# Optimization Method for Weighting Explicit and Latent Concepts in Clinical Decision Support Queries

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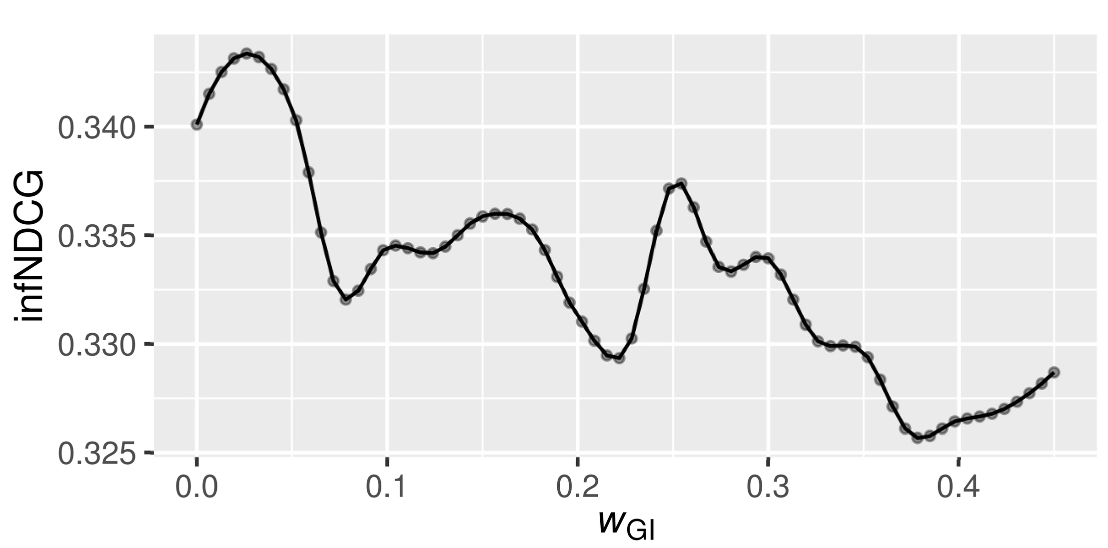
## Objectives

- a
- b

## Queries and Explicit and Latent Concepts (Example)

- **Query:** 33-year-old male presents with severe abdominal pain one week after a bike accident, in which he sustained abdominal trauma. He is hypotensive and tachycardic, and imaging reveals a ruptured spleen and intraperitoneal hemorrhage
- **Explicit concepts:** “bike accident”, “abdominal trauma”, “tachycardia”, “splenic rupture”, “intraperitoneal hemorrhage”
- **Latent concepts:** “splenic trauma”, “Injury of spleen”, “Traffic accidents”

## infNDCG retrieval metric by varying the weight of one of the features




## Optimization Problem

- Sample infNDCG for the following values of $w_\phi$:

$$\mathbf{w}_{s,\phi} = [w_{\phi,-M}, \ldots, w_{\phi,0}, \ldots, w_{\phi,M}]$$

- Using the fixed sampling interval ($\Delta w_\phi$):

$$w_{\phi,m} = w_{\phi,0} + m\Delta w_\phi, \; m \in [-M, \ldots, M]$$

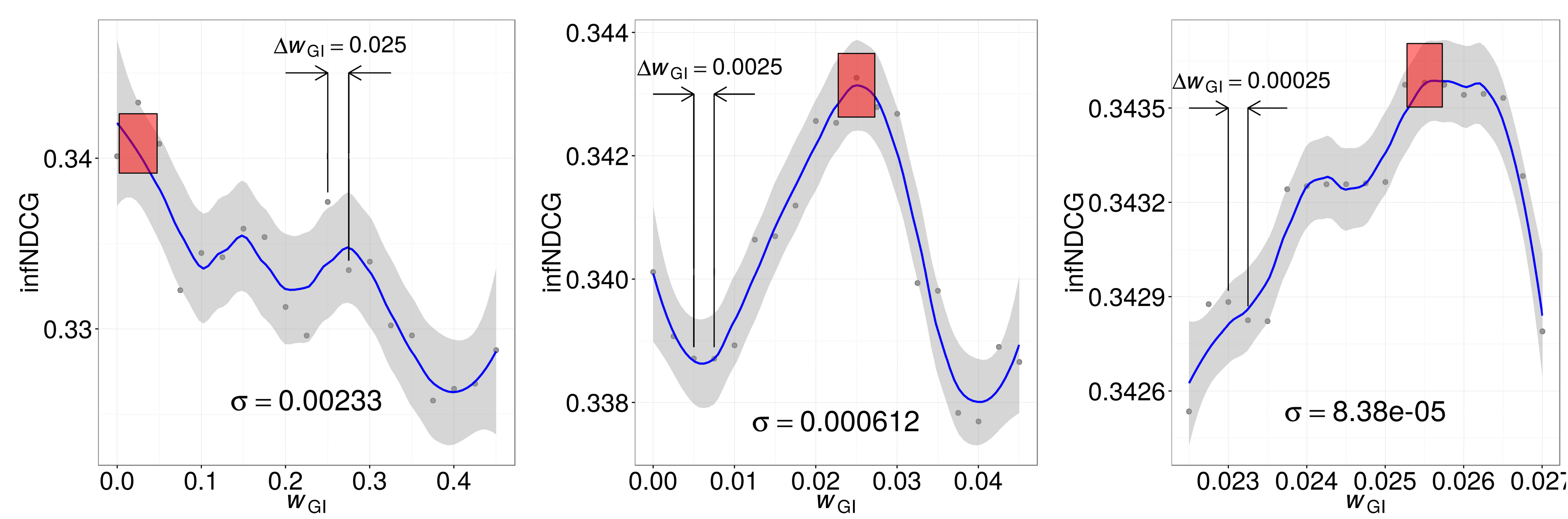
- Polynomial of degree $K$ is used for smoothing the objective function:

$$\tilde{E}(w_{\phi,m}) = \sum^{K} a_k m^k, \quad m \in [-M, \ldots, M]$$

## Proposed Method

- Represent verbose **domain-specific** queries using weighted unigram, bigram and multi-term concepts in a query itself, top retrieved documents and knowledge bases.
- Leverage **Graduated Non-Convexity Optimization (GNC)** method to jointly determine the importance weights for the query and expansion concepts depending on their type and source.

## The first three iterations...




(a) 1st Iteration (b) 2nd Iteration (c) 3rd Iteration

## Sources of Latent Concepts for Query Expansion

- Top retrieved documents
- External domain-specific knowledge repositories (e.g., UMLS)
- External general-purpose resources (e.g., Wikipedia)

## Algorithm

1: Identify explicit and latent concepts
2: Randomly initialize the feature weights vector ($\mathbf{w}_\phi$)
3: **for** $j = 1 : j_{\max}$ **do**
4: Randomly shuffle $\mathbf{w}_\phi$
5: **for** $n = 1 : N$ **do**
6: **for** each sampling policy **do**
7: Sample $E^{n,j}(w^n_\phi)$
8: Obtain $\tilde{E}^{n,j}(w^n_{\phi,m})$
9: Obtain the optimum point $\hat{w}^n_\phi$
10: Update $n$-th element of $\mathbf{w}_\phi$ by $\hat{w}^n_\phi$
11: **end for**
12: **end for**
13: **if** Convergence **then**
14: Break
15: **end if**
16: **end for**

## Results

| | | | |
|---|---|---|---|
| Best | 0.3109 | Best | 0.3109 |
| Median | 0.2689 | Median | 0.2504 |
| Mean | 0.2506 | Mean | 0.2496 |

| | | |
|---|---|---|
| Wayne State Univ. | 0.3109 | description |
| Northwest./Utah/UNC | 0.3019 | summary |
| Univ. of Michigan | 0.2954 | summary |
| Fudan Univ. | 0.2689 | description |
| Demo. Univ. of Thrace | 0.2318 | summary |

Figure 1: Task A-Manual

| | | | |
|---|---|---|---|
| Best | 0.2939 | Best | 0.2939 |
| Median | 0.2120 | Median | 0.2288 |
| Mean | 0.1973 | Mean | 0.2099 |

| | | |
|---|---|---|
| Wayne State Univ. | 0.2939 | description |
| Luxembourg IST | 0.2894 | summary |
| Univ. of Cambridge | 0.2823 | summary |
| East China Normal U. | 0.2680 | summary |
| Univ. of Delaware | 0.2676 | summary |

Figure 2: Task A-Automatic

| | | | |
|---|---|---|---|
| Best | 0.3809 | Best | 0.3809 |
| Median | 0.3208 | Median | 0.3212 |
| Mean | 0.2717 | Mean | 0.2842 |

| | | |
|---|---|---|
| Fudan Univ. | 0.3809 | description |
| Wayne State Univ. | 0.3690 | description |
| Univ. of Michigan | 0.3535 | summary |
| Northwest./Utah/UNC | 0.3255 | summary |
| Harbin Inst. of Tech. | 0.3168 | summary |

Figure 3: Task B-Manual

## Conclusions

- We proposed a method to represent CDS queries using explicit concepts from the original query and the latent concepts from the top retrieved documents and knowledge bases
- We proposed the features to individually weigh each query concept depending on its type and source
- We proposed to use graduated optimization method to directly optimize the parameters of the concept based retrieval model with respect to the