

# Soft Optimal Stop For 99% Guarantee

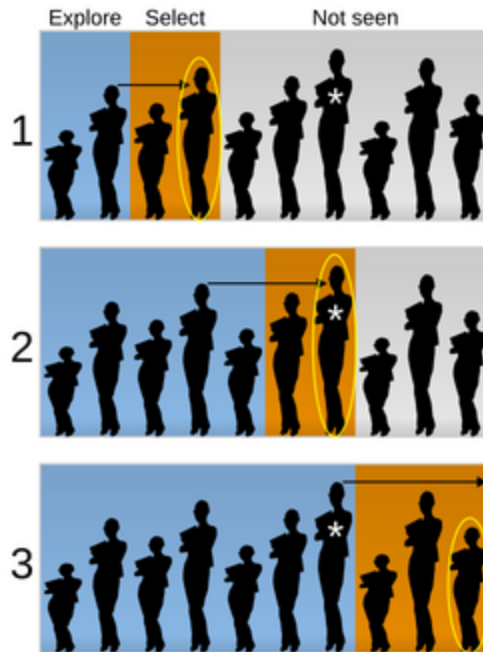
By Guillaume Lathoud, August 2025 (glat@glat.info) Github web PDF

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*The peculiarities of the Parisian real estate market inspired this work.*

Starting point: Secretary Problem

The rest of the present article assumes the reader to know the Secretary Problem. If not, please read it first.



(illustration by cmglee - Own work, CC BY-SA 4.0, original)

### Secretary Problem Strategy:

- ("explore") look at the first  $N\_STOP$  candidates
  - pick none of them
- determine  $threshold\_score := best\_score\_of\_N\_STOP$
- ("select") now look at the rest candidates
  - pick the first one with  $score > threshold\_score$
  - else pick the last one

In the Secretary Problem, the goal is "to have the highest probability of selecting the best applicant of the whole group". The best applicant is marked with a white star in the above figure.

For that goal, it is shown that the cutoff  $N\_STOP$  is optimal at around 37% of the total number of candidates.

### Issue

Such a goal, and its optimal stop solution (37%), sound nice ; however 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 - like in case 3 in the above figure - one already saw the best possible candidate (white star) before the 37% cutoff, then one mechanically ends up picking the last candidate (marked in yellow), 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.

### A different goal

Let us look at a slightly different problem: guarantee with 99% chance that we'll pick a "pretty good" candidate (not targetting the best one).

Then 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 Secretary Problem strategy, just a bit softer:

- ("explore") 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%
- ("select") now look at the rest candidates
  - pick the first one with  $score > threshold\_score$
  - else pick the last one

So the differences with the Secretary Problem are:

- in the problem & evaluation: for a given value of the cutoff  $N\_STOP$ , we repeat a simulation many times and look at the score of the lowest 1% percentile (instead of "percentage that picked the best candidate").
- in the solution: introduced a  $soft\_factor$

One possible implementation: uniform use case

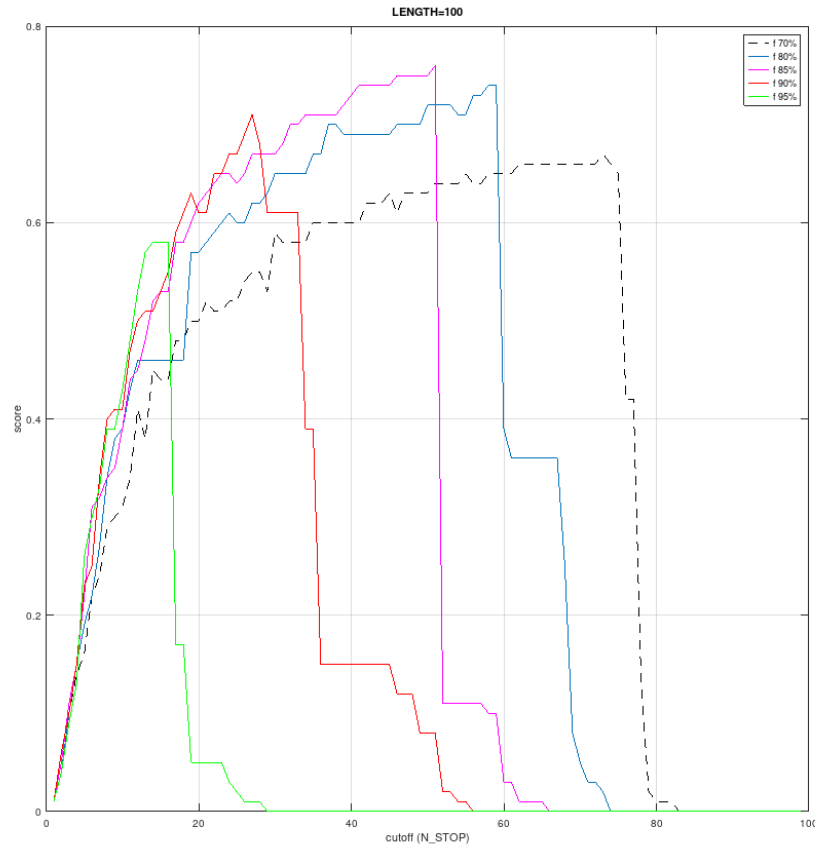
We don't know anything about the target market, so let's assume that the scores of the candidates are uniformly distributed, from worse (0.0) to best (1.0).

For a relatively small total 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 (N\_STOP) values:

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



In all cases, increasing too much the cutoff N\_STOP leads to failure.

My favorite would be soft\_factor=80% and cutoff threshold N\_STOP around 40/100, which gives a score of 0.68 at the lowest 1% percentile.

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, as shown below.

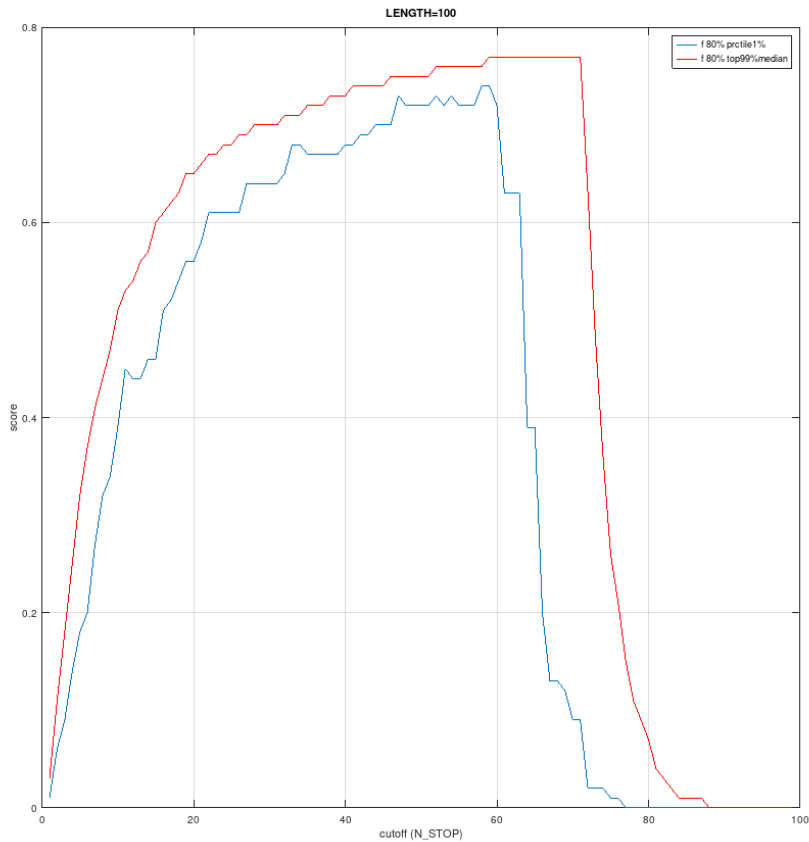
For `soft_factor=80%` and cutoff threshold around 40/100:

- 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" - our objective.

Figure: for `soft_factor=80%` and various cutoff values, score at the lowest 1% percentile, and median score of the top 99% percentiles:

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



### General Observation

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 above pictures show: with increasing N\_STOP, the score increases, then shows a plateau ; then when further increasing N\_STOP, the score abruptly falls down to zero.

In other words, about N\_STOP: to get a "pretty good" result, one should "explore" long enough (the score increases), but not too long either, in order to guarantee the objective of 99% success (otherwise the score abruptly falls down to zero).

### Conclusion

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

### Acknowledgments

Thanks to Julien Bourgeois for his comments.