Soft Optimal Stop For 99% Guarantee

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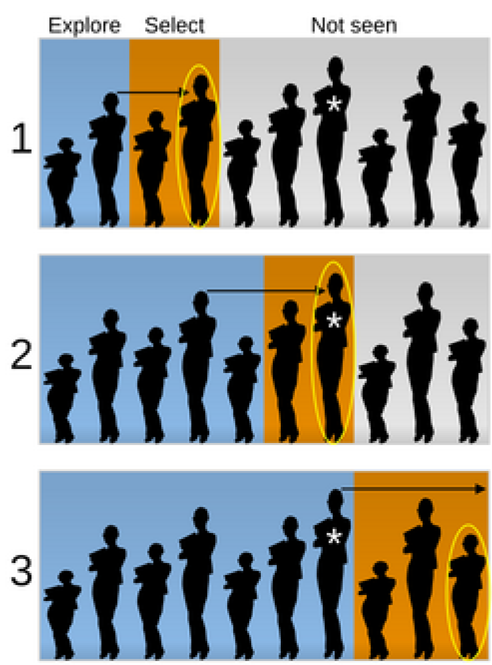
Starting point: `https://en.wikipedia.org/wiki/Secretary_problem`



(illustration by cmglee - Own work, CC BY-SA 4.0, `https://commons.wikimedia.org/w/index.php?curid=163173987`)

The Secretary Problem & its Optimal Stop solution (37%...) sound nice, but 37% also means that one has a 37% chance to end up with the fallback solution - i.e. to pick the last candidate. Indeed, if one already saw the best possible candidate before the 37% cutoff, then one mechanically ends up picking the last candidate (case 3 in the above figure), which gives a pretty random result. The output can be pretty bad, so the reliability is not guaranteed, at least not over a single pass.

And in life, there are quite a few single pass situations.

So instead, let us try to solve a slightly different problem: guarantee with 99% chance that we'll pick a "pretty good" candidate (not targetting the best one).

So we need a strategy to maximize the worst case. To that effect, we choose to maximize the score of the 1% lowest percentile across the results of many simulations.

Proposed strategy: very similar to the Optimal Stop one, but a bit softer:

- look at the first N_STOP candidates (e.g. cutoff 37%, or any other percentage of the whole number of candidates)
  - pick none of them
- determine threshold_score := soft_factor * best_score_of_N_STOP
  - example soft_factor: 80%
- now start looking at the rest candidates
  - pick the first one with score > threshold_score
  - else pick the last one

So the differences with the Optimal Stop are:

- in the problem & evaluation: for a given threshold, we repeat a simulation many times and look at the score of the lowest 1% percentile (instead of "percentage that picked the true best one").
- in the solution: introduced a soft_factor

One possible implementation: uniform use case

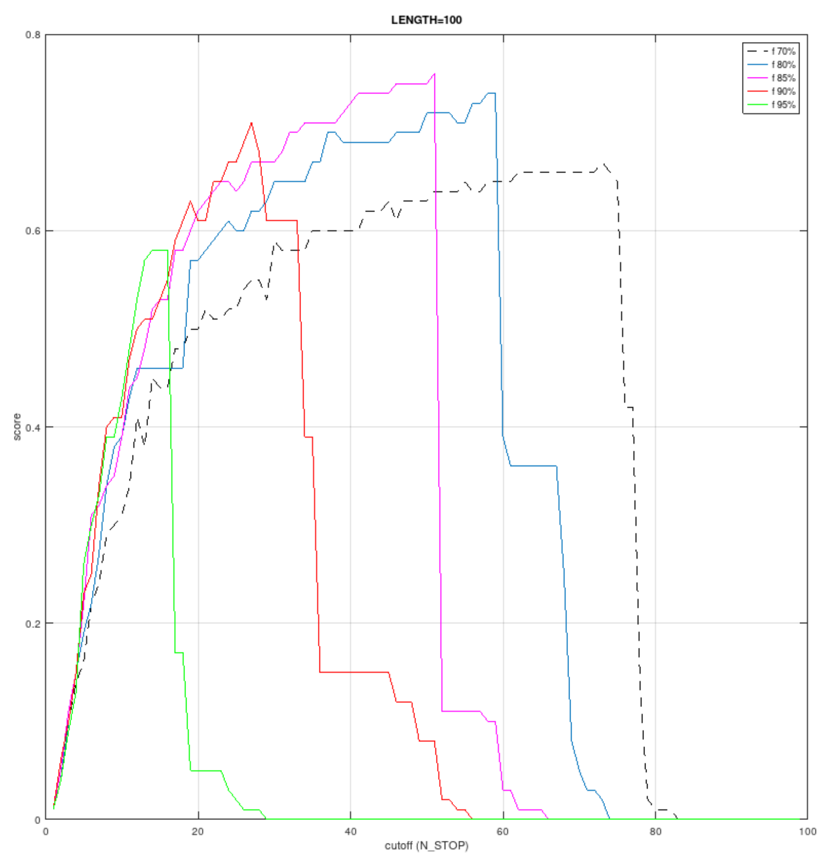
We don't know anything about the target market, so let's assume that the scores of the candidates are uniformly distributed, from worse (0.0) to best (1.0).

For a relatively total small number of candidates LENGTH=100 (for many scenarios, of a realistic order of magnitude), and various soft_factor values, here are the corresponding implementations:

- soft_factor=70%
- soft_factor=80% (my favorite)
- soft_factor=85%
- soft_factor=90%
- soft_factor=95%

Figure: score at the lowest 1% percentile for various soft_factor values and various cutoff values (for/with Octave):

- octave code to produce the figure
- figure (click here to open a bigger version):



The previous figure shows the score of the lowest 1% percentile. Notice in all cases the break off when increasing too much the cutoff N_STOP.

My favorite would be soft_factor=80% and cutoff threshold around 40/100, which gives a lowest 1% percentile with a score of 0.68.

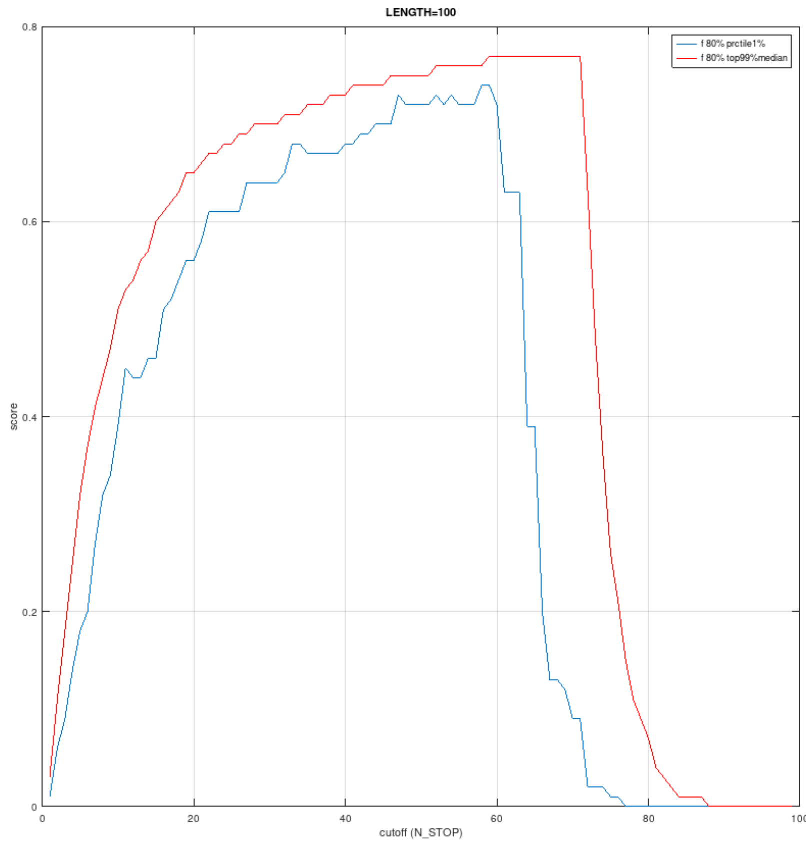
Tradeoff: When accepting the 1% risk, that result is a pretty good guarantee, and most likely in practice we'll end up with a better pick. For soft_factor=80% and cutoff threshold around 40/100:

- score at the lowest 1% percentile: around 0.68
- median score of top 99% percentile: around 0.72

Values around 0.72 can be judged as "pretty good", which was our objective.

Figure: for soft_factor=80% and various cutoff values, score of the lowest 1% percentile, and median score of the top 99% percentiles (for/with Octave):

- Octave code to produce the figure
- figure (click here to open a bigger version):



Observation: Generally, changing the order of magnitude of LENGTH can possibly change quite a bit the shape of the results. However, a common behaviour emerges, similar to what the pictures above show: with increasing N_STOP, increasing score, then a plateau whose width relative to the LENGTH value appears to be variable ; then when further increasing N_STOP, an abrupt cliff, falling down to zero.

Conclusion

By **not** targetting the best candidate, but rather a "pretty good" candidate, we built a strategy that guarantees 99% success.