \tau} c_j a_j + (\xi + \sum_{j \in \mathcal{W} \mid a_j \le \tau \le b_j} c_j) \tau$ If $s \le d$, set $\tau_{\text{L}} \leftarrow \tau$; if $s \ge d$, set $\tau_{\text{R}} \leftarrow \tau$ 7: 8: Reduce set of split points: $\mathcal{P} \leftarrow \mathcal{P} \cap [\tau_L, \tau_R]$ 9: Update tight-sum: $s_{\text{tight}} \leftarrow s_{\text{tight}} + \sum_{j \in \mathcal{W} \mid b_i < \tau_L} c_j b_j + \sum_{j \in \mathcal{W} \mid a_j > \tau_R} c_j a_j$ 10: Update slack-sum: $\xi \leftarrow \xi + \sum_{j \in \mathcal{W} \mid a_j \leq \tau_L \land b_j \geq \tau_R} c_j$ Update working set: $\mathcal{W} \leftarrow \{j \in \mathcal{W} \mid \tau_L < a_j < \tau_R \lor \tau_L < b_j < \tau_R\}$ 11: 12: 13: end while 14: Define $y^* \leftarrow (d - s_{\text{tight}})/\xi$ 15: Set $x_i^{\star} = \max\{a_j, \min\{b_j, y\}\}, \ \forall j \in [J]$

16: output: x^{\star} .

and

$$du_{j} = \sum_{i} \frac{\partial \alpha_{i}}{\partial u_{j}} d\alpha_{i}$$

$$= \mathbb{1}(j \in \mathcal{A}_{R}) \left(d\alpha_{j} - \frac{\sum_{i \in \mathcal{A}} d\alpha_{i}}{|\mathcal{A}|} \right)$$

$$= \mathbb{1}(j \in \mathcal{A}_{R}) (d\alpha_{j} - m), \qquad (16)$$

where $m = \frac{1}{|\mathcal{A}|} \sum_{j \in \mathcal{A}} \mathrm{d}\alpha_j$.

A.3 Linear-Time Evaluation

Finally, we present an algorithm to solve the problem in Eq. 6 in linear time.

Pardalos and Kovoor (1990) describe an algorithm, reproduced here as Algorithm 1, for solving a class of singly-constrained convex quadratic problems, which can be written in the form above (where each $c_j \ge 0$):

minimize
$$\sum_{j=1}^{J} c_j x_j^2$$

s.t.
$$\sum_{j=1}^{J} c_j x_j = d,$$
$$a_j \le x_j \le b_j, \quad j = 1, \dots, J.$$
 (17)

The solution of the problem in Eq. 17 is of the form $x_j^* = \max\{a_j, \min\{b_j, y\}\}$, where $y \in [a_j, b_j]$ is a constant. The algorithm searches the value of this constant (which is similar to τ in our problem), which lies in a particular interval of split-points (line 3), iteratively shrinking this interval. The algorithm requires computing medians as a subroutine, which can be done in linear time (Blum et al., 1973). The overall complexity in O(J) (Pardalos and Kovoor, 1990). The same algorithm has been used in NLP by Almeida and Martins (2013) for a budgeted summarization problem.

To show that this algorithm applies to the problem of evaluating csparsemax, it suffices to show that

our problem in Eq. 6 can be rewritten in the form of Eq. 17. This is indeed the case, if we set:

$$x_j = \frac{p_j - z_j}{2} \tag{18}$$

$$a_j = -z_j^2/2 \tag{19}$$

$$b_j = (u_j - z_j)/2$$
 (20)

$$c_j = 1 \tag{21}$$

$$d = \frac{1 - \sum_{j=1}^{J} z_j}{2}.$$
 (22)

B Examples of Translations

We show some examples of translations obtained for the German-English language pair with different systems. *Blue* highlights the parts of the reference that are correct and **red** highlights the corresponding problematic parts of translations, including repetitions, dropped words or mistranslations.

input	überlassen sie das ruhig uns .
reference	leave that up to us.
softmax	give us a silence .
sparsemax	leave that to us .
csoftmax	let's leave that .
csparsemax	leave it to us .

input	so ungefähr, sie wissen schon.
reference	like that, you know.
softmax	so , you know , you know .
sparsemax	so , you know , you know .
csoftmax	so , you know , you know .
csparsemax	like that , you know .

input	und wir benutzen dieses wort mit solcher verachtung.
reference	and we say that word with such contempt.
softmax	and we use this word with such contempt contempt.
sparsemax	and we use this word with such contempt .
csoftmax	and we use this word with like this.
csparsemax	and we use this word with such contempt .

input	wir sehen das dazu, dass phosphor wirklich kritisch ist.
reference	we can see <i>that</i> phosphorus is really critical.
softmax	we see that that phosphorus is really critical.
sparsemax	we see that that phosphorus really is critical.
csoftmax	we see that that phosphorus is really critical.
csparsemax	we see that phosphorus is really critical.

input	also müssen sie auch nicht auf klassische musik verzichten, weil sie kein instrument spielen.
reference	so you don't need to abstain from listening to classical music because you don't play an instrument.
softmax	so you don't have to rely on classical music because you don't have an instrument .
sparsemax	so they don't have to kill classical music because they don't play an instrument.
csoftmax	so they don't have to rely on classical music, because they don't play an instrument.
csparsemax	so you don't have to get rid of classical music, because you don't play an instrument.

input	je mehr ich aber darber nachdachte , desto mehr kam ich zu der ansicht , das der fisch etwas weiß .
reference	the more i thought about it, however, the more <i>i came to the view that this fish knows something</i> .
softmax	the more i thought about it, the more i got to the point of the fish.
sparsemax	the more i thought about it, the more i got to the point of view of the fish.
csoftmax	but the more i thought about it, the more i came to mind, the fish.
csparsemax	the more i thought about it, the more i came to the point that the fish knows.

input	all diese menschen lehren uns, dass es noch andere existenzmöglichkeiten, andere denkweisen, andere
	wege zur orientierung auf der erde gibt .
reference	all of these peoples teach us that there are other ways of being, other ways of thinking, other ways of
	orienting yourself in the earth.
softmax	all of these people teach us that there are others , other ways , other ways of guidance to the earth .
sparsemax	all these people are teaching us that there are other options, other ways, different ways of guidance on
	earth .
csoftmax	all of these people teach us that there's other ways of doing other ways of thinking, other ways of guidance
	on earth .
csparsemax	all these people teach us that there are other actors, other ways of thinking, other ways of guidance on
	earth .

input	in der reichen welt, in der oberen milliarde, könnten wir wohl abstriche machen und weniger nutzen,
	aber im durchschnitt wird diese zahl jedes jahr steigen und sich somit insgesamt mehr als verdoppeln,
	die zahl der dienste die pro person bereitgestellt werden .
reference	in the rich world, perhaps the top one billion, we probably could cut back and use less, but every year, this number,
	on average, is going to go up, and so, over all, that will more than double the services delivered per person.
softmax	in the rich world, in the upper billion, we might be able to do and use less use, but on average, that number
	is going to increase every year and so on , which is the number of services that are being put in .
sparsemax	in the rich world, in the upper billion, we may be able to do and use less use, but in average, that number
	is going to rise every year, and so much more than double, the number of services that are being put together .
csoftmax	in the rich world, in the upper billion, we might be able to take off and use less, but in average, this number
	is going to increase every year and so on , and that's the number of people who are being put together per person.
csparsemax	in the rich world, in the upper billion, we may be able to turn off and use less, but in average, that number will
	rise every year and so far more than double, the number of services that are being put into a person.