Appendix A. Analytical Treatment of ARLO's Scalability

The evaluation results depend on the experiment settings around two key assumptions on how the decision points are related and the architect's goals:

1. **Decision Point Dependency:** Whether the choices made within one group can affect other groups.
2. **Architect's Goal:** If we are maximizing the entire weighted score vs having non-linear constraints, such as if a QA has a weight higher than 0, it must be selected

Therefore, we would consider our evaluation in the following two settings:

Setting	Decision Choice Dependency	Architect's Goal Linearity
S1: Assuming both of these	Independent	Linear
S2: Assuming at least one of these	Dependent	Non-Linear

We first provide a mathematical model of ARLO and use it to show how a specific setting can impact ARLO's results, which helps with conducting the evaluations.

Lema: *If choice groups are independent and the object function is linear (S1), the optimization problem reduces to several intra-group optimization problems that could be solved independently.*

Lema's Proof:

Given:

- A matrix where each row represents a choice and each column represents a QA, with values {+1,−1,0}.
- Weights associated with each quality, {w1,w2,...,wn}, where n is the number of QA.

The objective is to maximize the weighted sum of these values for each choice within a group. The weighted sum for a choice i is given by:

$$S_i = \sum_{j=1}^{n} w_j \cdot M_{ij} \quad (1)$$

A change in the value of an element Mij could result in a change in the selected choice if the change alters the relative order of scores such that a different choice, k, now has a higher score than the previously selected choice, or vice versa.

Mathematically, let's assume Mij is altered by ΔMij, resulting in a new score:

$S'i = Si + wj \cdot \Delta Mij$ (2)

For a change in selection from choice i to choice k, it must be true that $Sk' > Si'$ when previously $Si \geq Sk$. Therefore, the selection change occurs if the adjustment leads to

$(Sk-Si) > wj \cdot \Delta Mij$ (3)

S1 reduces the optimization to several independent optimizations (one per group). Therefore, we can make the following assertions on how ARLO would scale:

- Adding more groups would have a linear impact on the scale since we need to solve a linear multiple of optimization problems.
- Adding more choices for groups: While the optimization problem regarding the number of choices has exponential order, this is less significant since we only expect a handful of choices per group.

With S2, we cannot divide the initial problem into multiple optimization problems. The optimization problem is, in general, NP. The behavior of ARLO depends on the following factors and could be calculated given parameters' values by using simulation methods such as Monte Carlo analysis:

1. Matrix values
2. QA weights
3. Dependency among choices
4. The definition of the optimization goal

Algorithm 1 is used to identify condition groups. It has two loops: the outer loop reviews all requirements with conditions, and the inner loop reviews the existing groups to see which can contain each requirement.

Algorithm 1 Categorize ASRs into Condition Groups

```
groups ← [ ]
for all asr in asrs do
    cond ← extract_cond(asr)
    group_found ← false
    for all group in groups do
        if logic_equiv(cond, group['nominal_cond']) then
            group['asrs'].append(asr)
            group_found ← true
            break
        end if
    end for
    if not group_found then
        new_group ← {nominal_cond: cond, asrs: [asr]}
        groups.append(new_group)
    end if
end for
```

1. In the worst case, each requirement is an ASR and has a condition, and all conditions are mutually exclusive. This means that the inner loop is Algo 1 has to repeat equal to the number of requirements added before it. So the total will be 0+1+n-1 = n(n-1)/2, or the complexity of the Algorithm is $O(n^2)$, where n is the number of NLRE.
2. In the normal case, we assume 20% of requirements are ASR, and 50% contain a condition. We can further assume every 5 conditions can be placed in the same group. This reduces the time complexity to $kO(n^2)$, K ~ 0.02. These numbers are selected based on several real cases, including Bamboo, Aptana, and SpringXD mentioned in the paper.

The LLM call to evaluate the condition takes about 1 second (for 20 words per requirement). Based on what I found on the OpenAI site:

- OpenAI GPT-3.5-turbo: 73ms per generated token
- Azure GPT-3.5-turbo: 34ms per generated token
- OpenAI GPT-4: 196ms per generated token

We can consider three systems to see how long it would take to run the Algorithm:

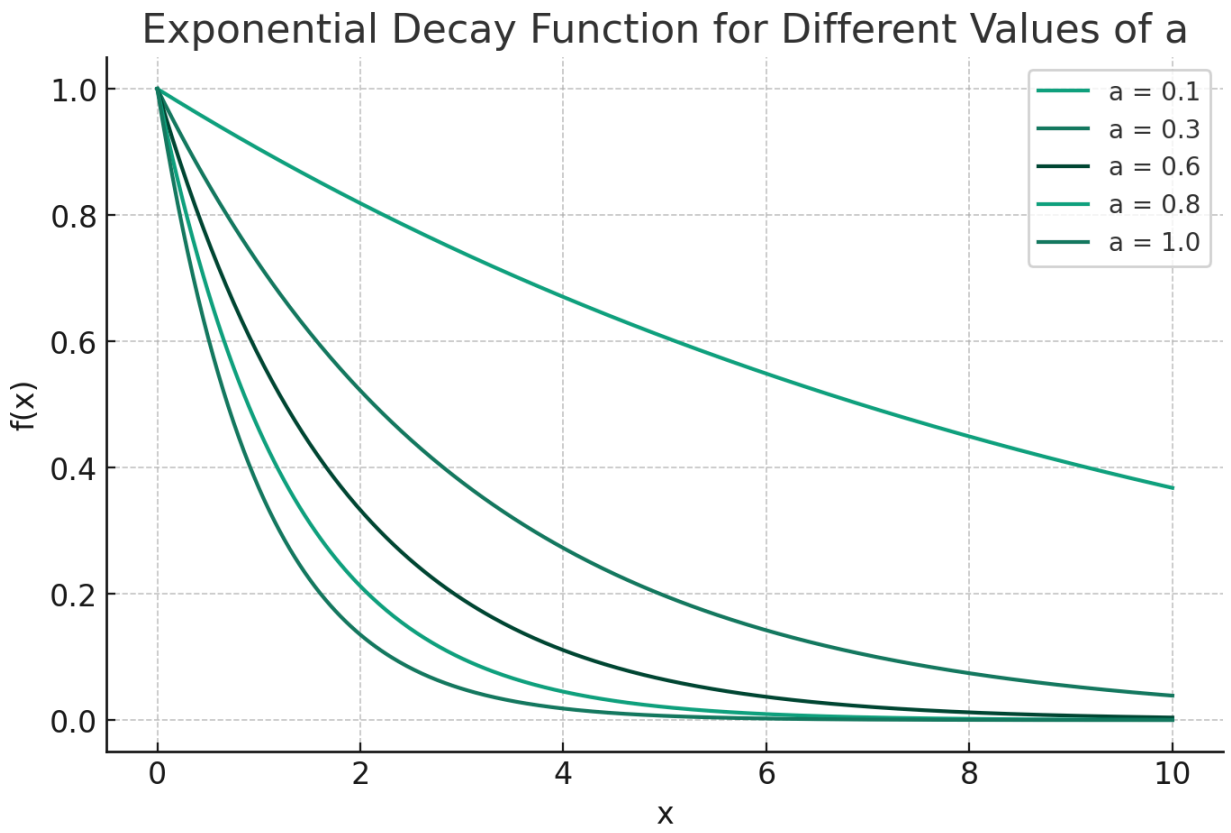
System Size	Group Fitting Check Count	Normal Case	Worst Case
Small (Trello) ~ 100 Rs	4,950	10 Sec	8 Min
Medium (Shopify) ~ 1000 Rs	499,500	16 Min	13 hours
Large (Salesforce) ~ 2000 Rs	1,999,000	1 Hour	55 hours
X Large (SAP) ~ 5000 Rs	12,497,500	7 hours	14 days

Impact of Iterative Development

In iterative development, such as agile, the project is broken down into multiple sprints, and requirements are specified and provided to the development team over time rather than all simultaneously. We would like to analyze the scalability of ARLO in such an interactive process.

Analysis

- n_i requirements are provided in sprint i.
- a_i ($0 < a_i < 1$) denotes the ratio of conditional ASR requirements.
- For each new requirement in sprint i, we need to check them against the nominal condition group we had formed up until sprint i-1 and groups created in the current sprint based on conditional ASRs visited so far. In the worst case, we get a new group for each requirement ($a_i = 1$ for all i). In the average case, we can assume a_i starts from a number such as 20% and shrinks (since as we get more conditions, the chance of seeing a new condition reduces). So, we can model a_i as an exponential decay: $a_i = k.exp(-ai)$, where a shows how fast the function reduces. For example, choosing a= 0.1 makes this almost linear for the first 10 iterations.



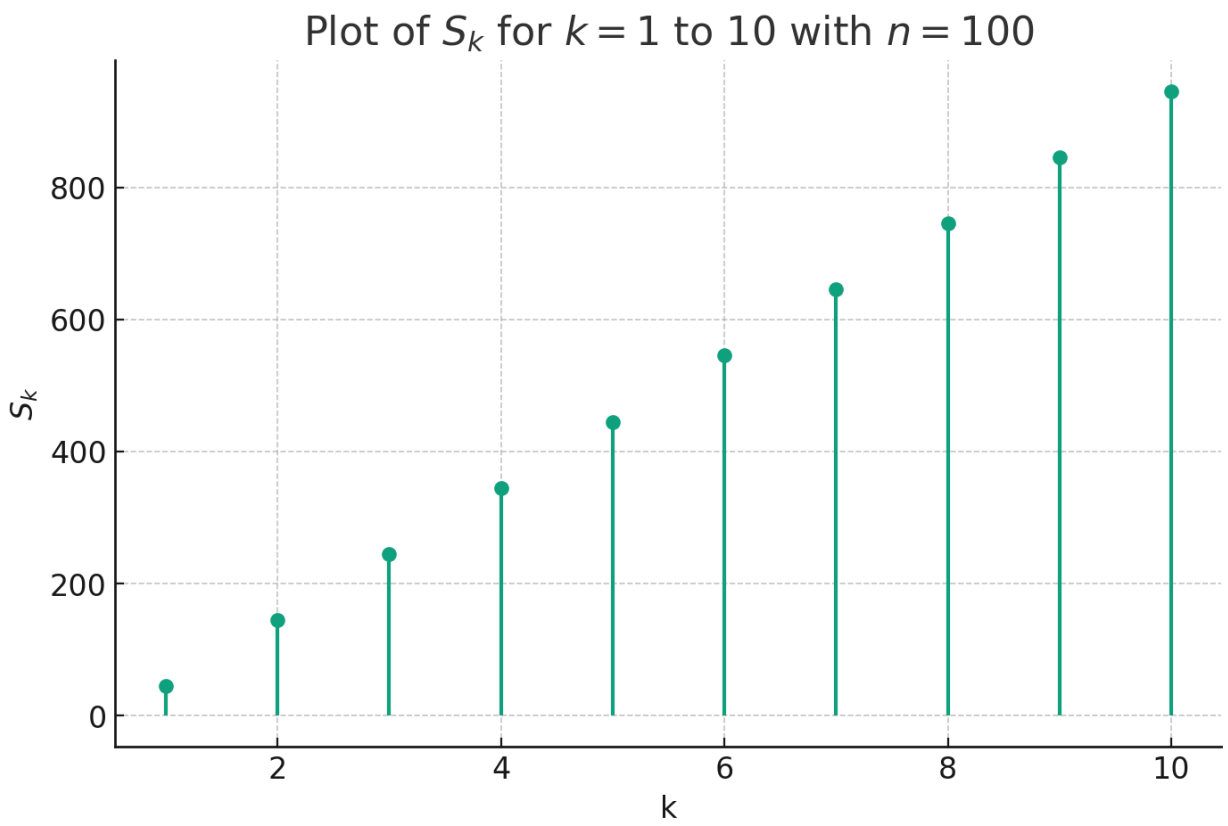
Let's make some assumptions to get to a mathematical model for the number of loop iterations for sprint i (S_i) and S for the total number of loop iterations.

1. The project has 10 sprints.
2. Same number of requirements over 10 sprints, so n_i = 0.1n.

Worst Case Calculations:

- a_i = 1
- Sprint 1: S_1 = 0 + 1 + … + 0.1n - 1 = 0.05n(0.1n - 1)
- Sprint 2: S_2 = 0.1n + 0.1n + 1 + … + 0.2n-1 = 0.1n(0.2n - 1) - 0.05n(0.1n - 1) = 0.05n(0.4n-2-0.1n+1) = 0.05n(0.3n-1)
- …
- Sprint 10: S_10 = 0.9n + 0.9n + 1 … + n - 1 =0.05n · (1.9n−1)
- Or in general S_i = 0.05n[0.1(2k-1)n-1]
- The total number of iterations is the same as just having one iteration, S = 0.5n(n-1).

The plot for S_k is shown below:



Average Case Calculations:

- Set the ratio of new condition groups at iteration i to a_i = 0.2exp(0.1(i-1)).
- Sprint 1, S_1 = 0 + 1 + … + 0.02n = 0.01n(0.02n-1)
- S_i = [0.02n.exp(0.1(i-1))][0.02n.exp(0.1(i-1)) -1]/2
- We cannot come up with a closed form for S, but we can numerically calculate S_i for different numbers of requirements shown below:

n	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Total	Time
100	1	1	2	2	3	4	5	6	8	10	41	4 Sec
1,000	190	233	286	351	430	527	646	791	968	1,185	5,608	9 Min
2,000	780	955	1,169	1,431	1,751	2,142	2,620	3,204	3,918	4,791	22,759	37 Min
5,000	4,950	6,052	7,398	9,043	11,053	13,509	16,509	20,175	24,654	30,125	143,469	4 Hours

This shows that iterative development can, in fact, reduce processing time by helping (assuming that we get fewer condition groups in later iterations).