Opinosis:

A Graph Based Approach to Abstractive Summarization of Highly Redundant Opinions

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1867

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Opinion Summarization Today…

Customer Reviews

Average Customer Rating

(1,432 customer reviews)

5 star:	(1,040)
4 star:	(227)
3 star:	(63)
2 star:	(25)
1 star:	(77)

Opinion Summary for **iPod**

Appearance	(1,213)
Ease of use	(1,212)
Portability	(1,202)
Sound quality	(1,196)

› See and rate all 1 ttributes.

Most Helpful Customer R

3,677 of 3,770 people fou

WARNNING fo 1, 2009

By Hassan B. Bn Hadhra

REAL NAME

Existing methods: Generate structured ratings for an entity

[Lu et al., 2009; Lerman et al., 2009;..]

Amazon Verified Purchase (What's this?)

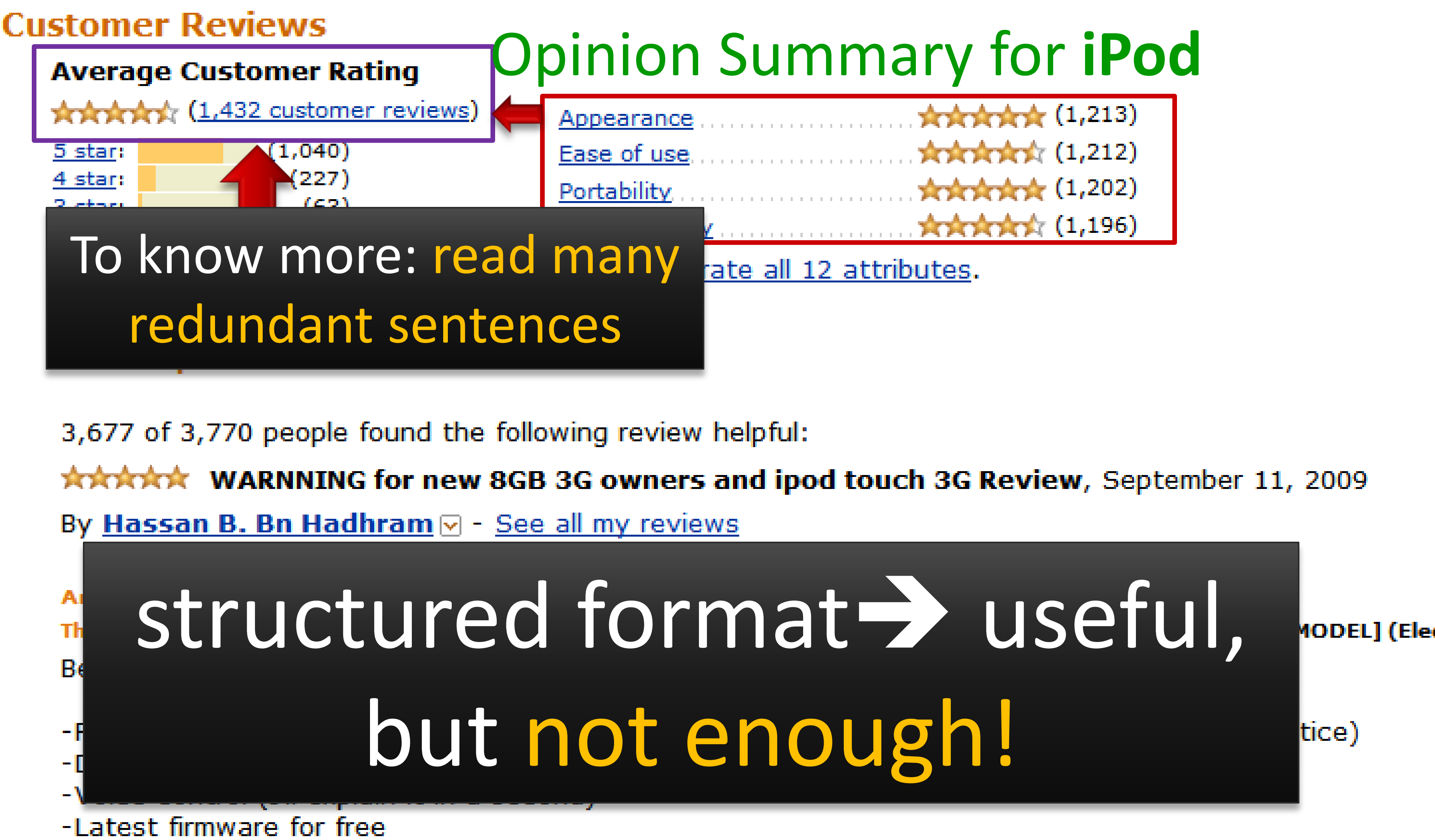
This review is from: Apple iPod touch 8 GB (2nd Generation--with iPhone OS 3.1 Software Installed) [NEWEST MODEL] (Ele

Before i start let me just tell you "what's New" with the iPod touch Third generation" :

-Faster Cpu/Double the ram/Better graphic (faster Boot time/faster loading is all what i did notice)
-Double the storage for the same old price
-Voice control (I'll explain it in a second)
-Latest firmware for free

Opinion Summarization Today…

Opinion Summary for **iPod**



To know more: read many redundant sentences

structured format→ useful, but not enough!

Ideally, we need….

Supporting textual summary!

A good <u>textual</u> Opinion Summary should...

- **Summarize the major opinions**
  - What are the major complaints/praise in an aspect?

- **Concise**
  - Easily digestible
  - Viewable on smaller screens

- **Readable**
  - Easily understood

An Ideal Summary

"The iPhone's battery lasts long and is cheap but it's bulky.

- Important information summarized
- Concise
- Readable

How to generate such summaries?

Extractive Summarization

- **Widely studied for years**
  [Radev et al.2000; Erkan & Radev, 2004; Mihalcea & Tarau, 2004…]
- **But, not suitable for:**
  - Generating concise summaries
  - Summarizing highly redundant text
- **Problems**
  - **Bias:** with limit on summary size
    - selected sentence may have missed critical info
  - **Verbose:** May contain irrelevant information
    - not suitable for smaller devices

Extractive Summarization

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- **Problems**
  - **Bias:**
    - sele
  - **Verb**
    - not

Extractive ✗
Abstractive ✓

Abstractive Summarization - HARD!!

Existing methods:

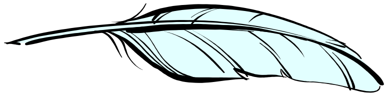
- **Some methods require manual effort**
  [DeJong1982] [Radev and McKeown1998] [Finley and Harabagiu2002]
  - Need to define <u>templates</u> to be filled

- **Some methods rely heavily on NL understanding**
  [Saggion and Lapalme2002] [Jing and McKeown2000]
  - Domain dependent
  - Impractical – high computational costs

Our Method: Opinosis

- `Shallow’ abstractive summarizer

- Generates concise summaries using:
  - existing text
  - inherent redundancies

- Uses minimal external knowledge
  - lightweight 

Opinosis: High Level Overview

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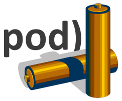
Input

Set of sentences:

- **Topic** specific (ex. battery life of ipod) 
- **POS** annotated

Opinosis: High Level Overview

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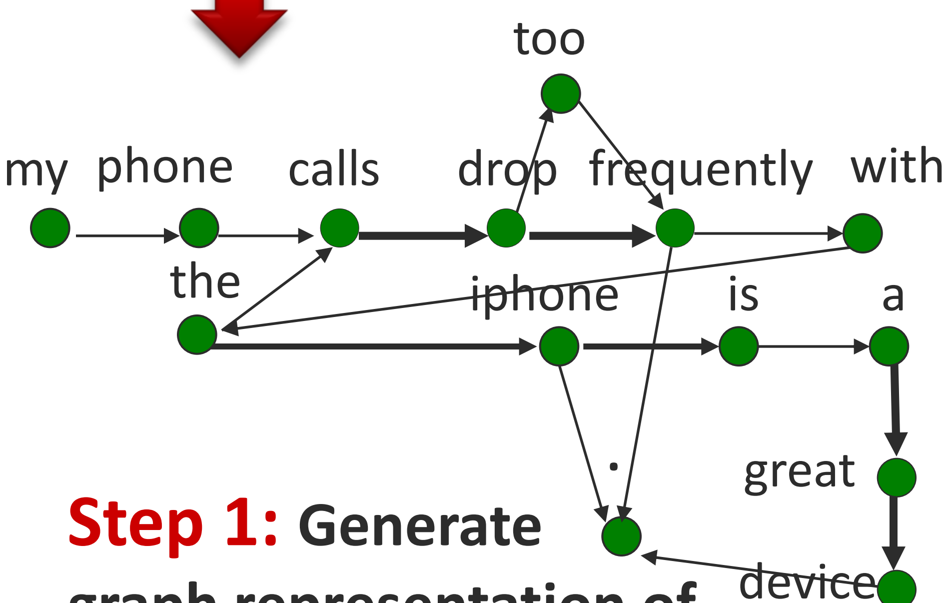

Step 1: **Generate <u>graph representation</u> of sentences (Opinosis-Graph)**

Opinosis: High Level Overview

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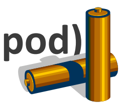
- **Topic specific** (ex. battery life of ipod) 
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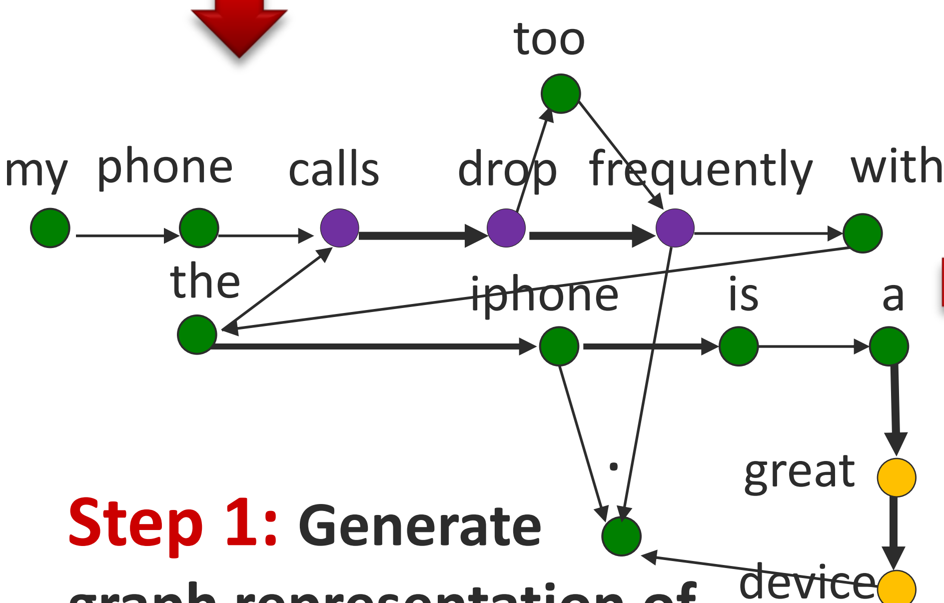
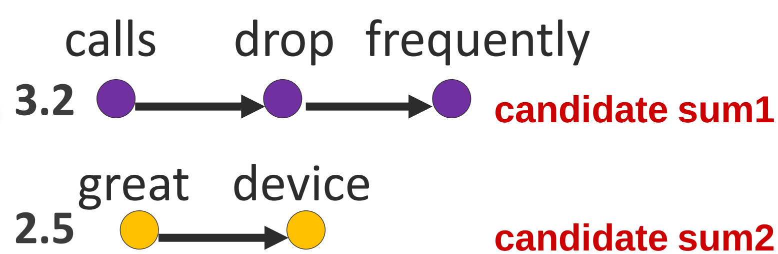


Step 1: Generate graph representation of sentences (Opinosis-Graph)



Step 2: Find promising paths (candidate summaries) & score these candidates

Opinosis: High Level Overview

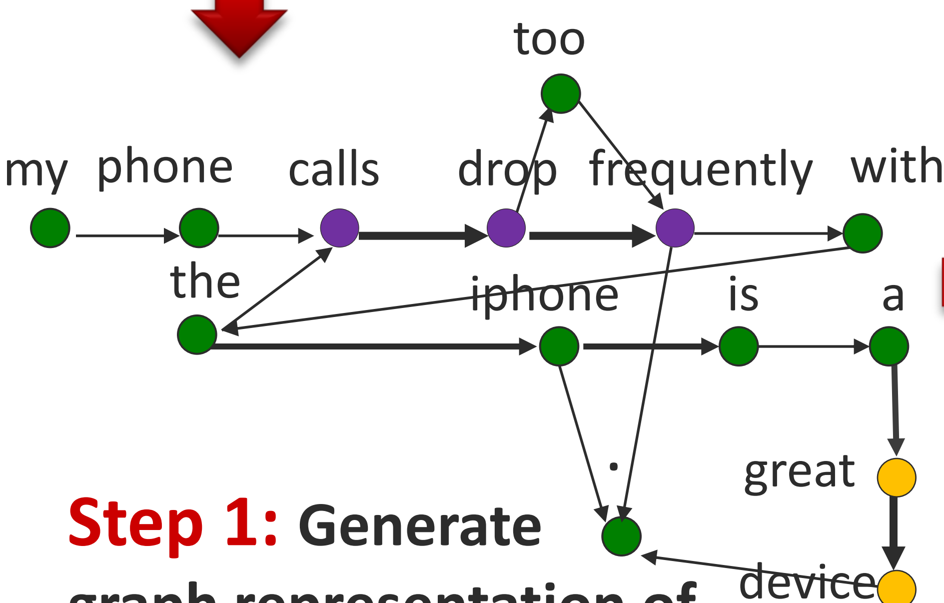
Input

Set of sentences:

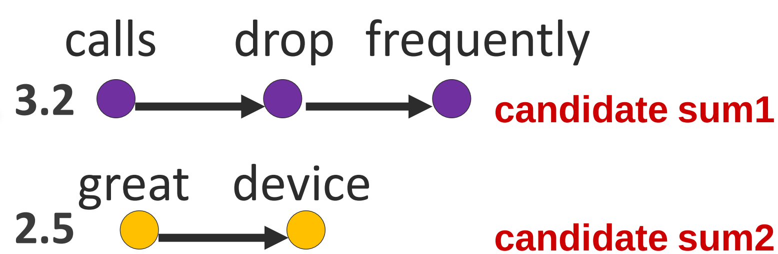
- **Topic specific** (ex. battery li
- **POS annotated**

The iPhone is a great device, but calls drop frequently.

Step 3: Select <u>top scoring candidates</u> as final summary



Step 1: Generate <u>graph representation</u> of sentences (**Opinosis-Graph**)



Step 2: Find <u>promising paths</u> (candidate summaries) & <u>score these candidates</u>

Step 1: Building the Opinosis-Graph

Building Opinosis-Graph

Assume:

- 2 sentences about "*call quality of iphone*"

> 1. *My phone calls drop frequently with the iPhone.*
> 2. *Great device, but the calls drop too frequently.*

- Opinosis-Graph is empty

Building Opinosis-Graph

1. *My phone calls drop frequently with the iPhone.*

Building Opinosis-Graph

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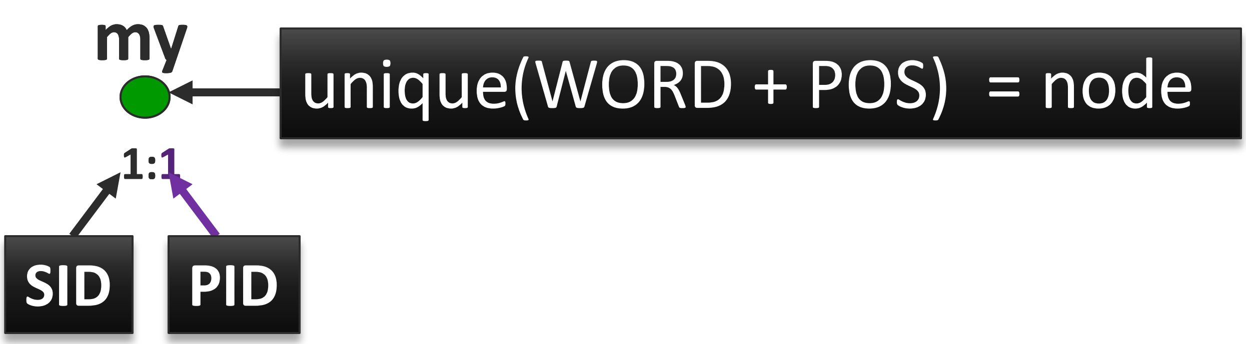
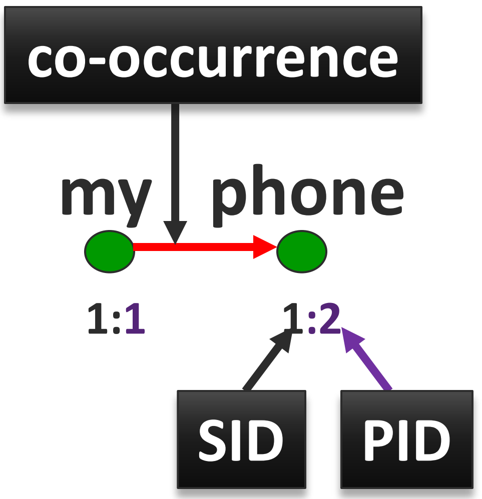


Positional Reference Information

Building Opinosis-Graph

1. *My phone calls drop frequently with the iPhone.*



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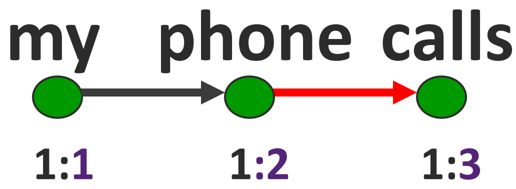

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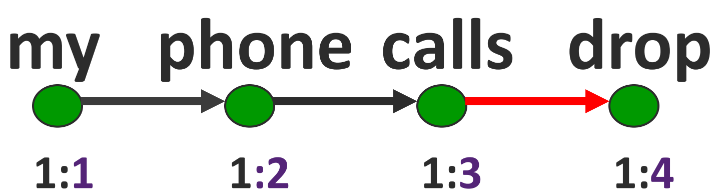

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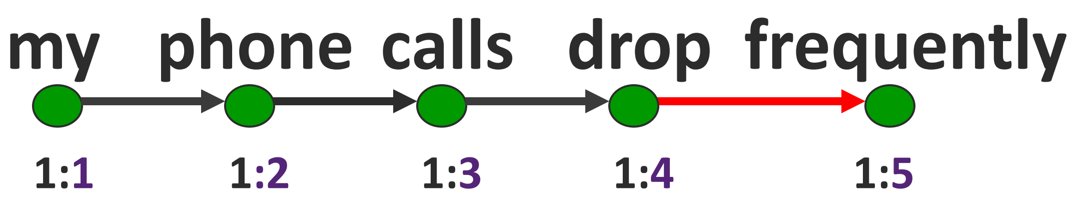

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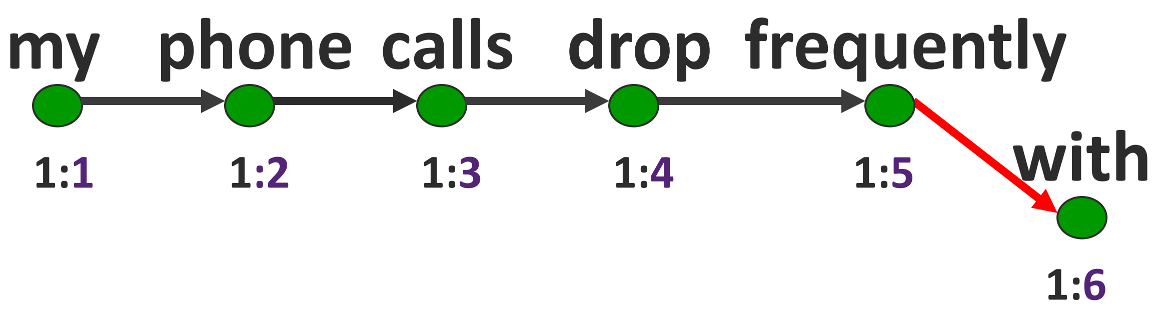

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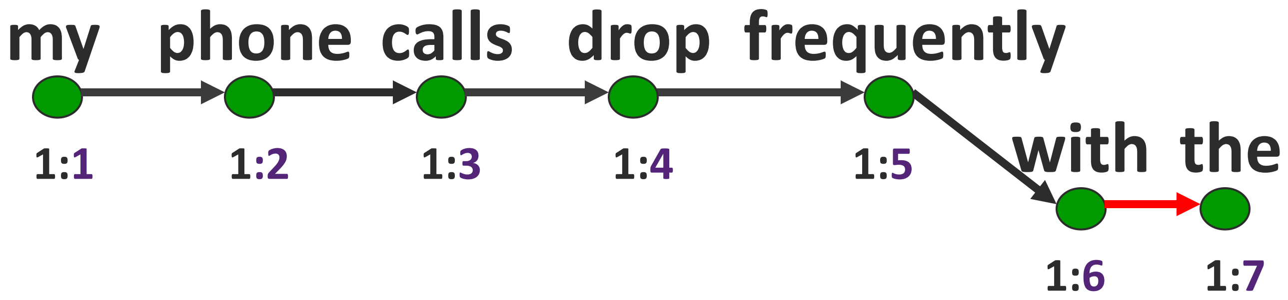

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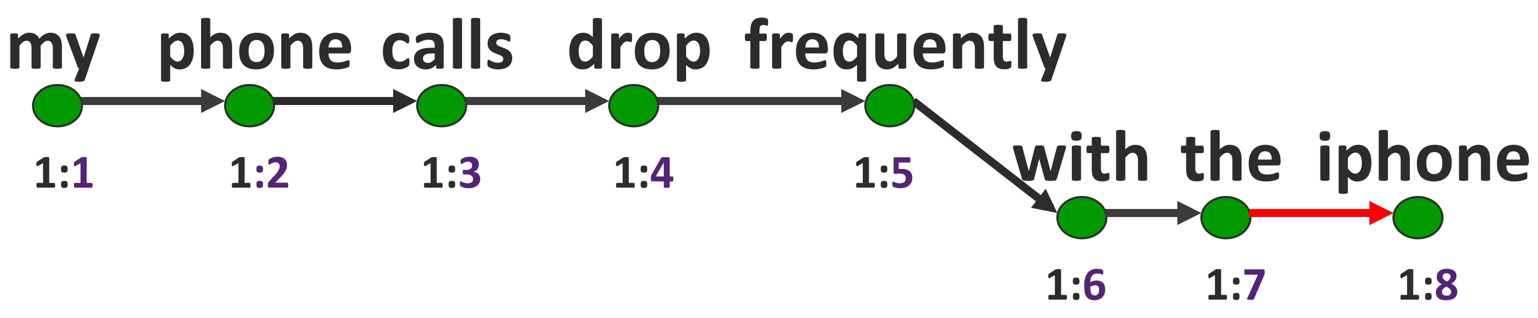

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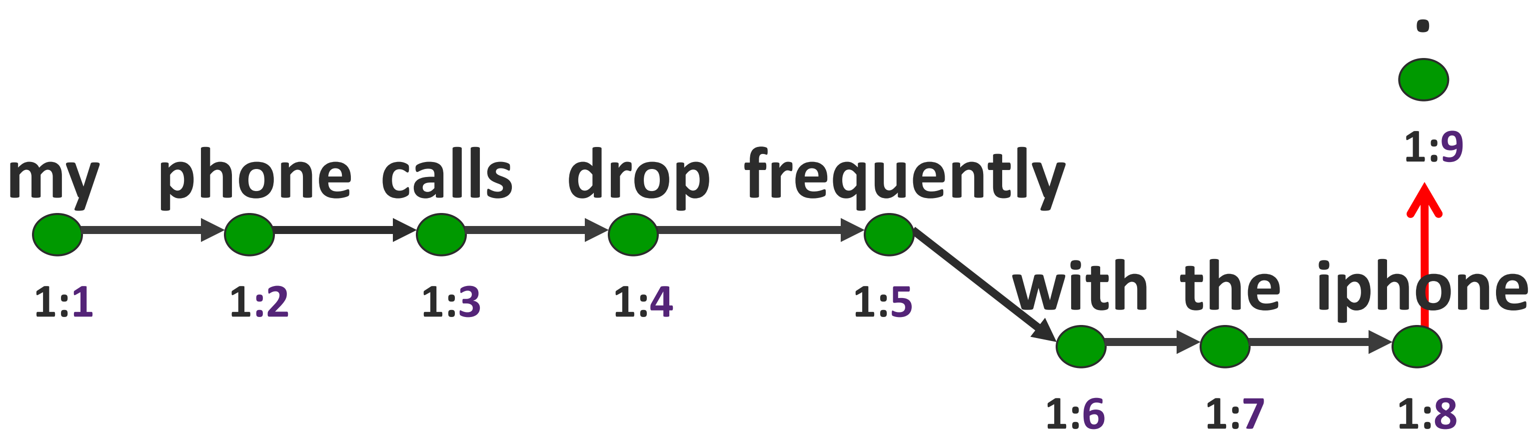

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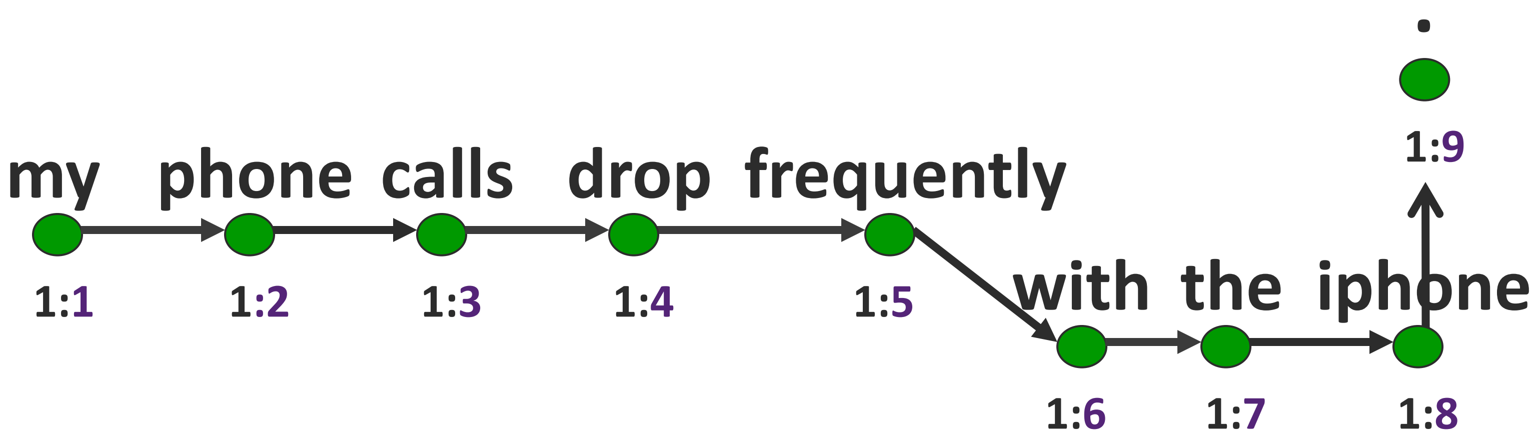
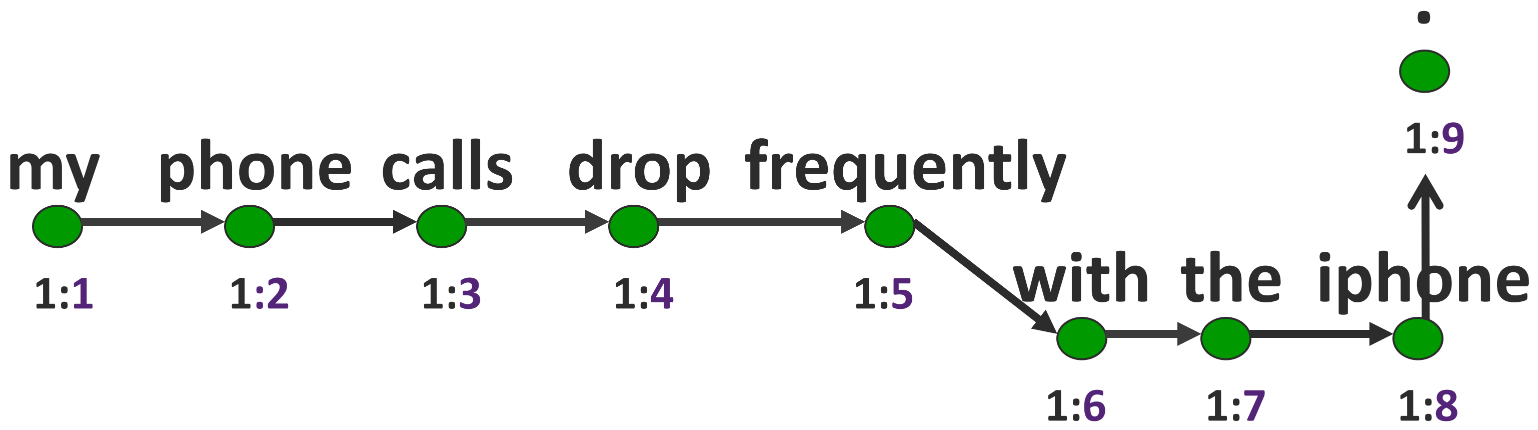


Building Opinosis-Graph

2. *Great device, but the calls drop too frequently.*



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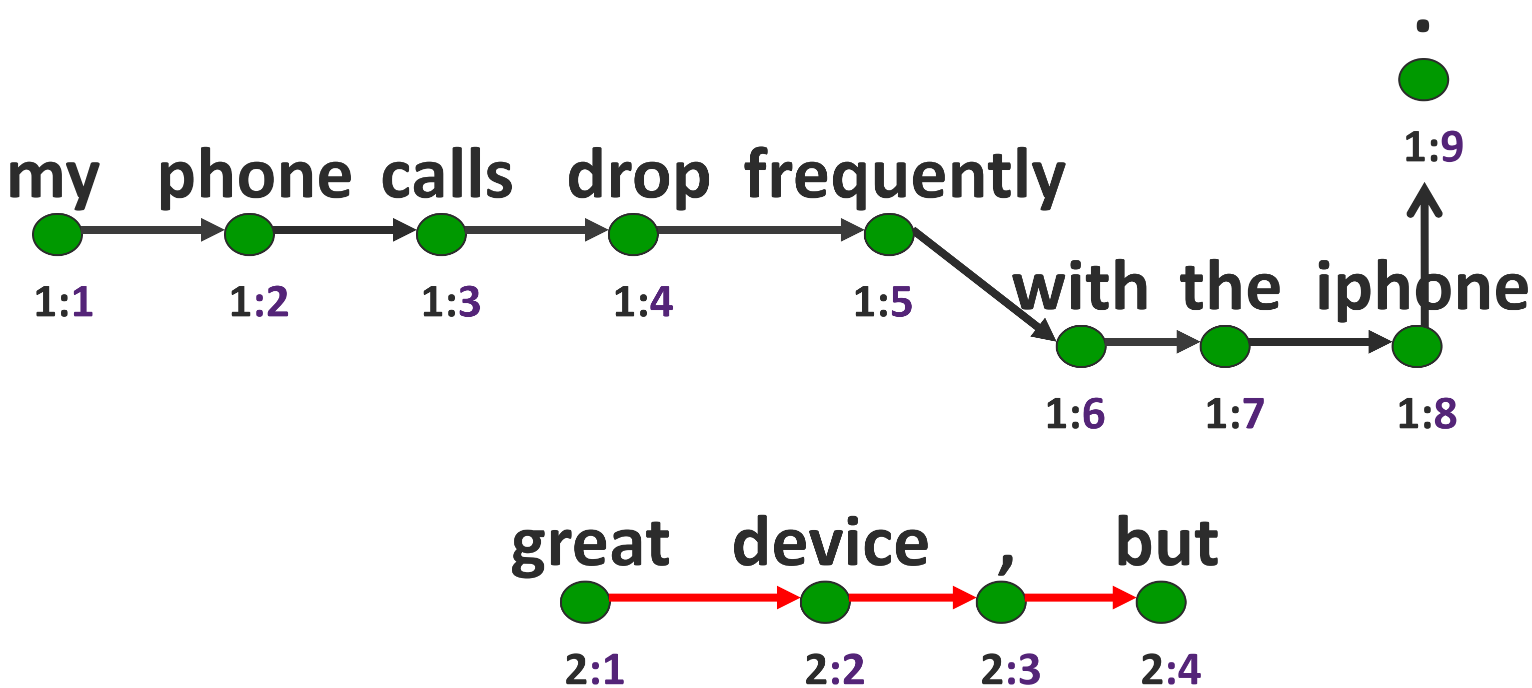

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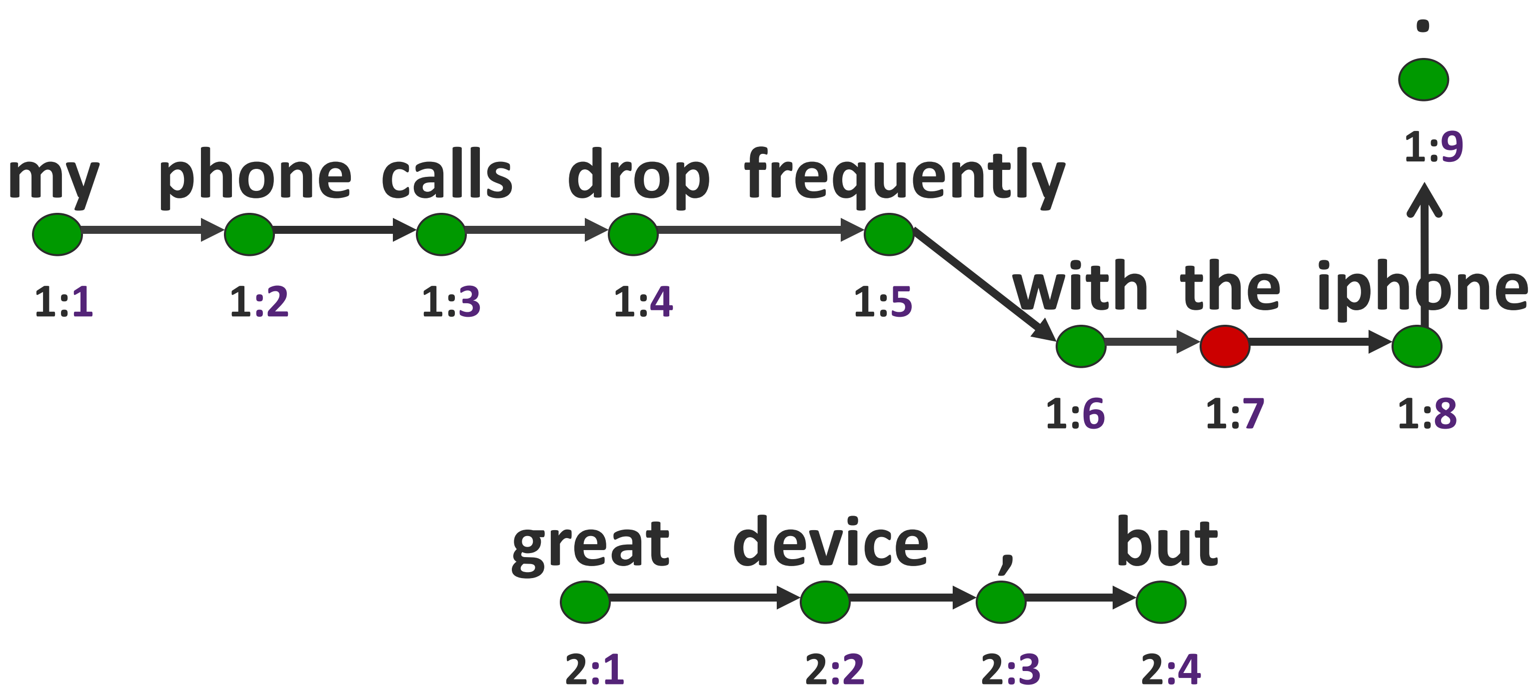

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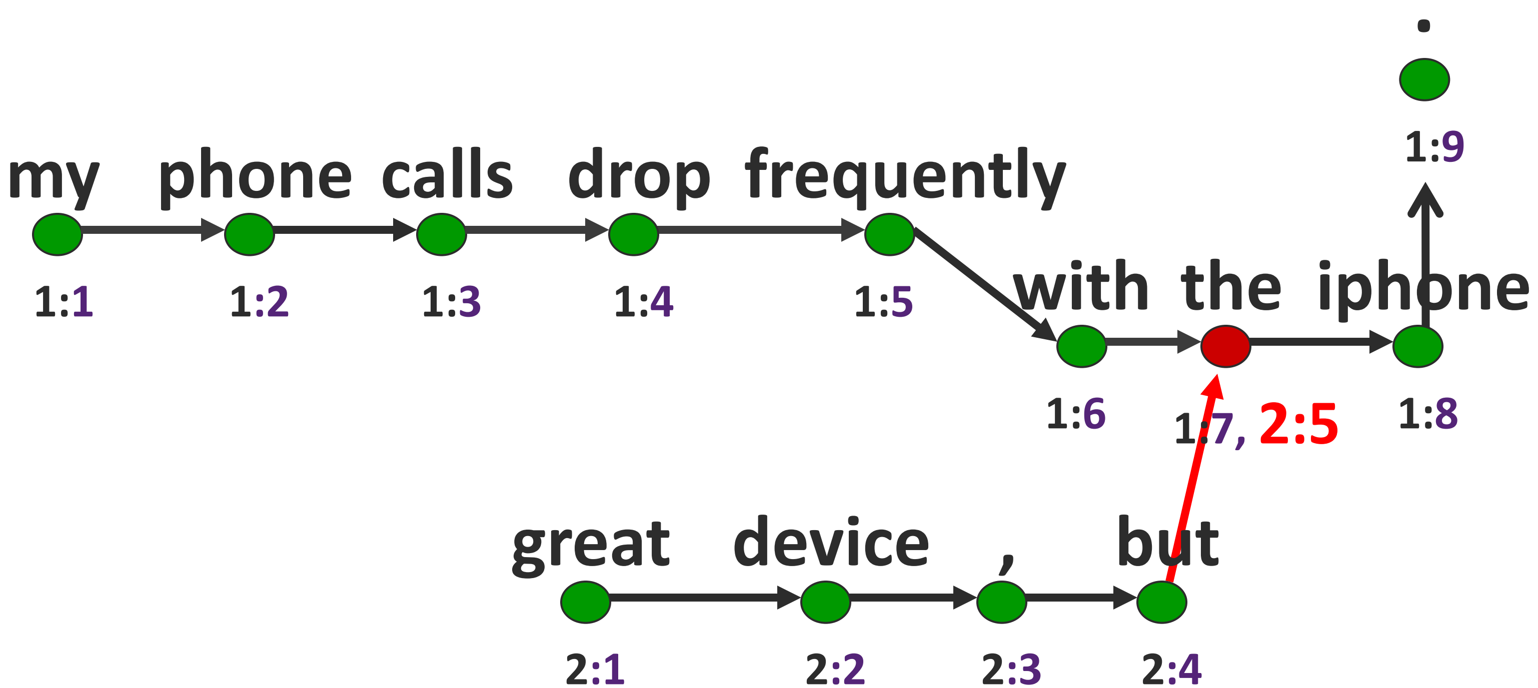

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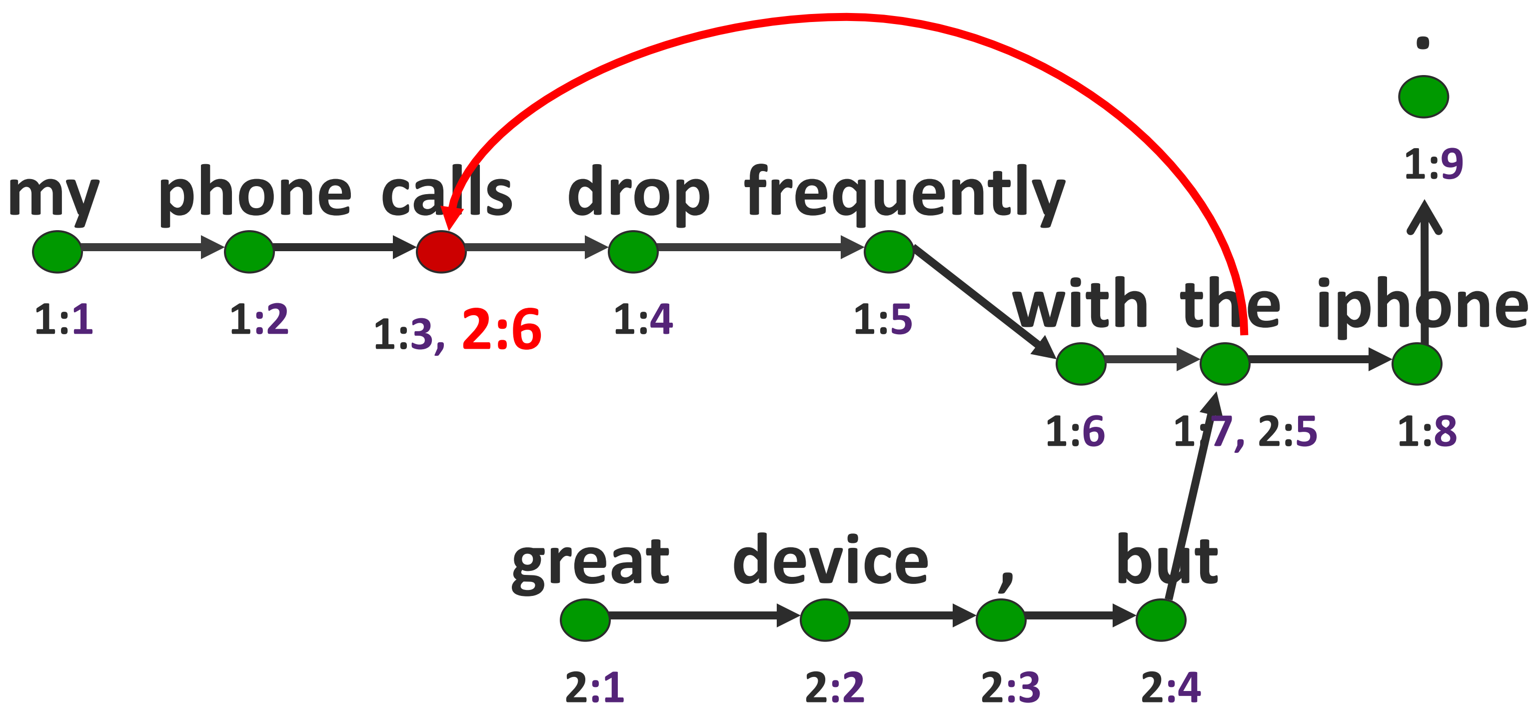

Building Opinosis-Graph

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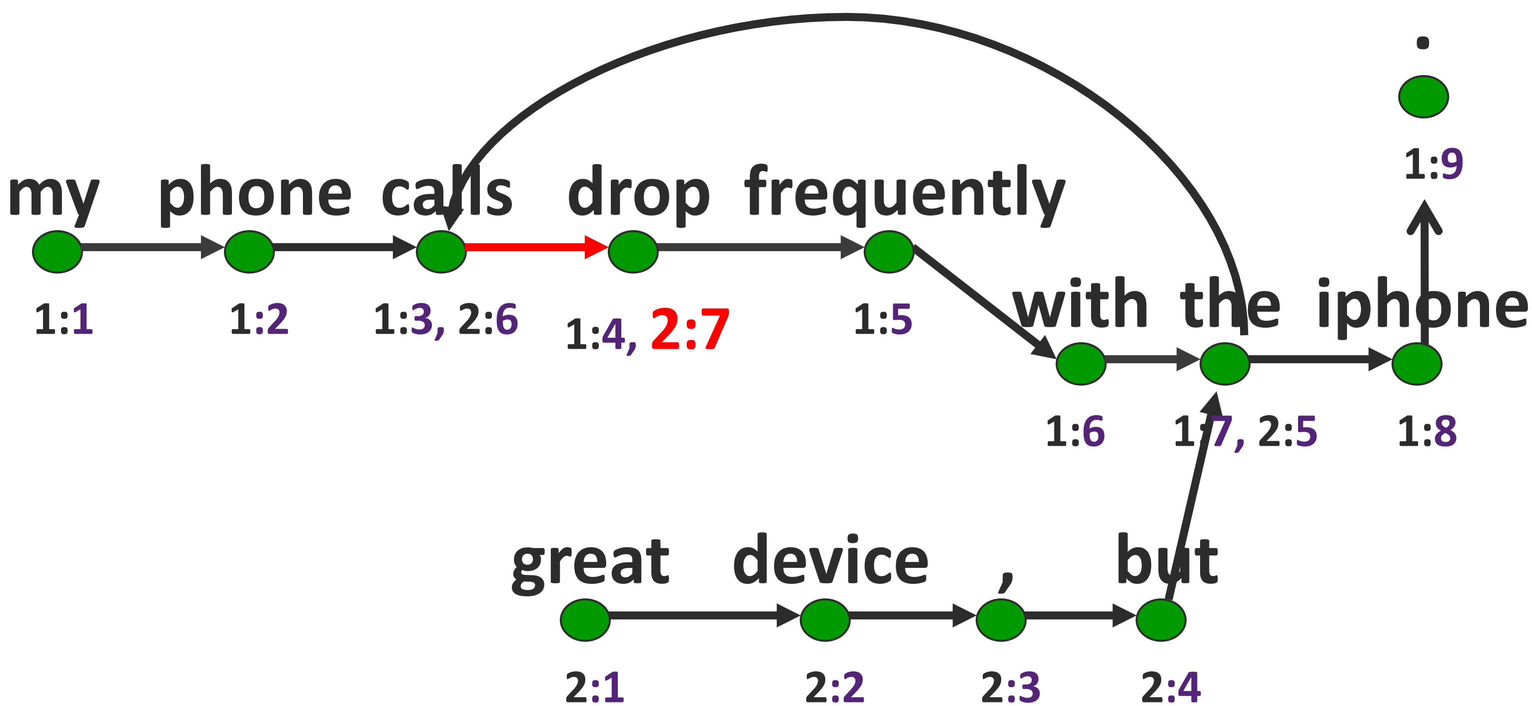

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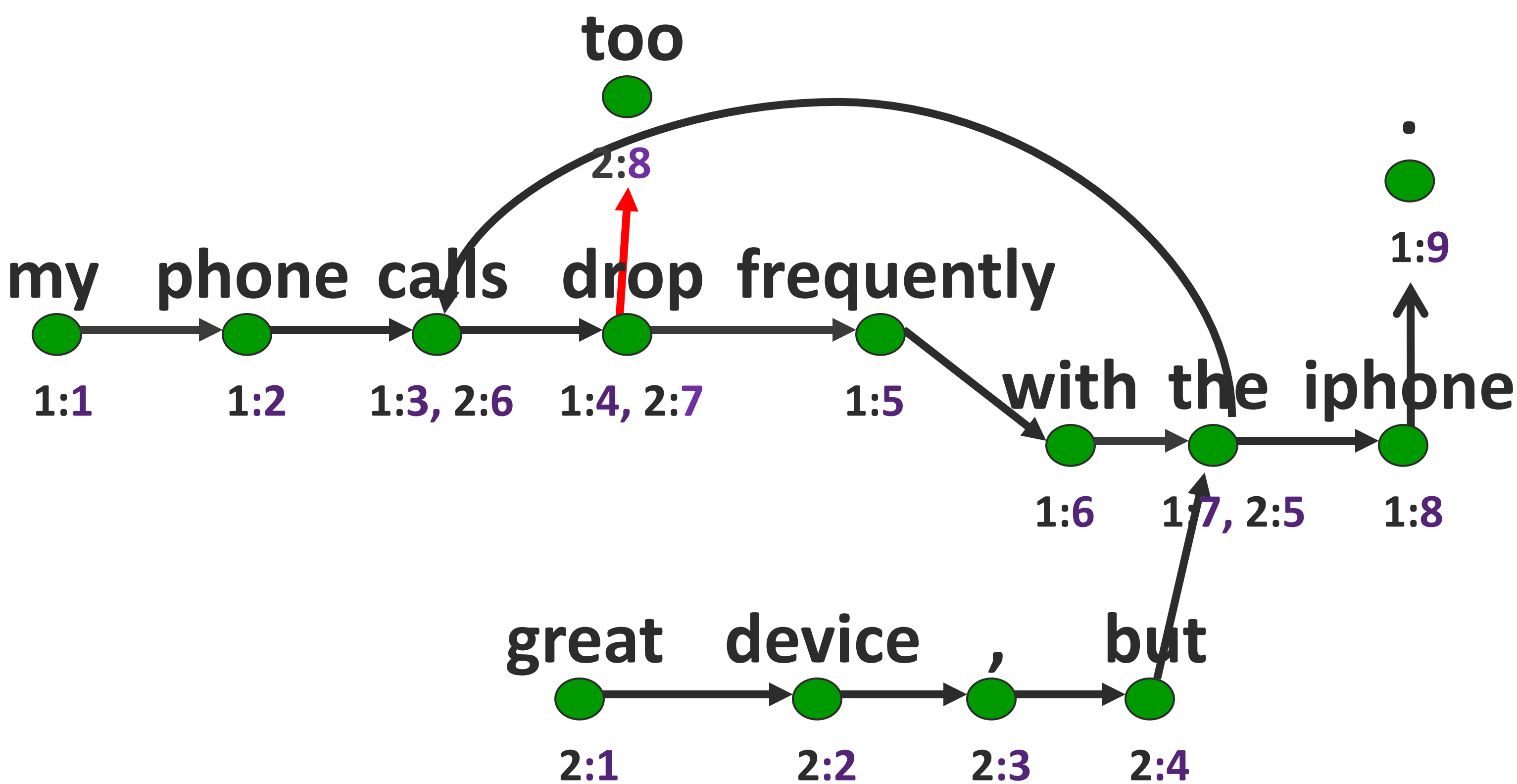

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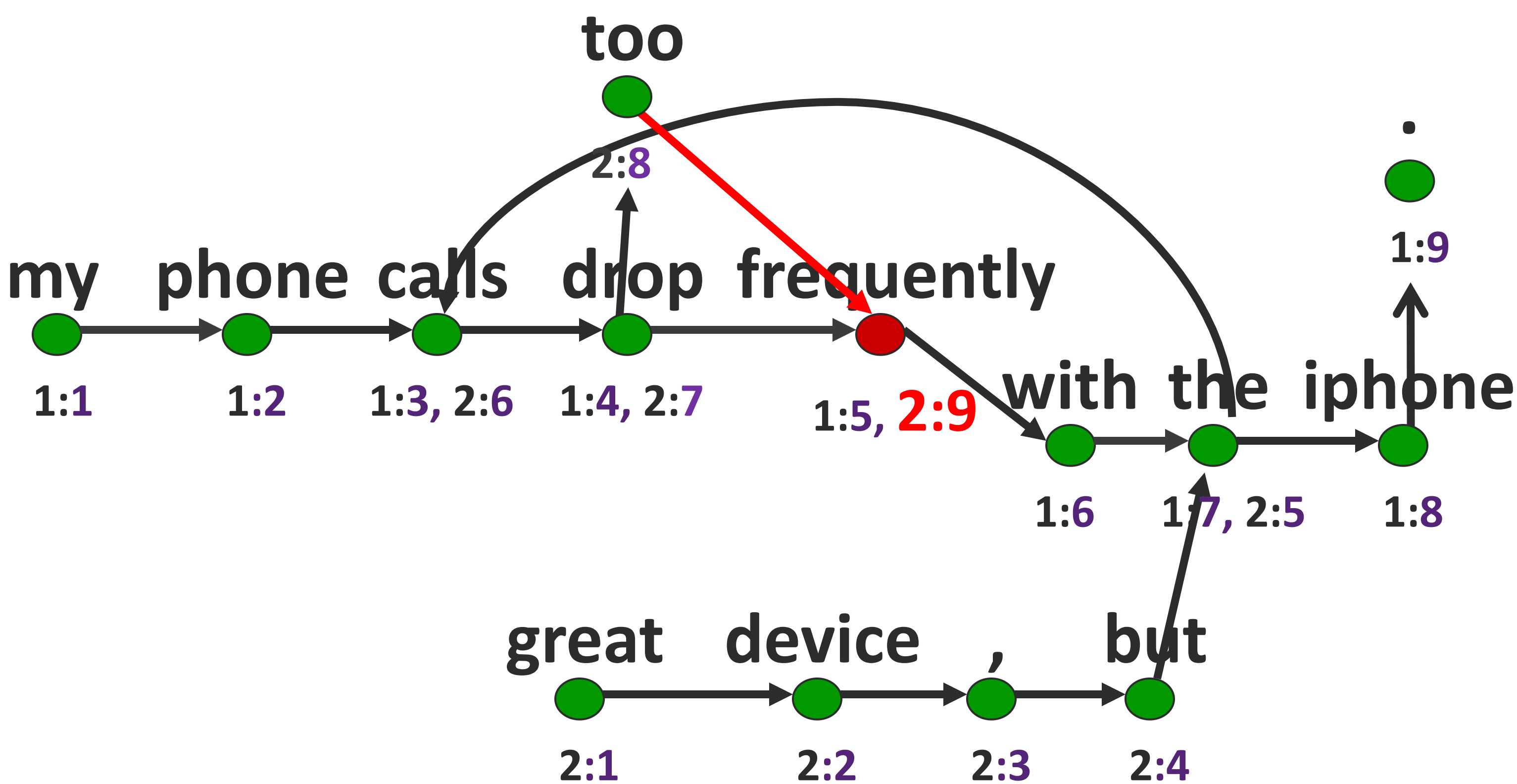

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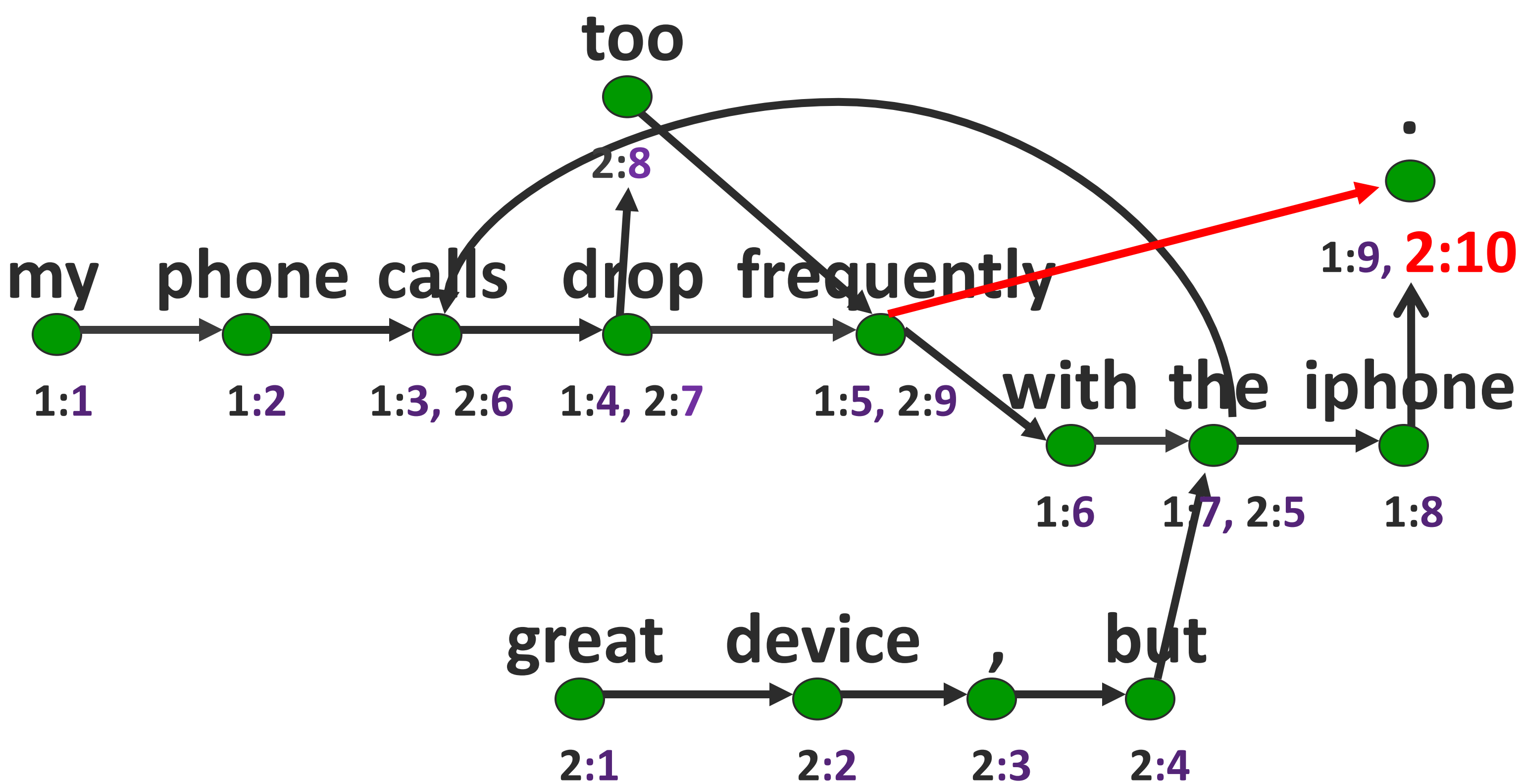
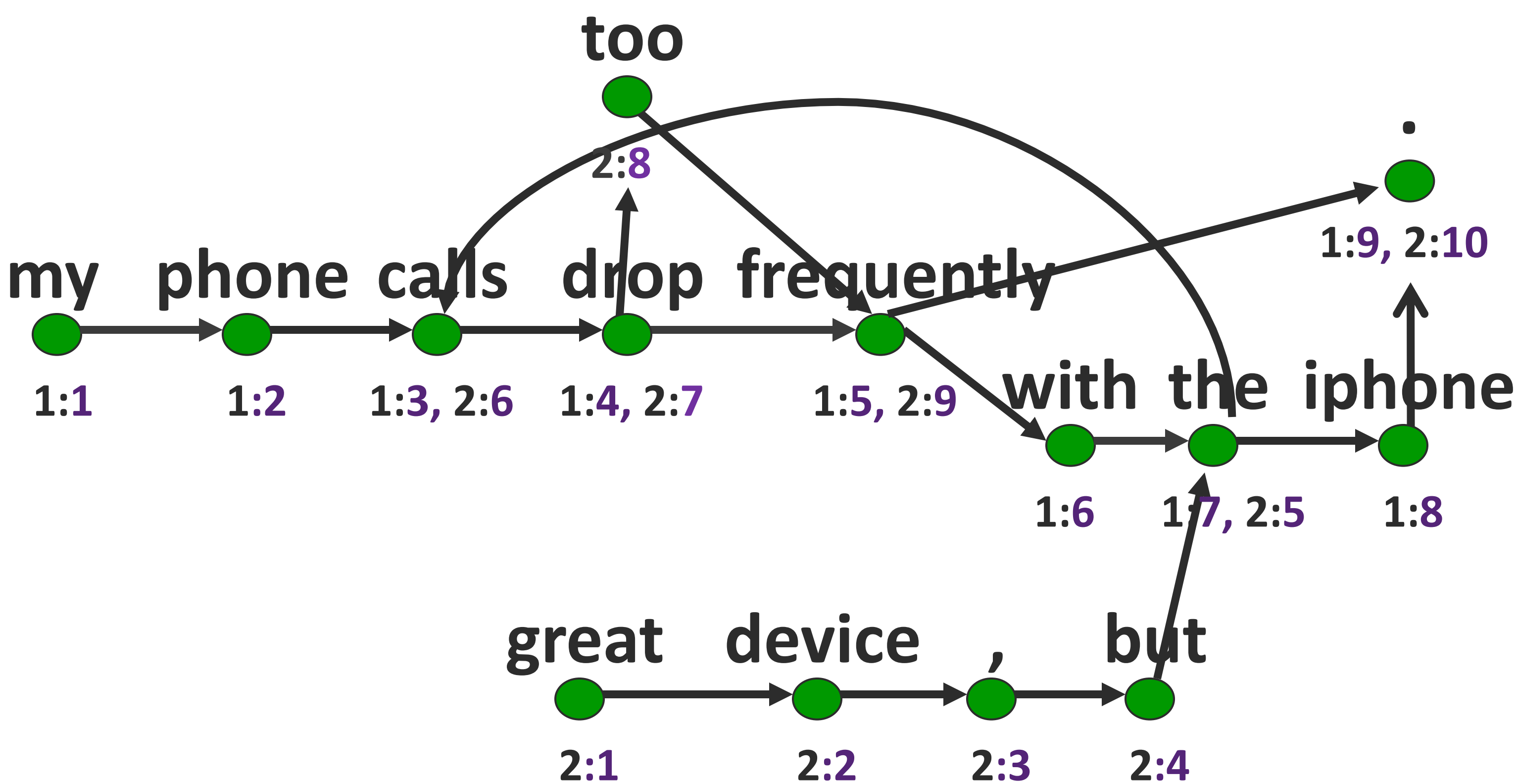


Building Opinosis-Graph

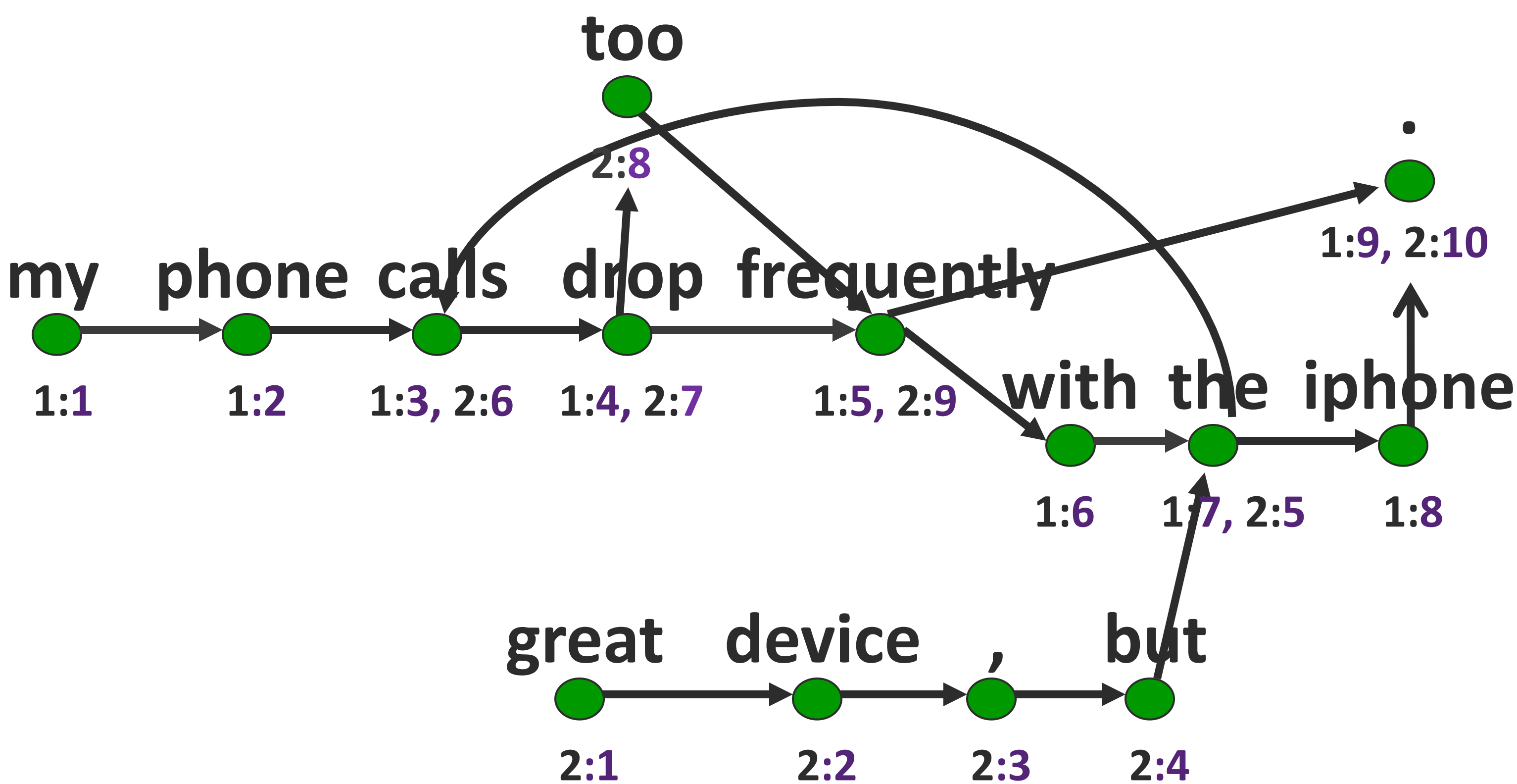
Graph is now ready for Step 2!



3 Important Properties of the Opinosis-Graph

Property 1

Naturally captures redundancies



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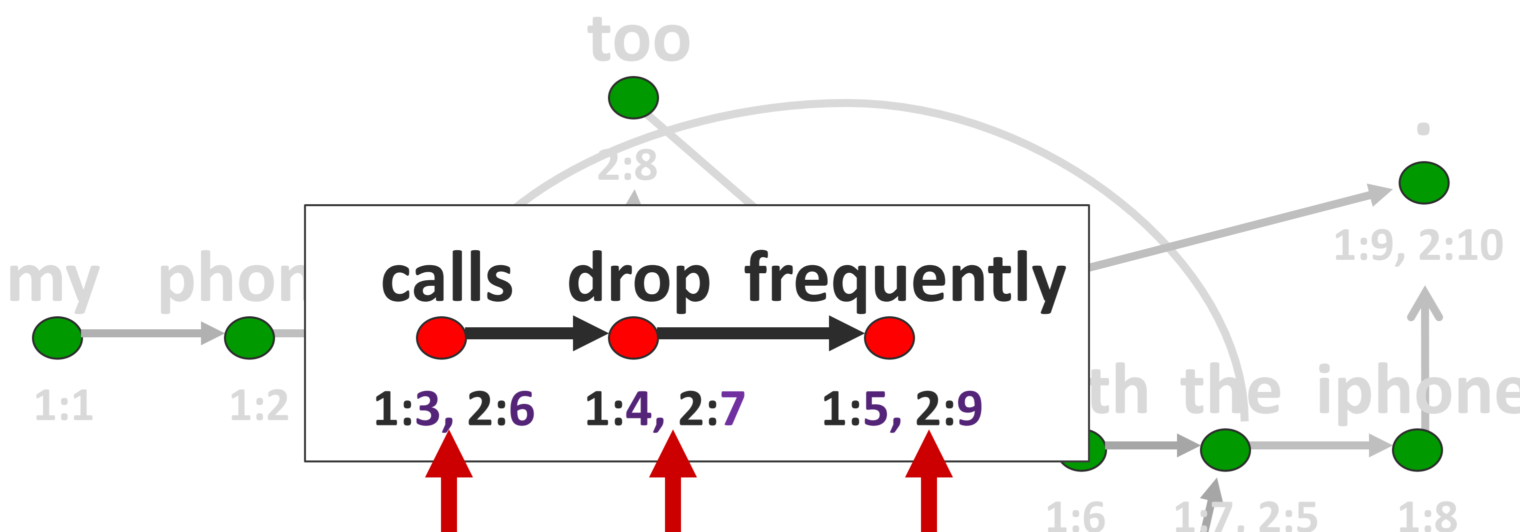
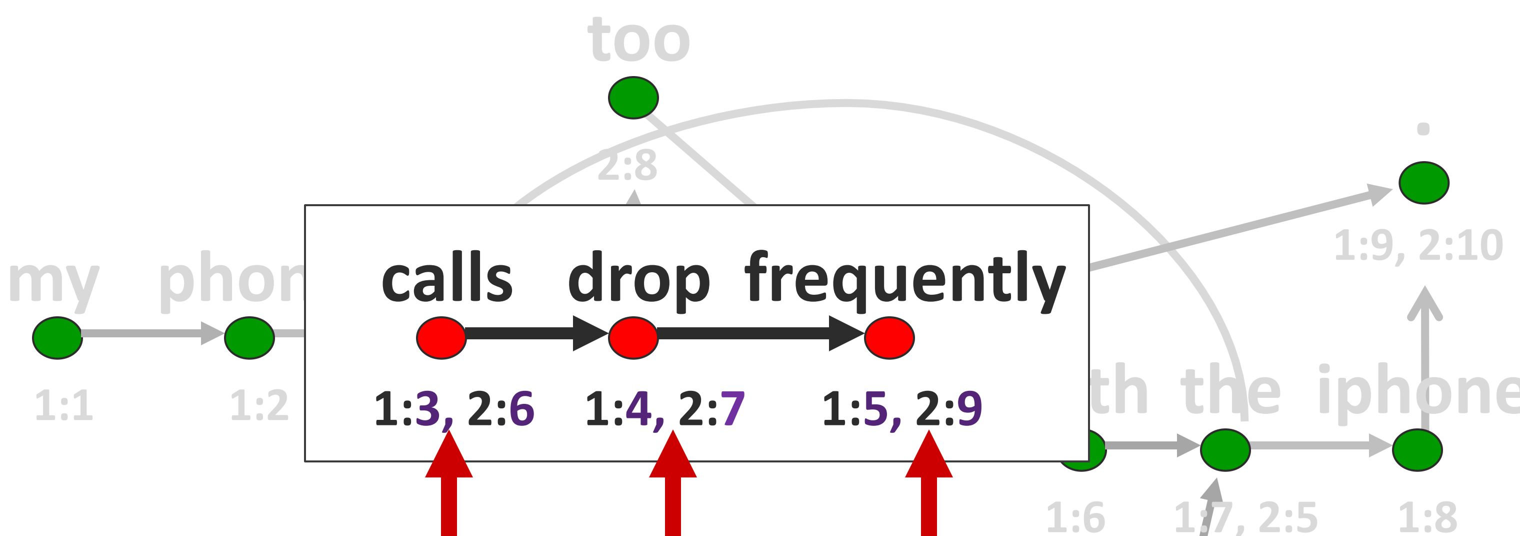


Path shared by 2 sentences naturally captured by nodes

Property 1

Naturally captures redundancies



Easily discover redundancies for high confidence summaries

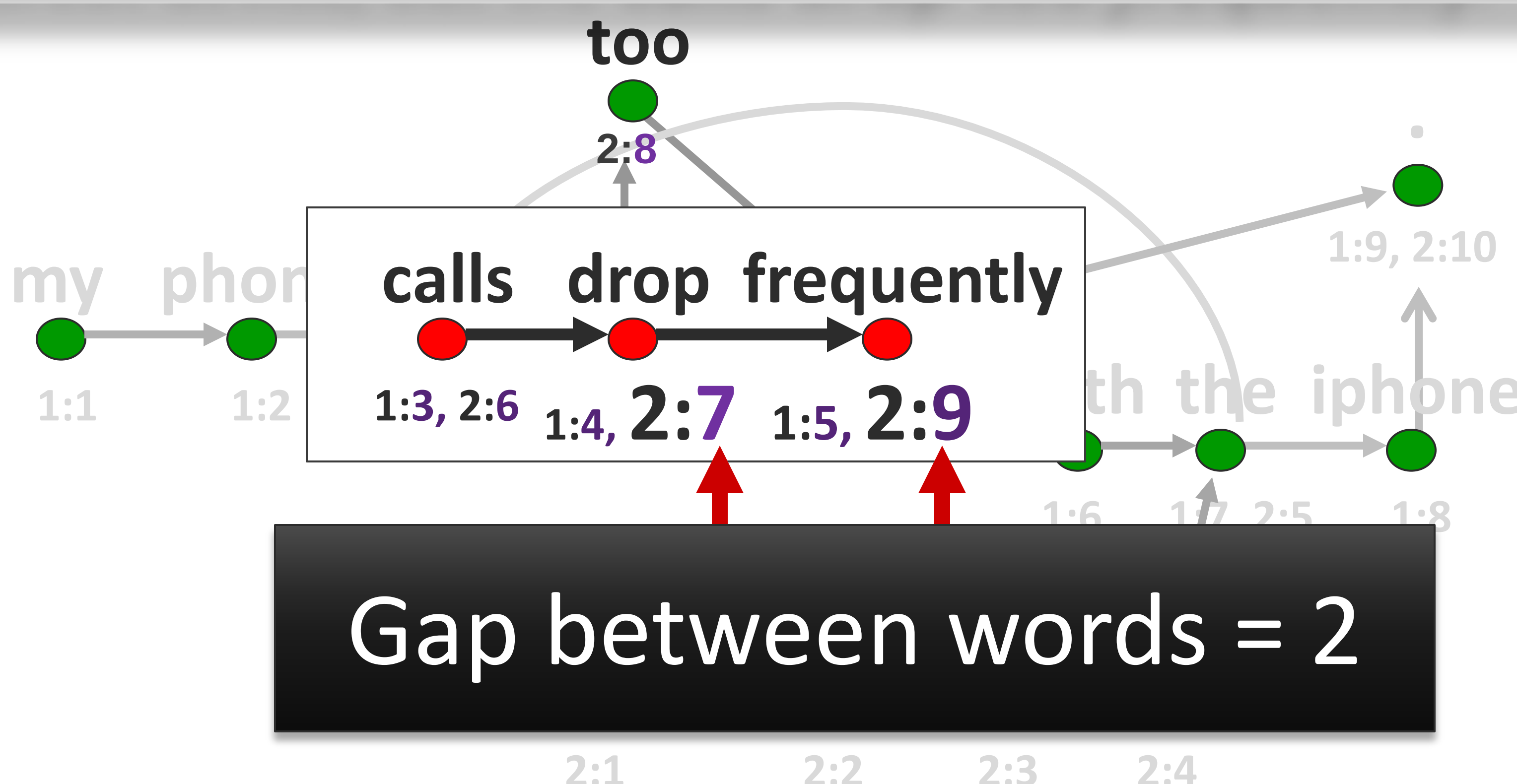
Property 2

Captures gapped subsequences

1. *My phone **calls drop frequently** with the iPhone.*
2. *Great device, but the **calls drop too frequently**.*

Property 2

1. *My phone **calls drop frequently** with the iPhone.*
2. *Great device, but the **calls drop too frequently**.*



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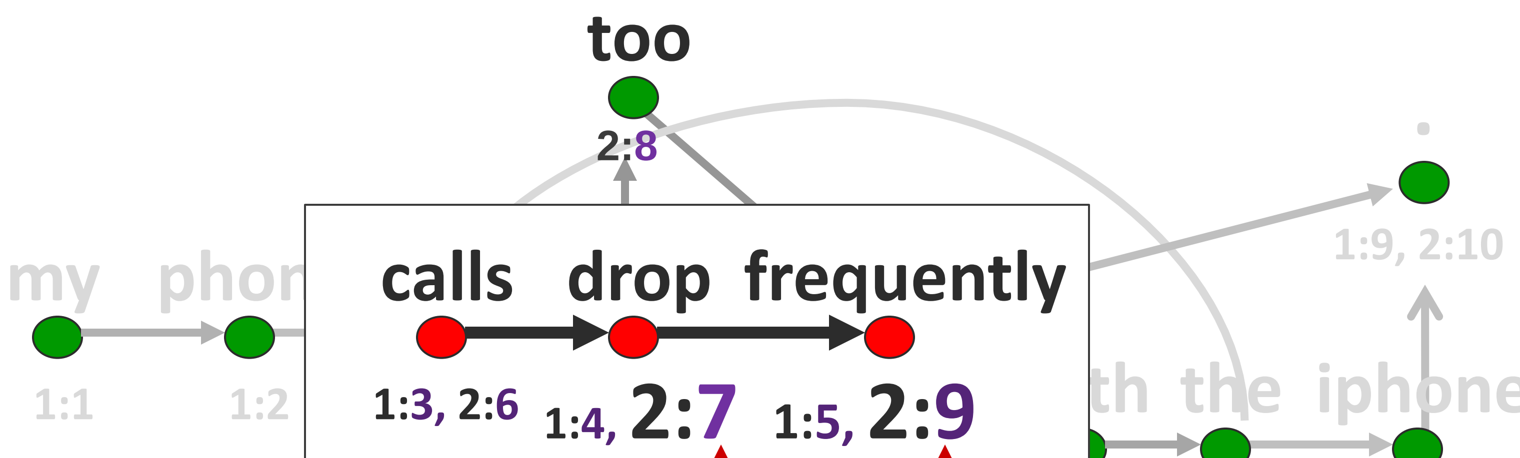


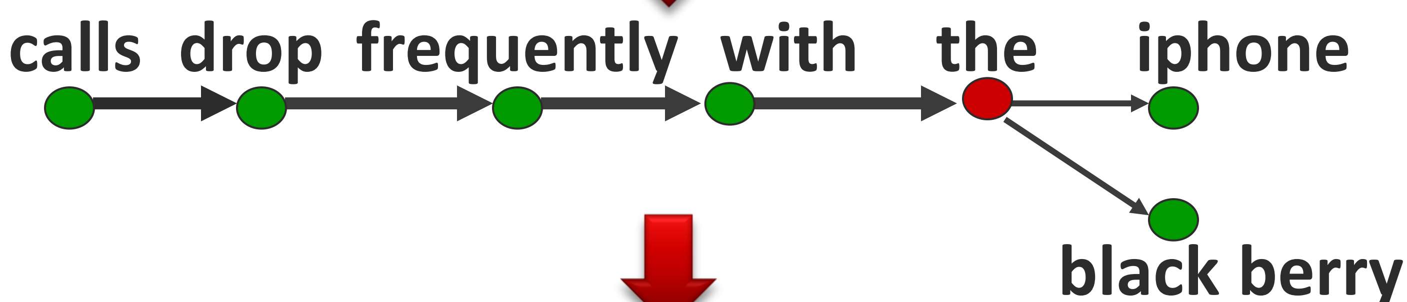
Gapped subsequences allow:

- redundancy enforcements
- discovery of new sentences

Property 3

Captures collapsible structures

1. *Calls drop frequently with the* ***iPhone***
2. *Calls drop frequently with the* ***Black Berry***

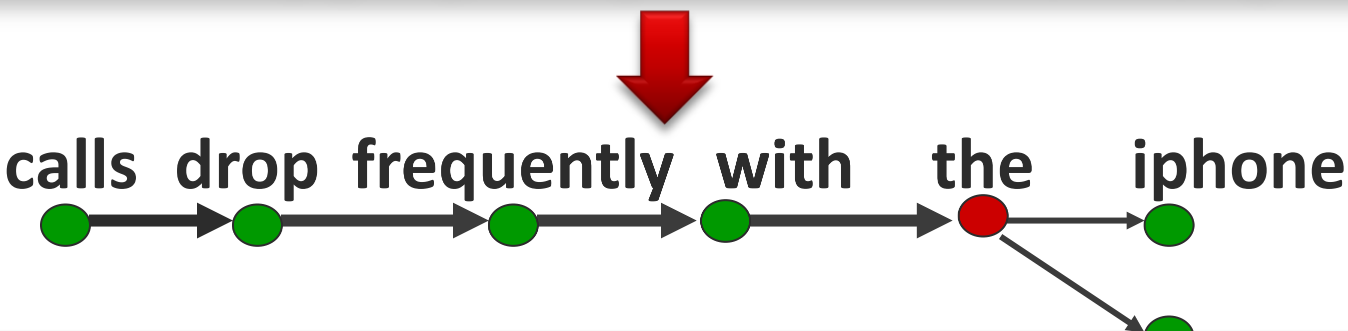


Calls drop frequently with the iPhone and Black Berry

Property 3

Captures collapsible structures

1. *Calls drop frequently with the **iPhone***
2. *Calls drop frequently with the **Black Berry***



- Can easily be discovered using OG
- Ideal for collapse & compression

Step 2a: Generate Candidate Summaries

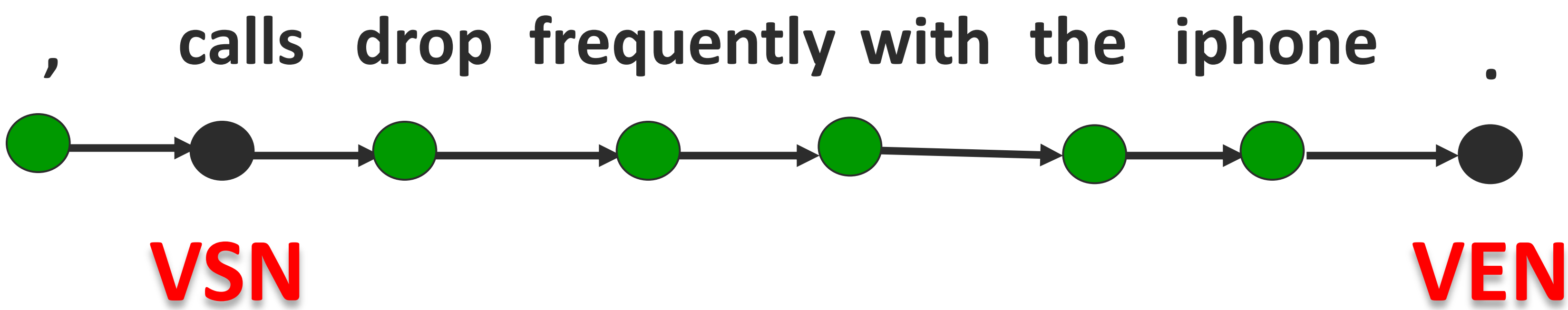
Generate Candidate Summaries

Repeatedly search the Opinosis-Graph for a Valid Path

Valid Path

- **Set of connected nodes**
- **Has a Valid Start Node (VSN)**
  - Natural starting point of a sentence
  - Opinosis uses avg. positional information
- **Has a Valid End Node (VEN)**
  - Point that completes a sentence
  - Opinosis uses <u>punctuations</u> & <u>conjunctions</u>

Finding Candidate Summaries



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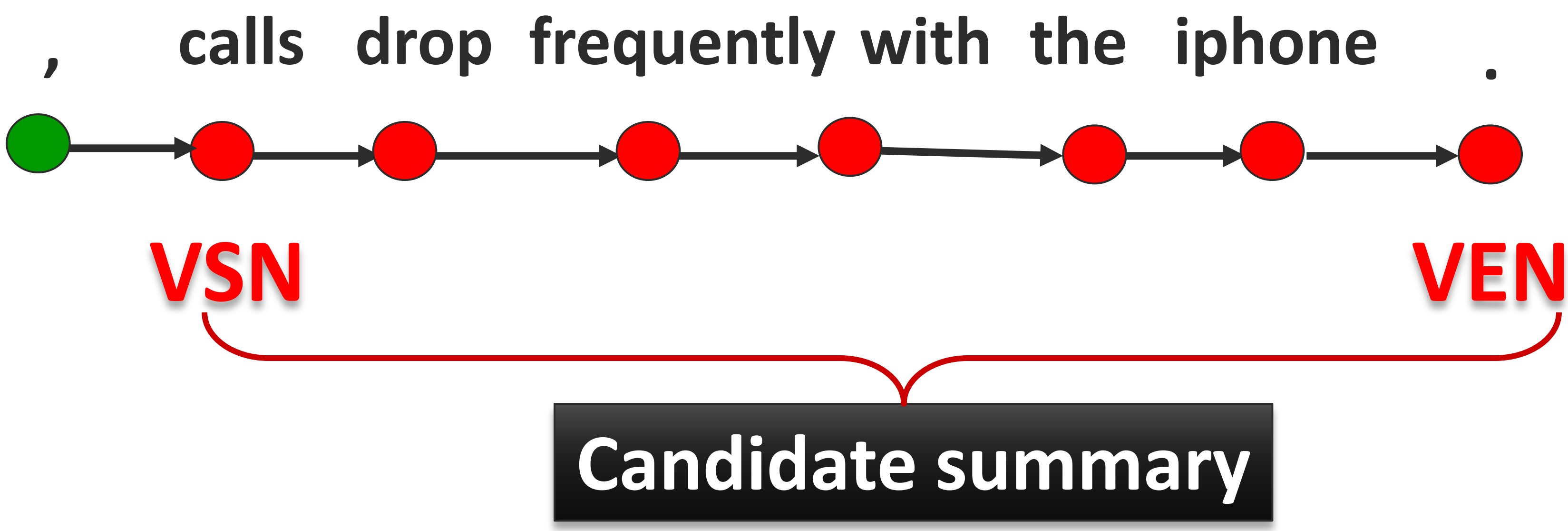

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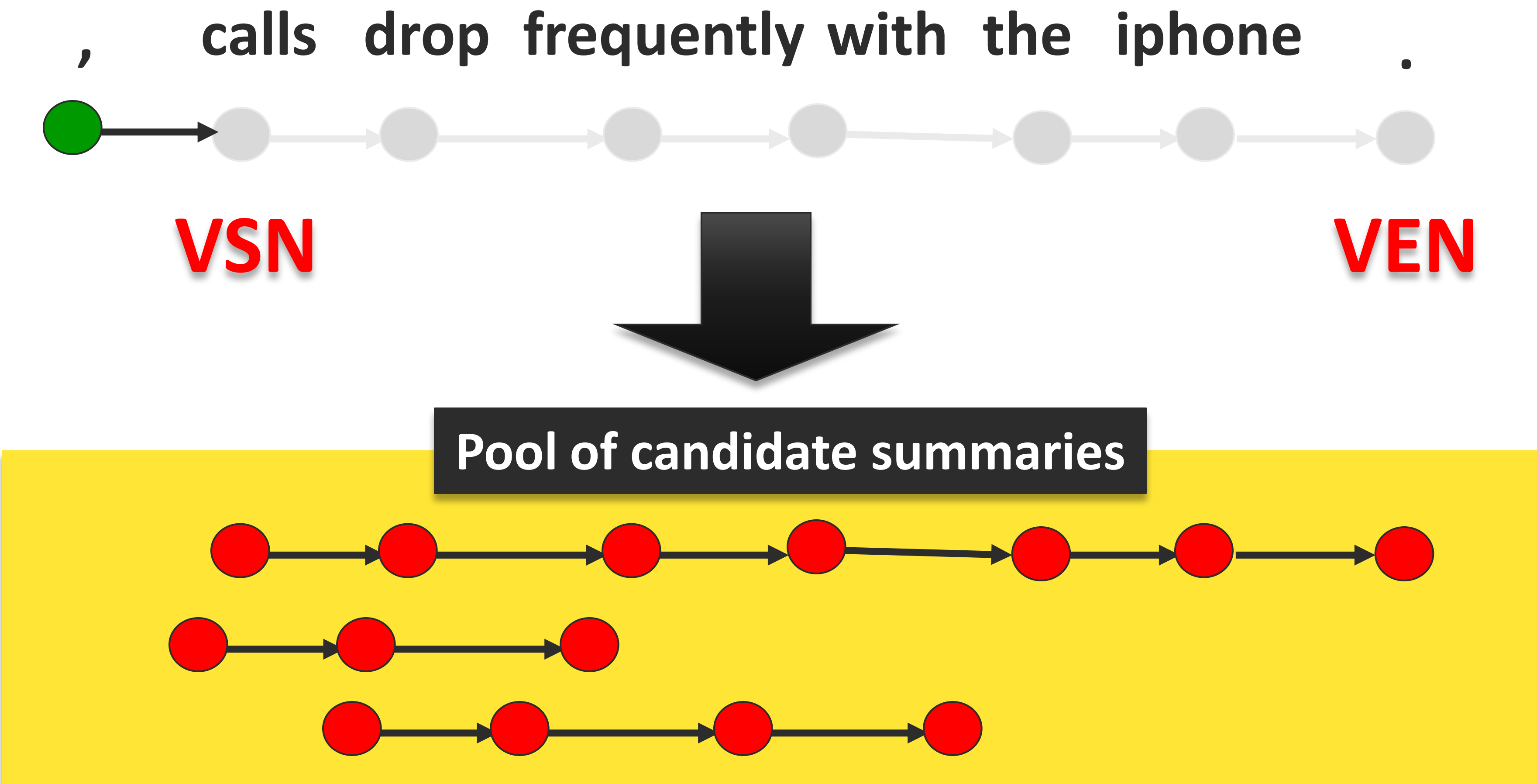


Collapsible Structures

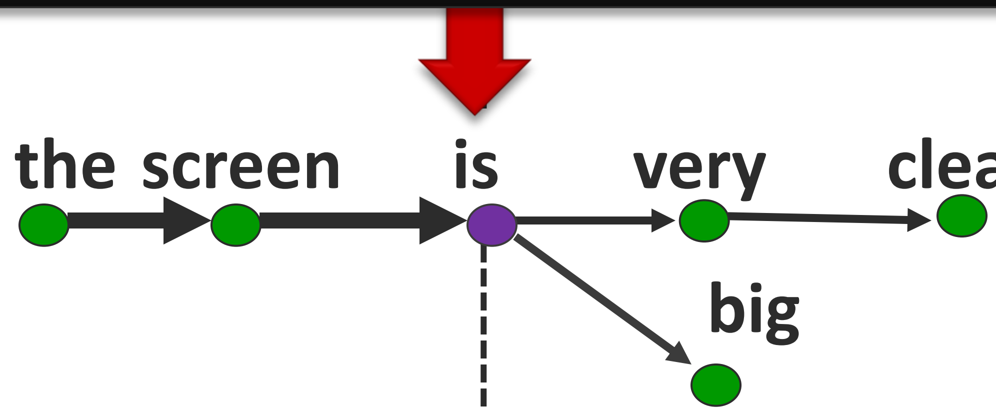
- **Some paths are collapsible**

- **Identify such paths through a collapsible node**

- **Treat linking verbs (e.g. is, are) as collapsible nodes**
  - Linking verbs have hub-like properties
  - Commonly used in opinion text

A Collapsible Structure

linking verb = collapsible node



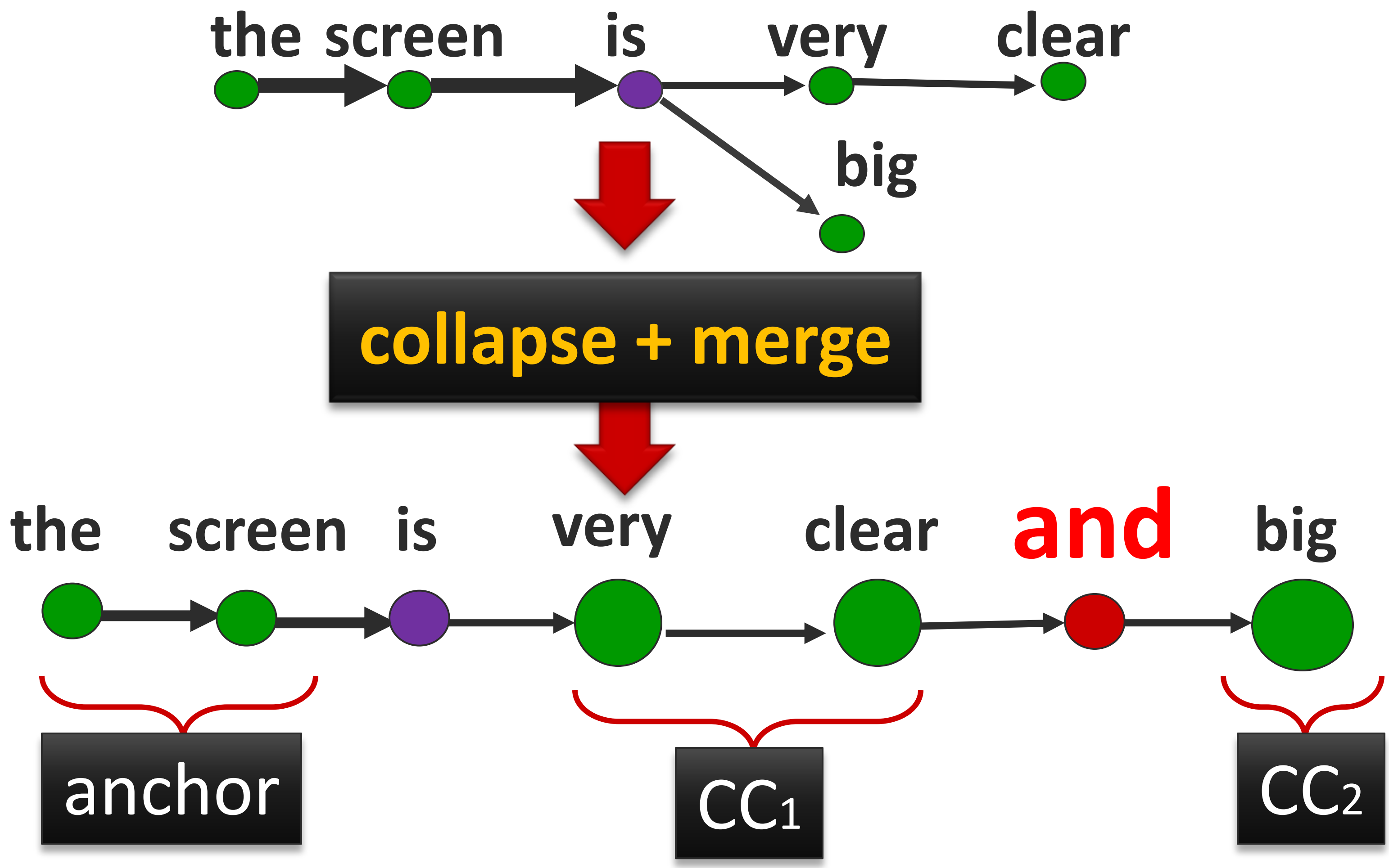
anchor

- *Common structure*
- *High redundancy path*

collapsed candidates (CC)

- *Subgraphs to be merged*

A Collapsible Structure



How to Merge Structures?

- **CC after linking verbs:** concatenate using commas

  "The screen is <u>very clear</u>, <u>bright</u>, <u>big</u>"

  CC_1 CC_2 CC_3

- **Better readability:**

  "The screen is <u>very clear</u>, <u>bright</u> ***and*** *<u>big</u>"*

Find last connector using hints from OG

Step 2b: Score Candidate Summaries

Scoring Options

Type 1: High confidence summaries

- Select candidates with <u>high redundancy</u>
  - # of sentences sharing same path
  - controlled by gap threshold, σ_{gap}

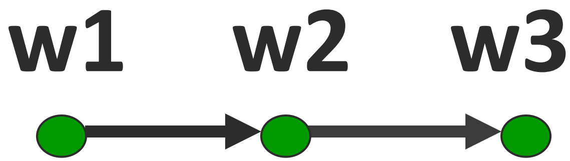
Type 2: + Good coverage

- Select <u>longer candidates</u>
- redundancy * length of candidate paths
  - Favor longer but redundant candidates

Gap Threshold (σ_{gap})

- Gaps vary between sentences sharing nodes

Candidate X



Sentence 1	1	2
Sentence 2	4	4
Sentence X	m	n
	gap	gap

Gap Threshold (σ_{gap})

- σ_{gap} enforces maximum allowed gap between two adjacent nodes

w1 → w2

Candidate X

Sentence 1 1 < σ_{gap} ✓

~~Sentence 2 4 > σ_{gap}~~ ✗

-Lower risk of ill-formed sentences

-Avoids over-estimation of redundancy

Step 3: Final Opinosis Summaries

- **After candidate scoring:**
  - Select top 2 scoring candidates
  - Most dissimilar candidates

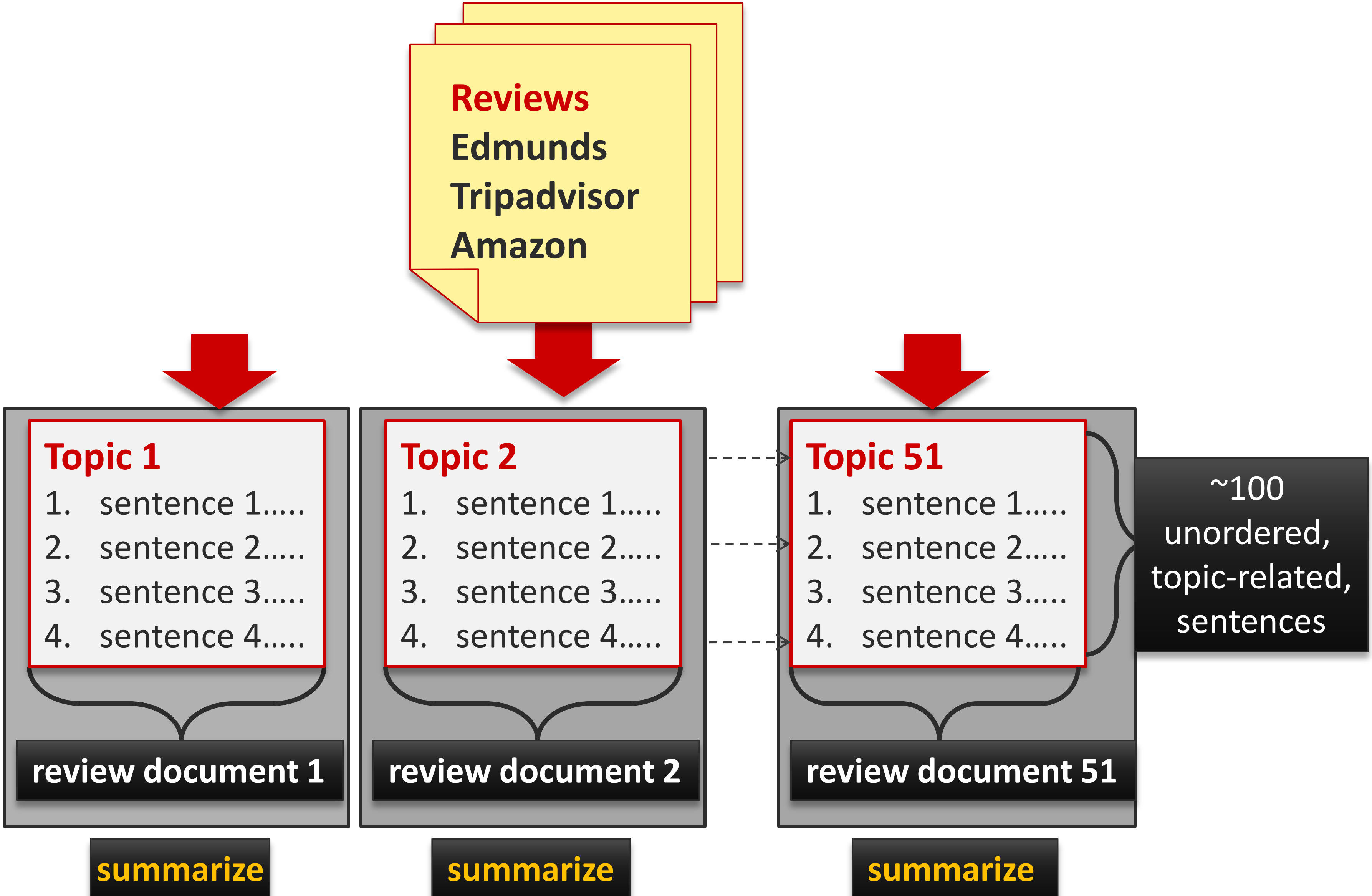
Evaluation

Data

User Reviews:

- **Hotels**: Tripadvisor.com
- **Products**: Amazon.com
- **Cars**: Edmunds.com

Summarization Task



Gold Standard

- **Human composed summaries**
  - Concise (<25 words)
  - Focus on summarizing major opinions
  - ~4 human summaries per topic

Baseline

- **Hard to find 'general' abstractive summarizer**

- **Use MEAD - Extractive based method** [Radev et al.2000]
  - Select **2 sentences** as the summary

Evaluation Measures

- **ROUGE** (rouge-1, rouge-2, rouge-su4)
  - Standard measure for summarization tasks

- **Readability Test**
  - Measures: How different Opinosis summaries are compared to human composed summaries?

Results

Human Performance

- **Estimate:** How much one summary writer agrees with the rest

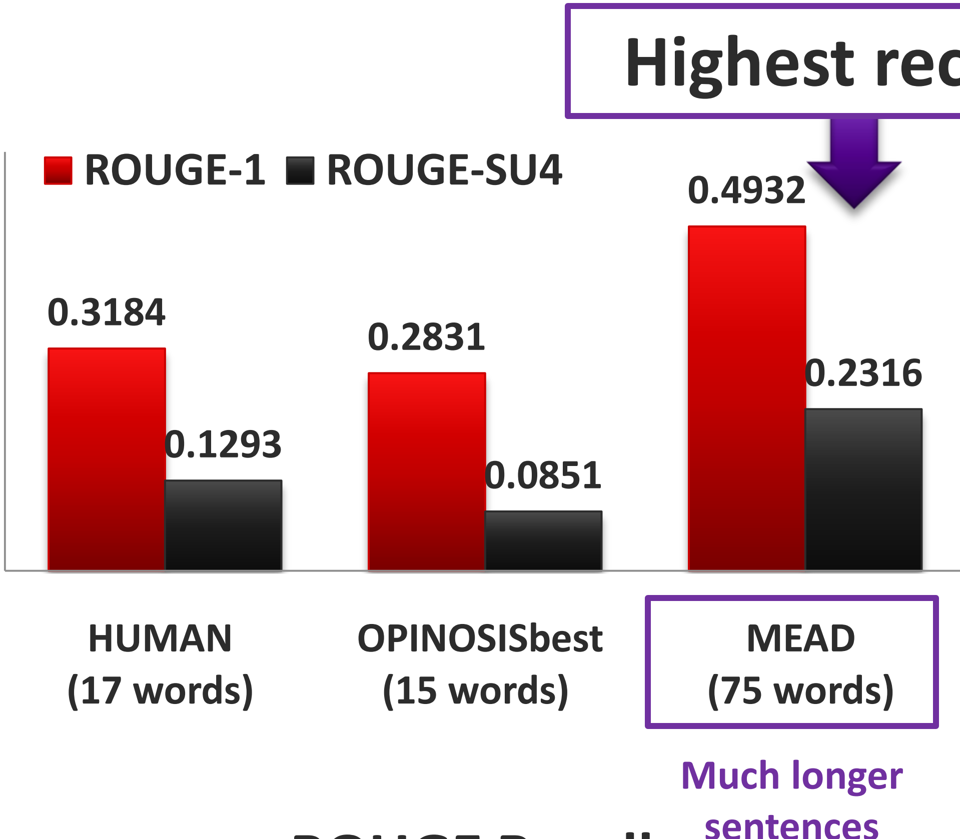
Human Performance

ROUGE Scores		
ROUGE-1	Precision	0.34
	Recall	0.32
	F-score	0.31
ROUGE-SU4	Precision	0.16
	Recall	0.13
	F-score	0.11

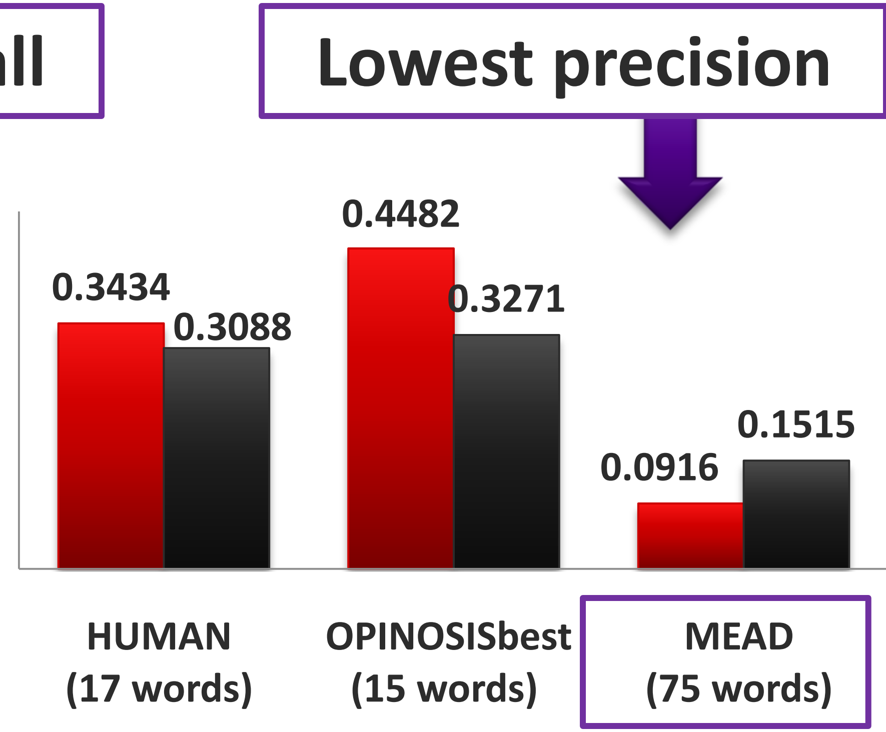
Human summaries - semantically similar. Slight difference in word usage.

Human vs. Opinosis vs. MEAD

Human vs. Opinosis vs. MEAD

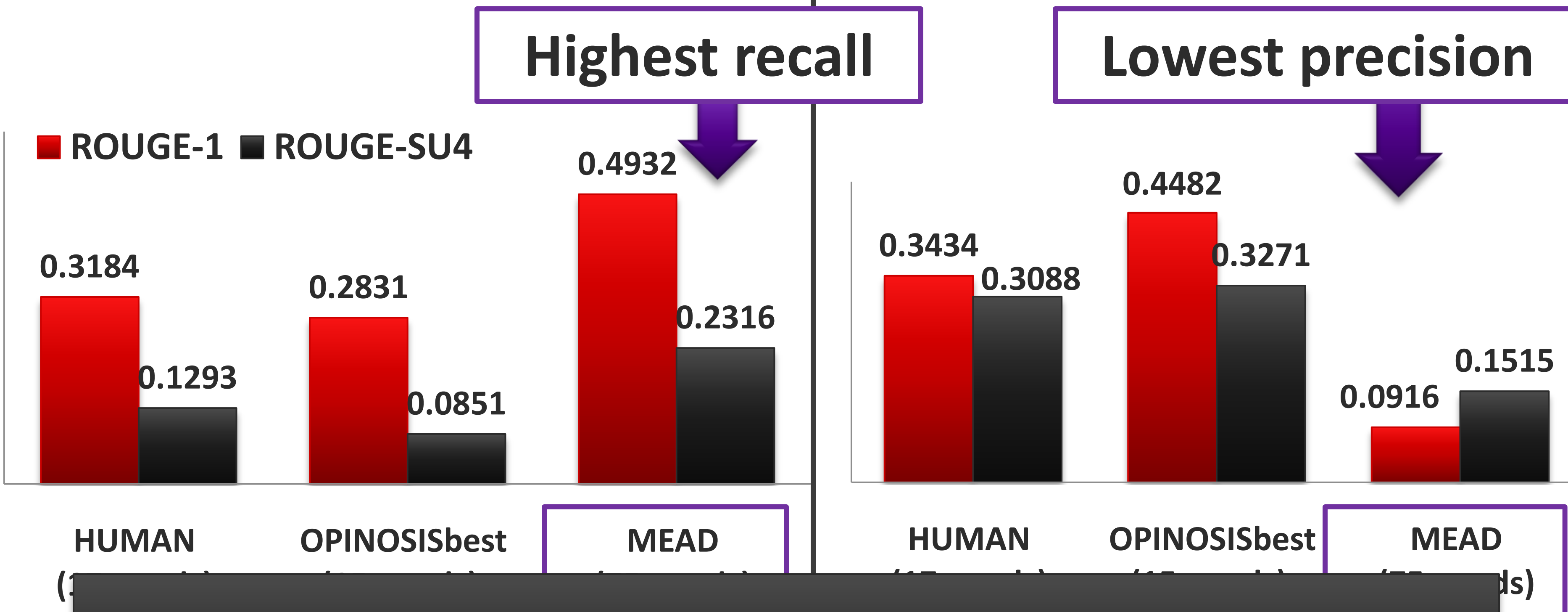


ROUGE Recall



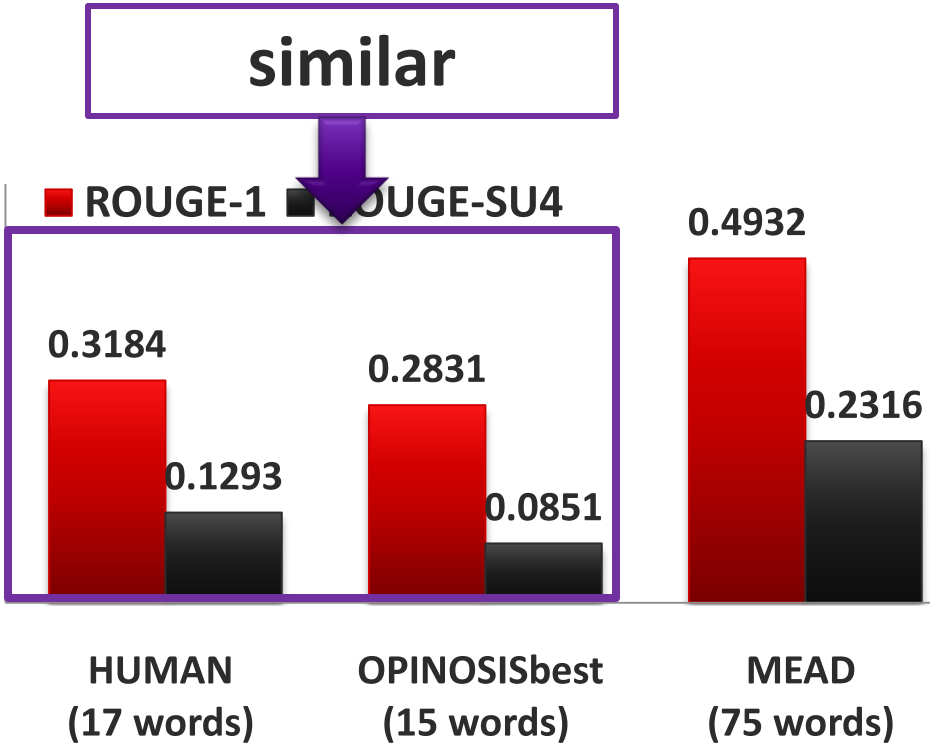
ROUGE Precision

Human vs. Opinosis vs. MEAD

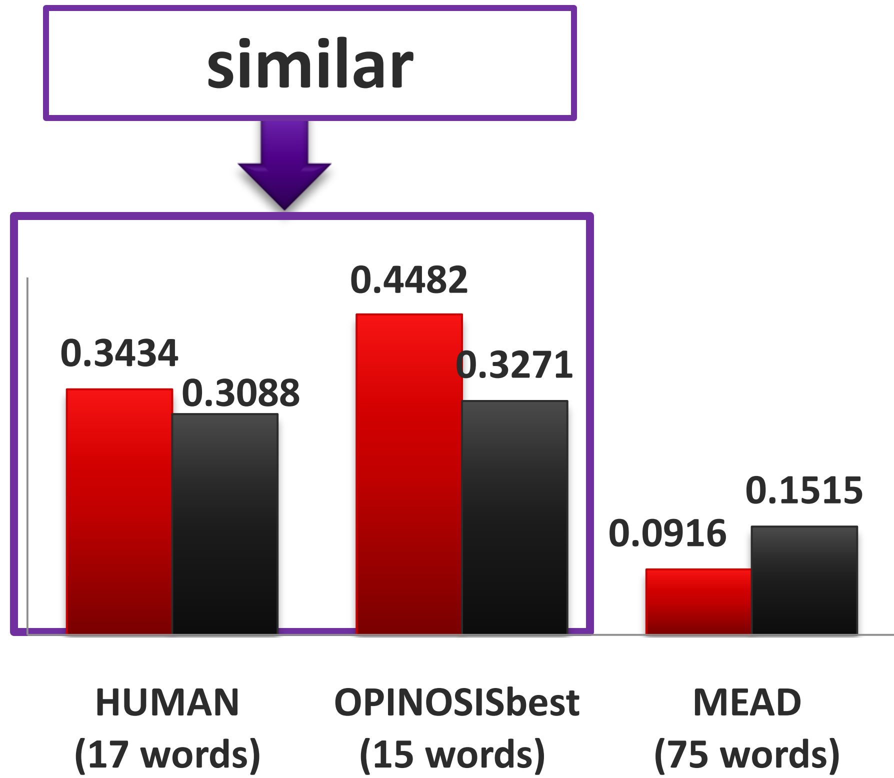


Overall: Baseline does not do well in generating concise summaries.

Human vs. Opinosis

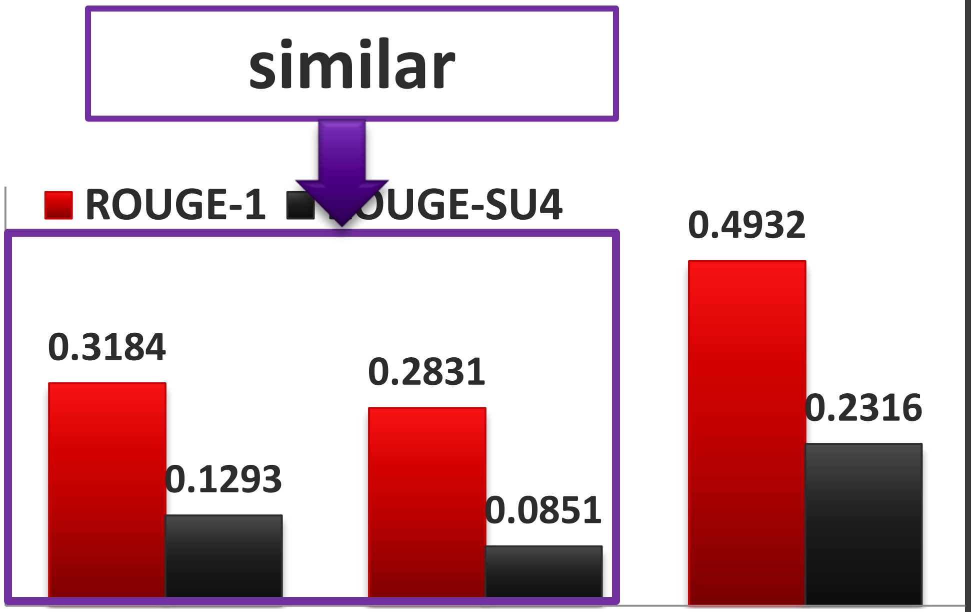


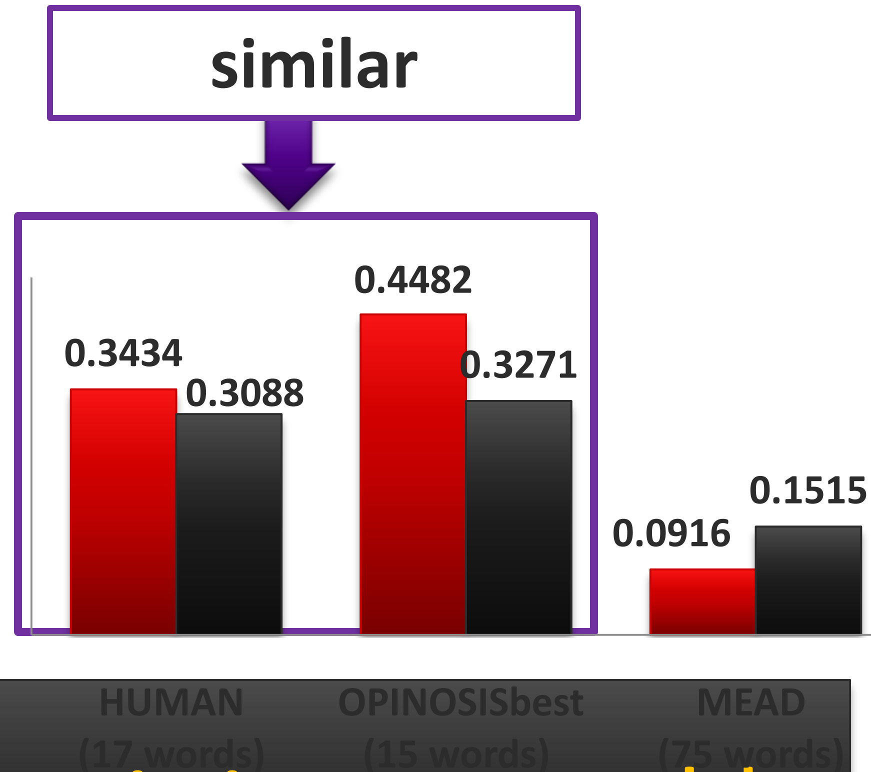
ROUGE Recall



ROUGE Precision

Human vs. Opinosis



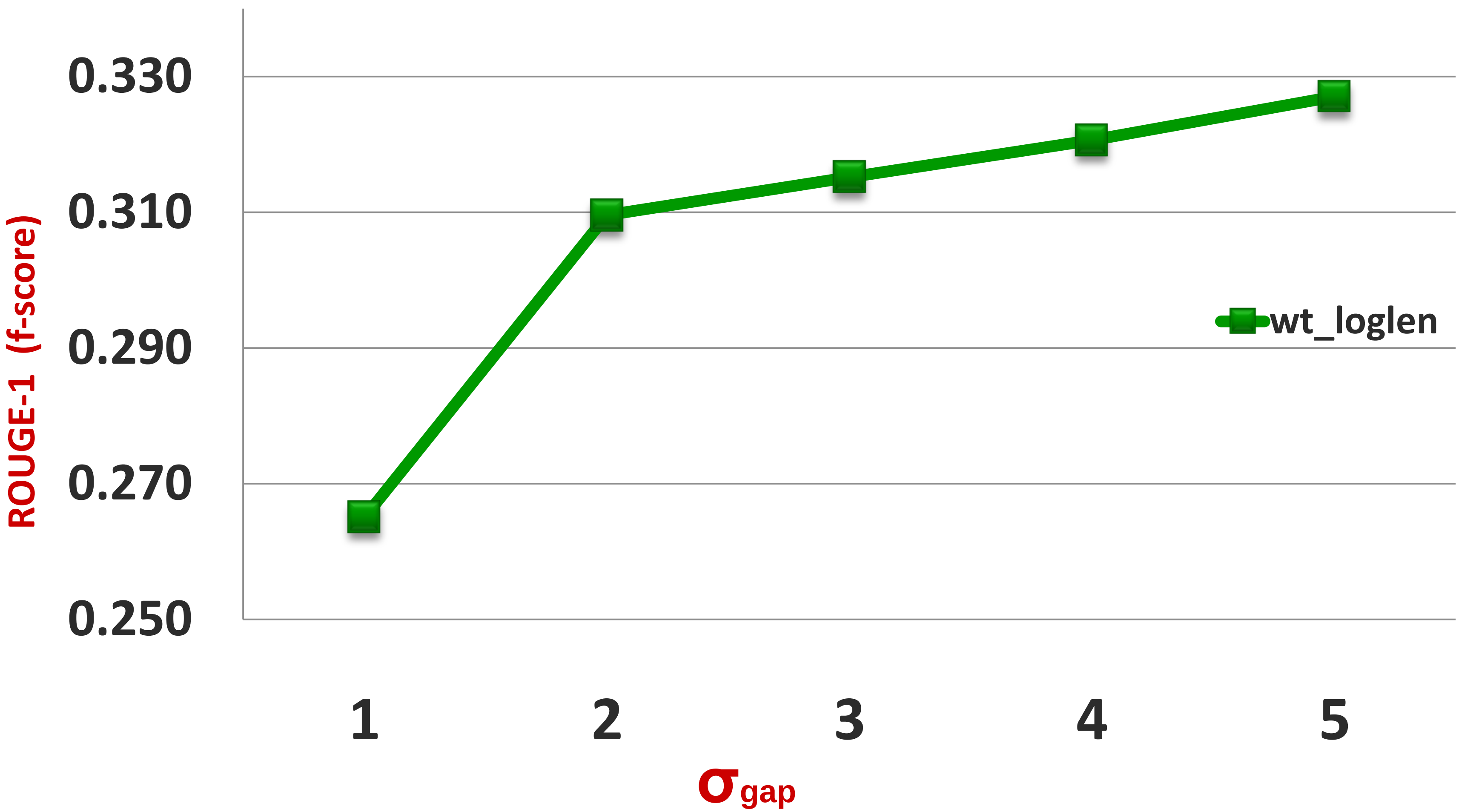


Performance of Opinosis is reasonable

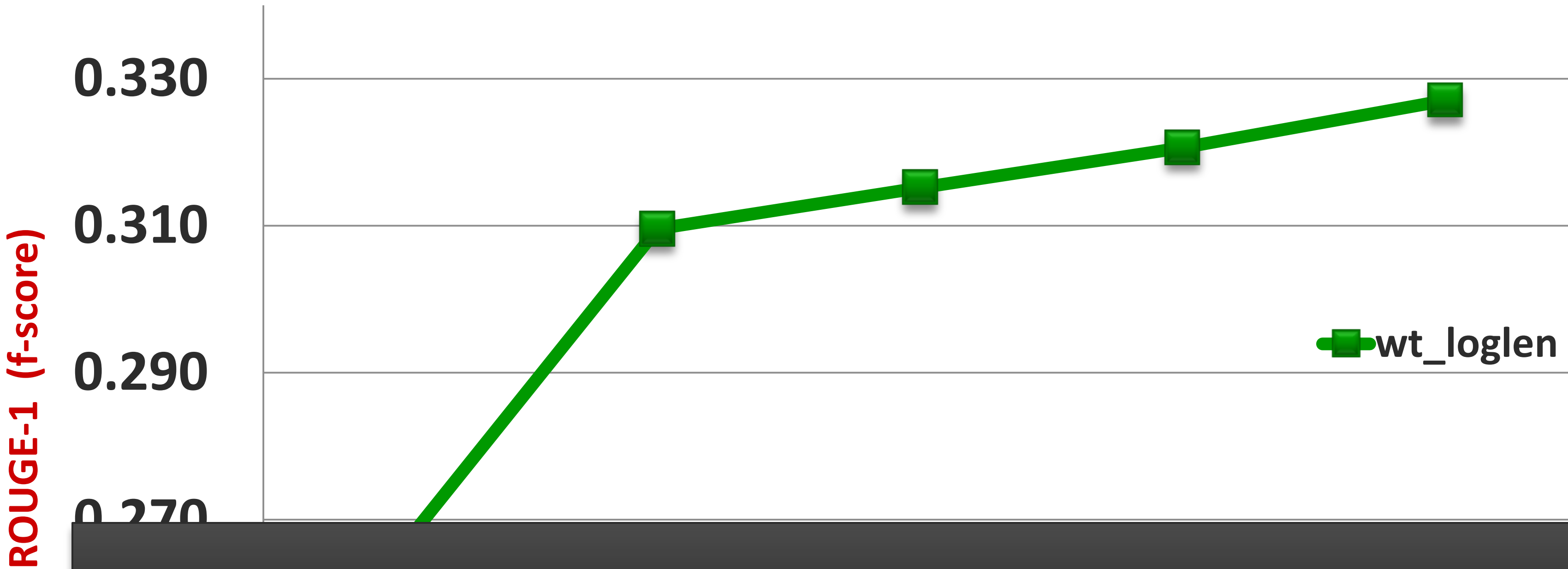
→ similar to Human performance

Effect of Gap Threshold (σ_{gap})

Effect of Gap Threshold (σ_{gap})

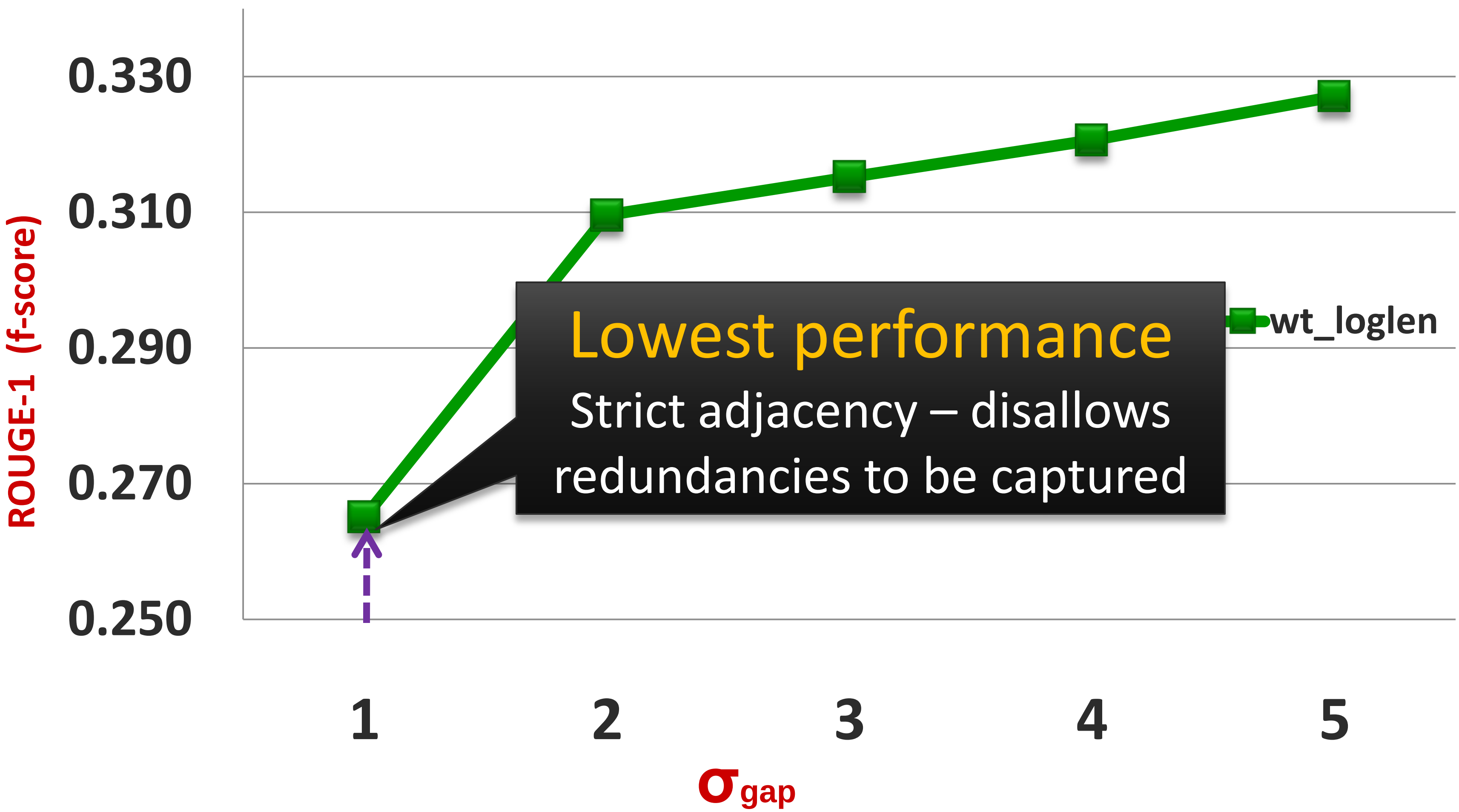


Effect of Gap Threshold (σ_{gap})

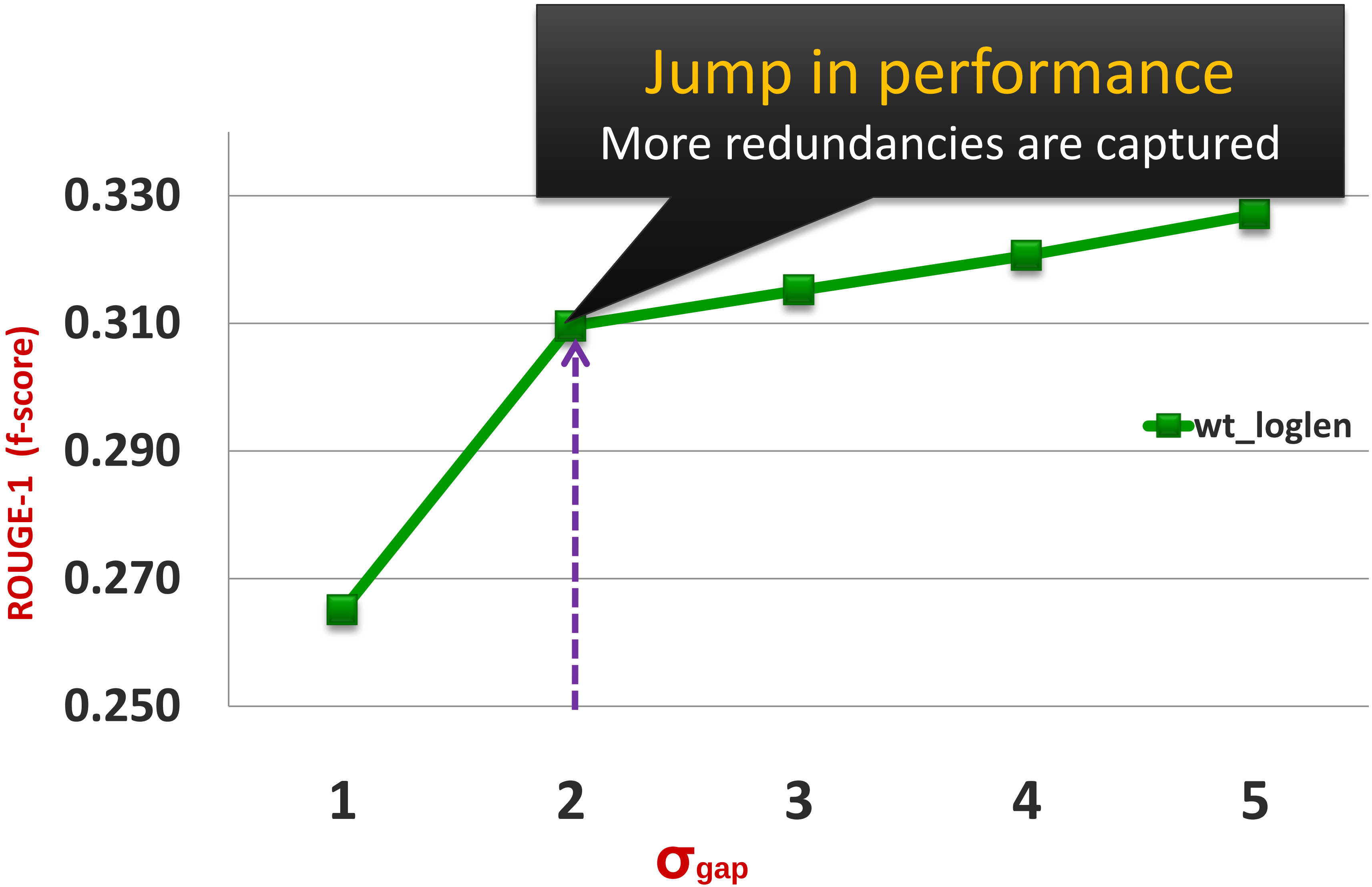


small σ_{gap} → words in summary close together in original text

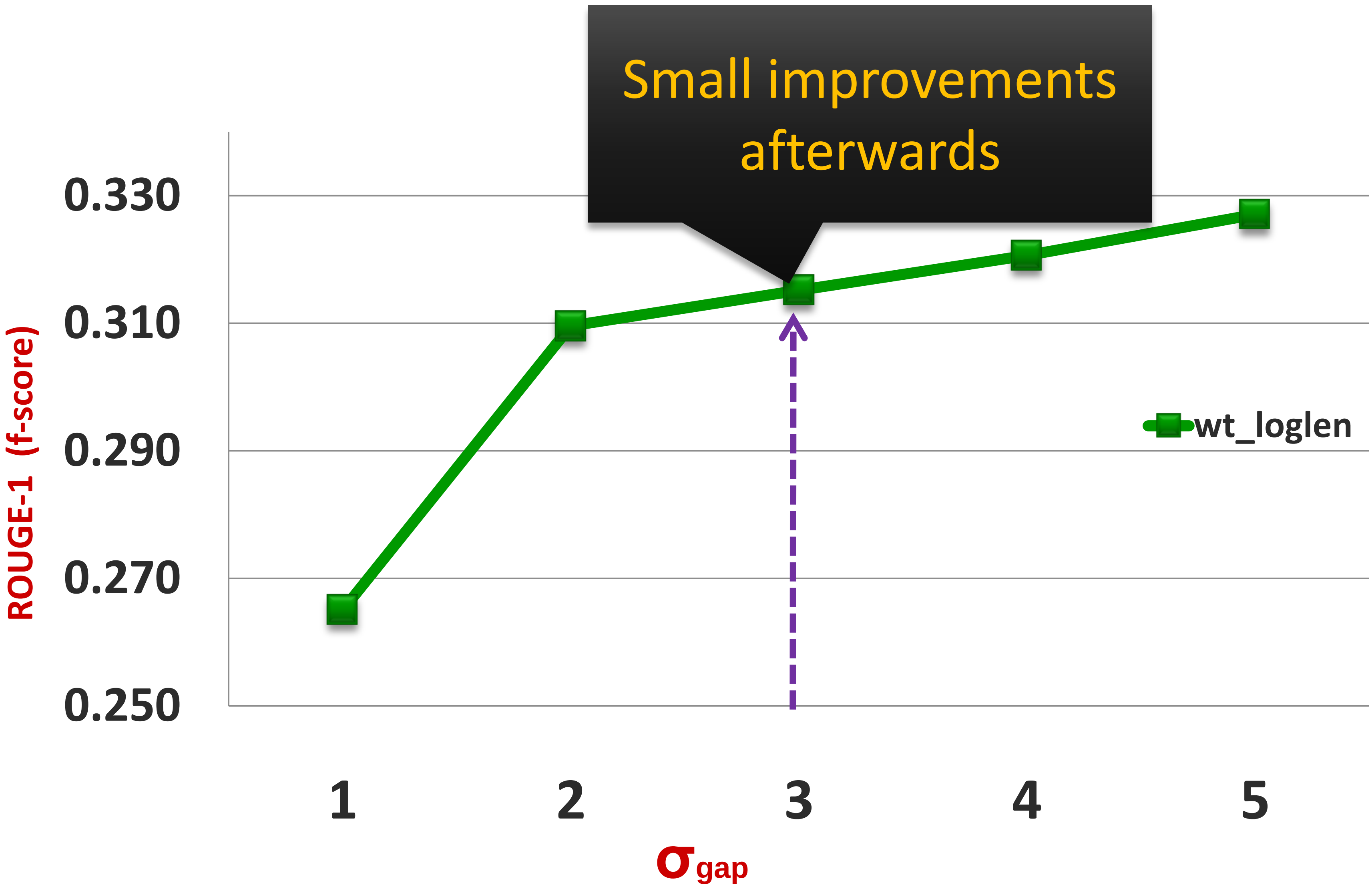
Effect of Gap Threshold (σ_{gap})



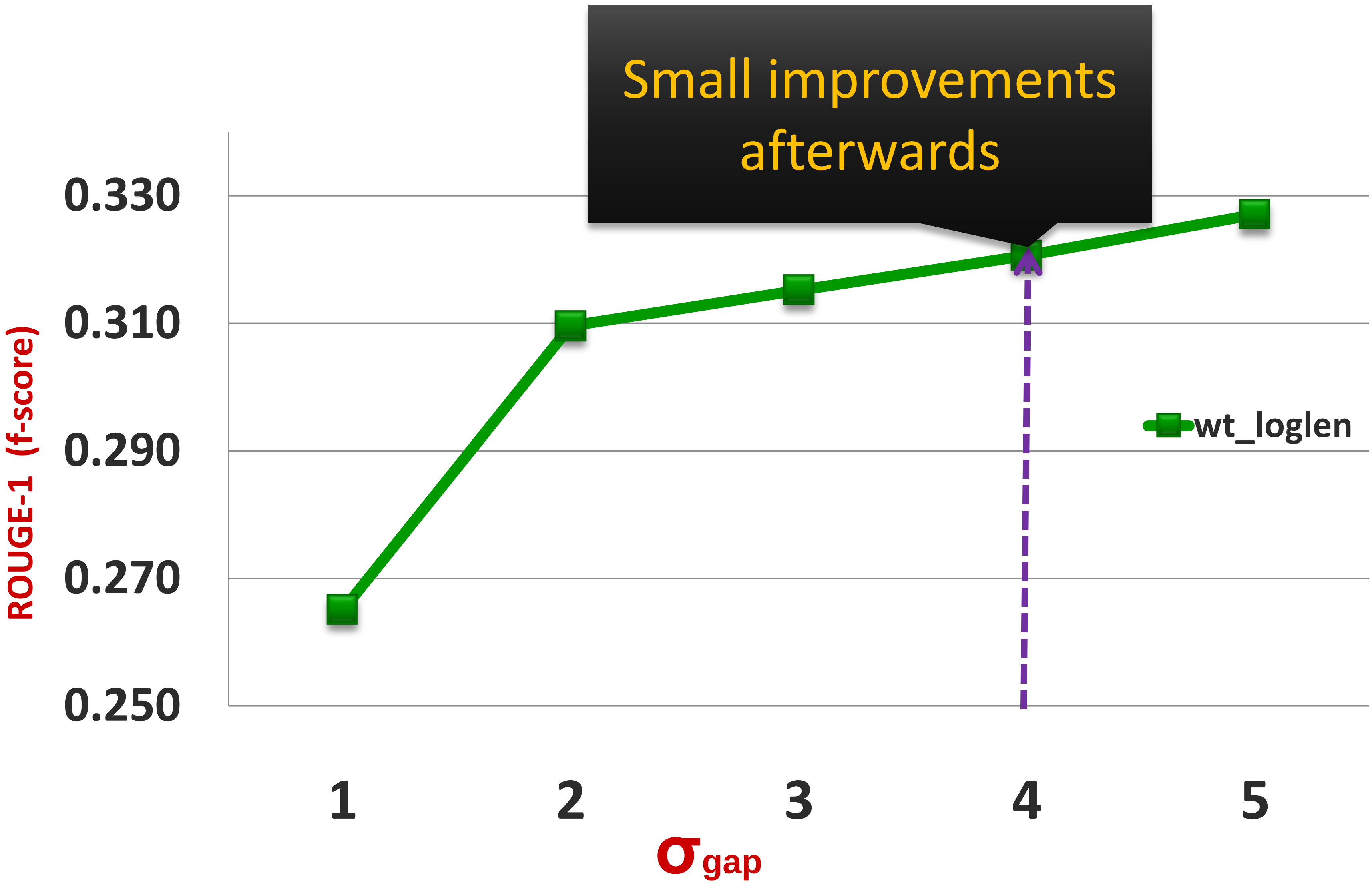
Effect of Gap Threshold (σ_{gap})



Effect of Gap Threshold (σ_{gap})



Effect of Gap Threshold (σ_{gap})



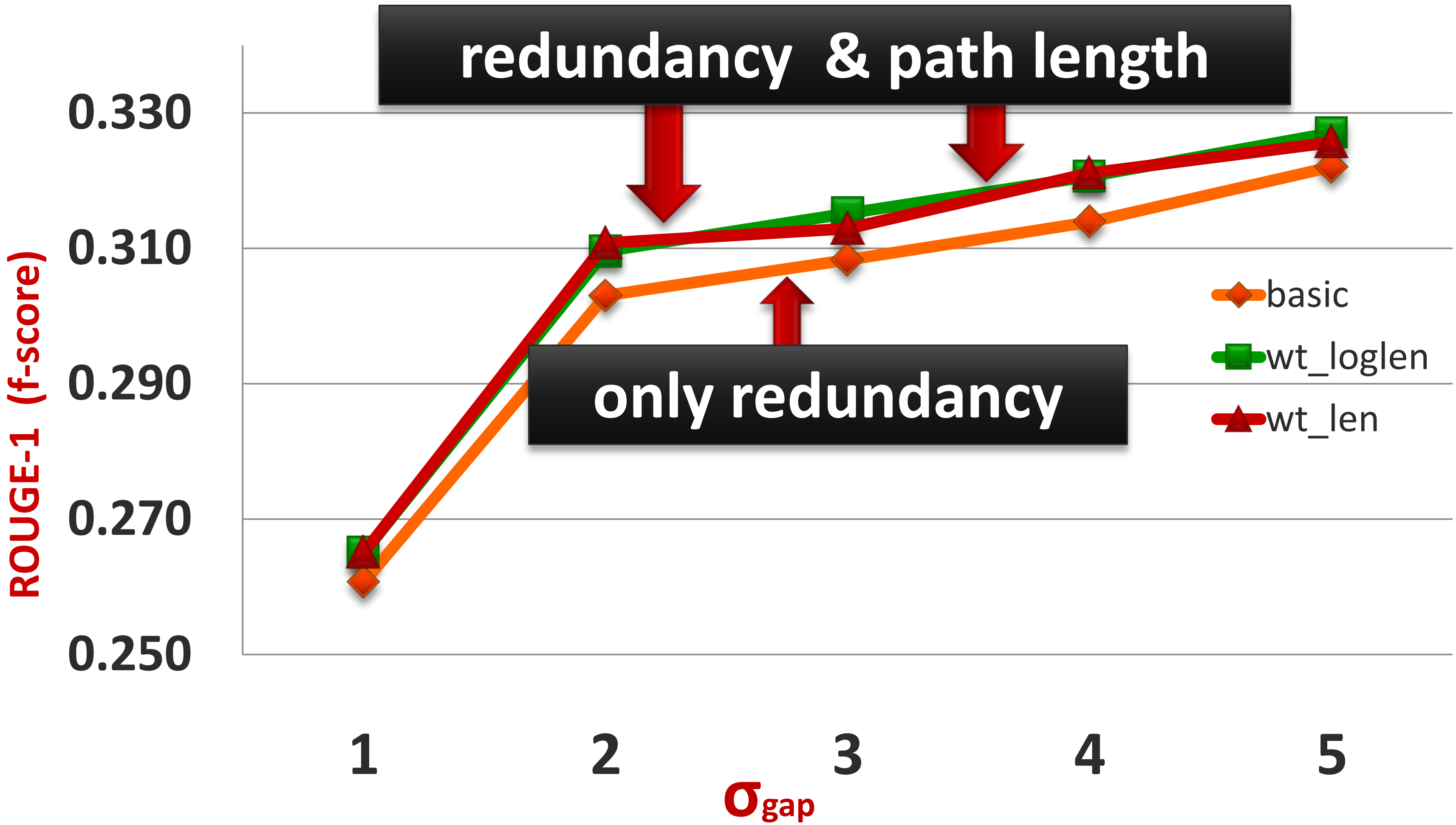
Effect of Gap Threshold (σ_{gap})

σ_{gap} too large: ill formed sentences

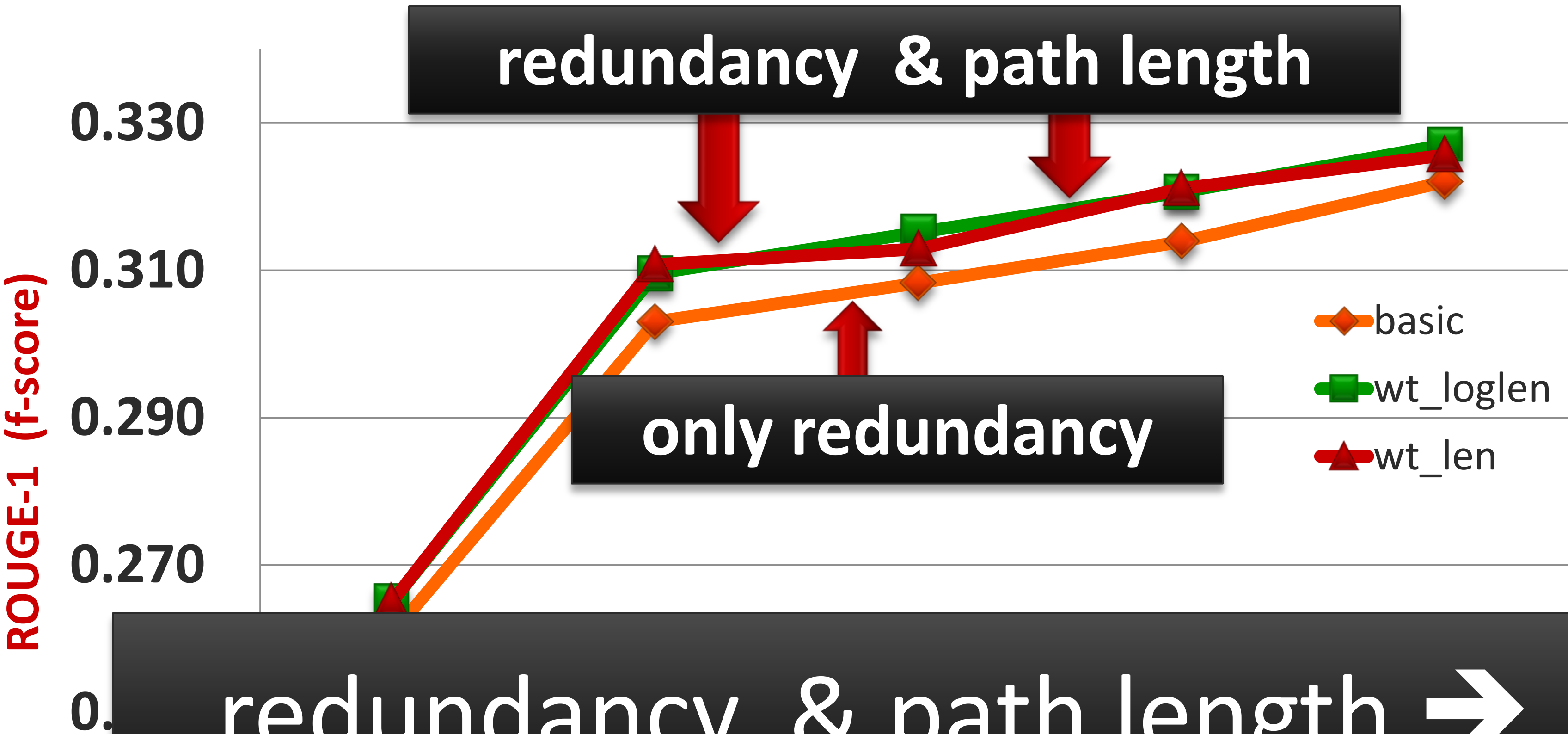
Set σ_{gap} to low value

Compare: Scoring Functions

Compare: Scoring Functions

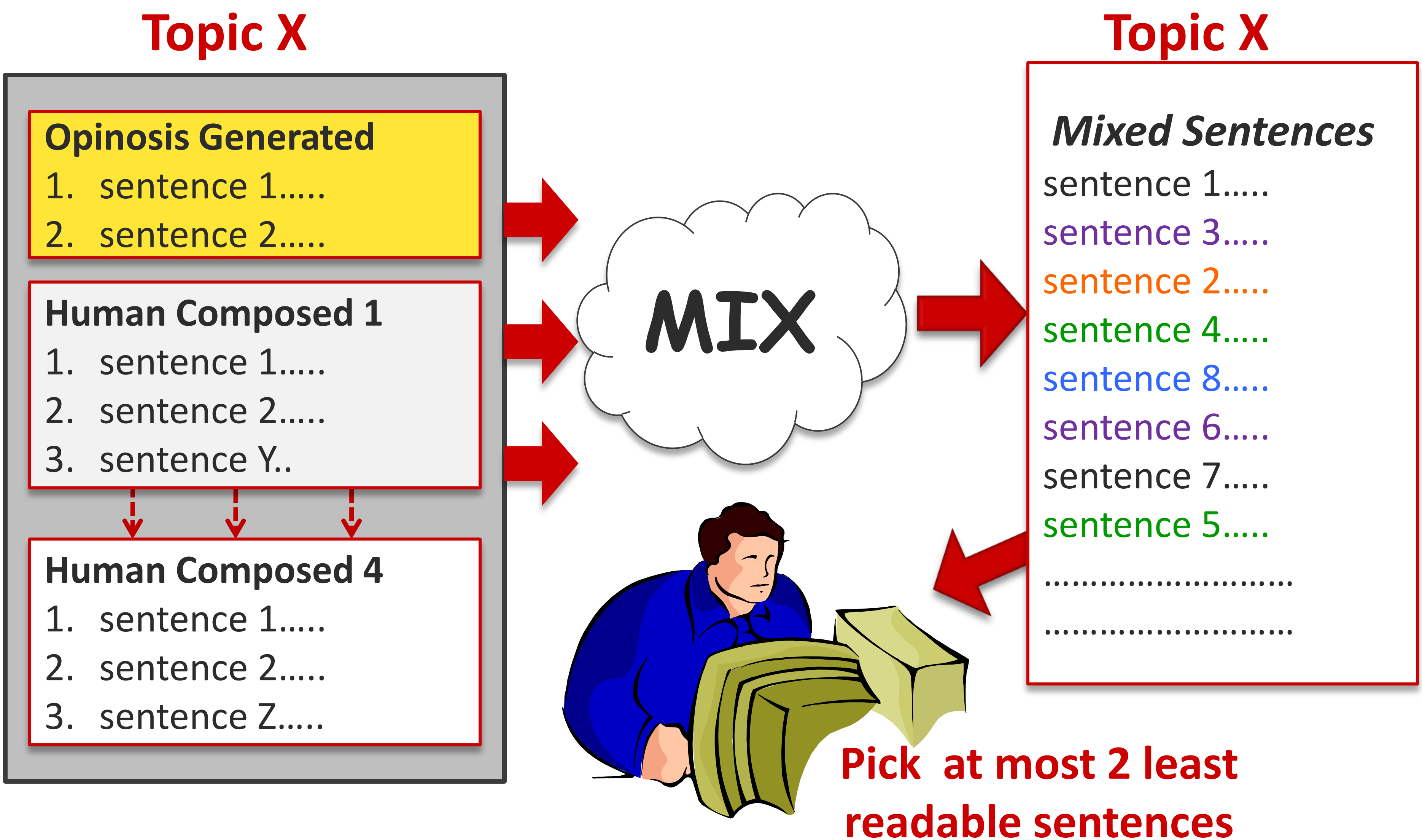


Compare: Scoring Functions



redundancy & path length →
summaries with better coverage

Readability Test



Readability Test

- **Assessor often picks:**
  - **Opinosis** sentences - Opinosis summaries have readability issues
  - **Non-Opinosis sentences or makes no picks** - Opinosis summaries similar to human summaries

Our Readability Test

- **Assessor picked:**
  - **34/102** Opinosis generated sentences as least readable

Our Readability Test

- **Assessor picked:**
  - **34/102** Opinosis generated sentences as least readable

> 60% of Opinosis sentences are not very different from human composed sentences

Summary

- A framework for summarizing **highly redundant opinions**

- **Use graph representation** to generate concise abstractive summaries

- **General & lightweight:** Can be used on any corpus with high redundancies (Twitter comments, Blog comments, etc)

Dataset and Demo Software is available

http://timan.cs.uiuc.edu/downloads.html

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Thank You...

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