


# Extending Q-Grams to Estimate Selectivity of String Matching with Low Edit Distance

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# Introduction

- Suppose a user wants to
  - List members in **Vienna** city
  - List branches where member **Sylvie** (?) works



<i>Member</i>	<i>City</i>	<i>Country</i>	<i>Branch</i>	...
Silvia	Vancouver	Canada	...	
Silvie	Viena 	Austria	...	
Sylvie	Vienna	Austria	Liesing	
...	...	...	...	

1. Typos in the database

2. Similar names or Different spelling usage

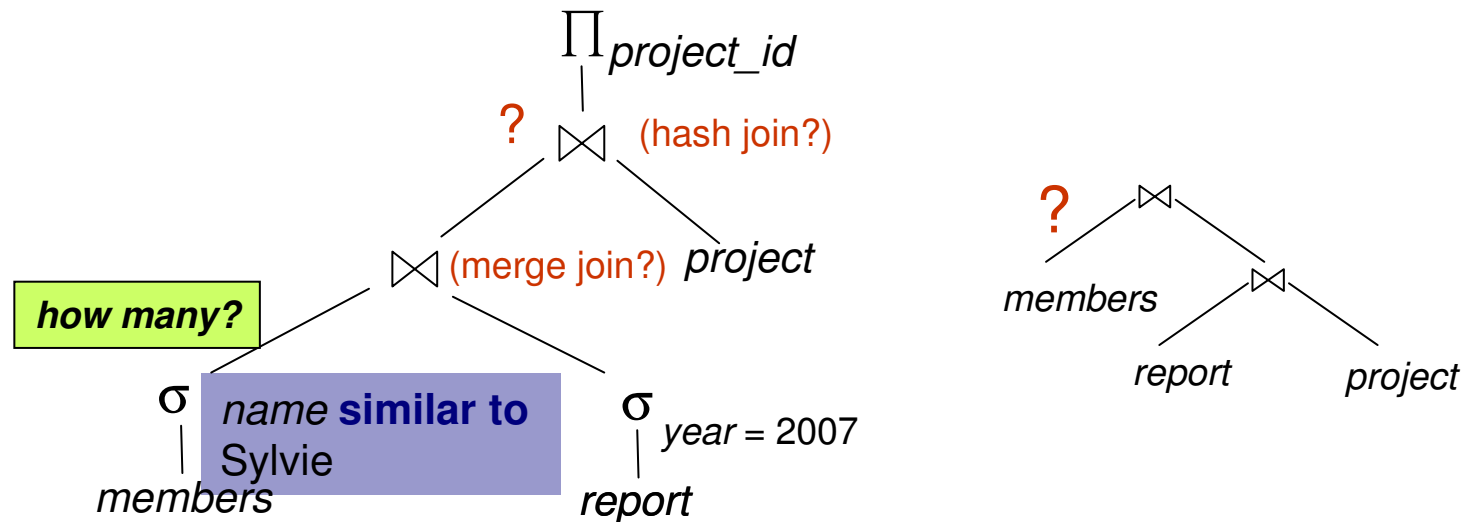


# Introduction (cont.)

- Approximate string matching queries
  - Find cities **similar to** *Vienna*
  - Find names **similar to** *Sylvie*
- Approximate string matching is important in
  - Data cleaning, data integration
    - Pervasive errors or heterogeneity in the database
  - Searching
    - Uncertain query formulation (query correction)
    - Different spelling usages

# Query Optimization of Approximate String Matching

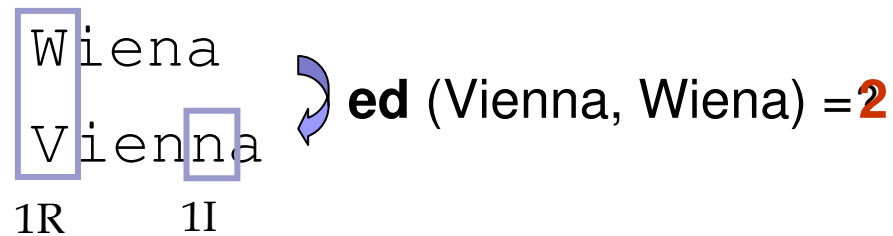
- Optimization of approximate query processing
  - Join ordering, access method selection,...



- Estimating selectivity of approximate predicates
  - Important in making a good query execution plan

# How Do We Define “Similar”?

- String similarity functions
  - Edit distance, Hamming distance, Jaccard coefficient,...
- Edit distance
  - The minimum # of edit operations (Insert, Delete, Replace) to convert one string to the other

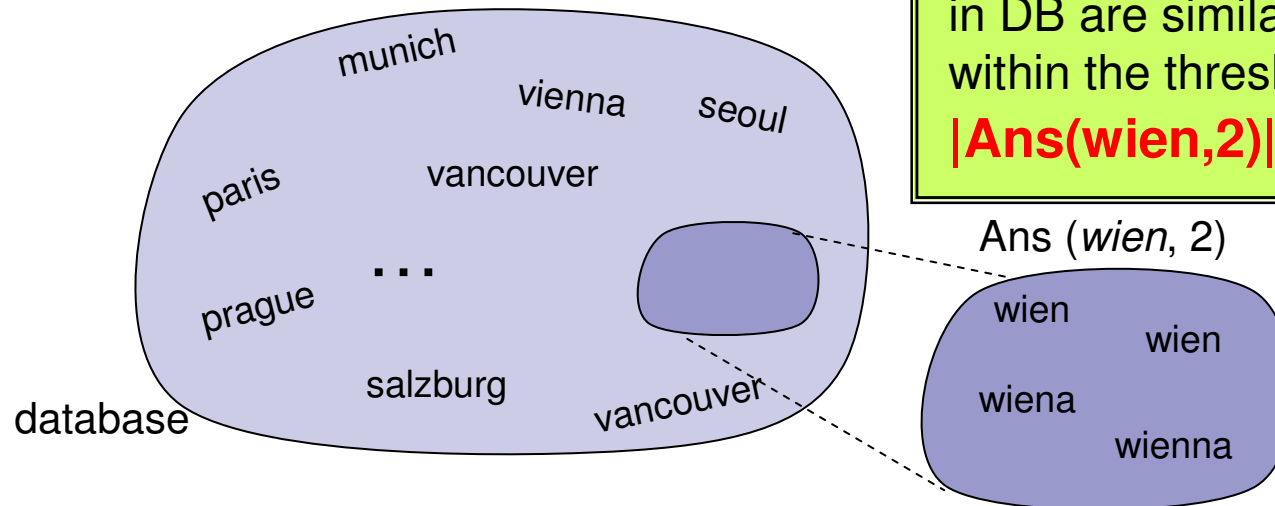
  
1R      1I      **ed (Vienna, Wiena) = 2**

- Focus on low edit distance  $k$ , say  $k=1 \sim 3$  or  $4,5$ 
  - Low edit distance offers a lot to database applications
    - E.g., [AGK06](data cleaning) employed  $k=1 \sim 3$  for address
  - High edit distance can be error prone
    - E.g., Even  $k=2$ : Vienna  $\rightarrow$  Vietnam

# Problem Statement

- Given a query string  $s_q$  and an edit distance threshold  $k$ , estimate *the # of strings  $s$*  in the database that satisfy  $ed(s_q, s) \leq k$ .

Query  $\equiv (wien, 2)$



**How many** strings in DB are similar to *wien* within the threshold  $k$ ?  
 **$|\text{Ans}(wien, 2)| = ?$**

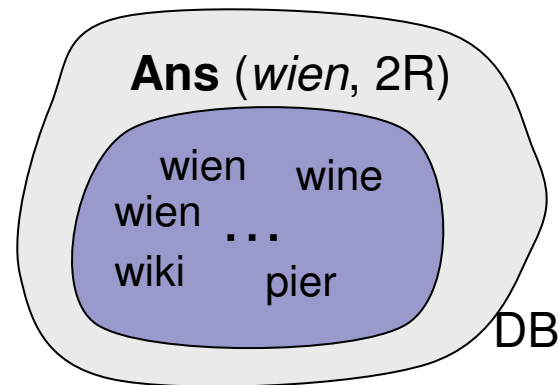


# Overview

- Introduction
- Contributions
  - **Formulas for special cases**
    - **Replace only case**
    - Delete only case
    - Insert only case
  - Algorithm BasicEQ
  - Optimizations
  - Extended Q-grams
- Empirical evaluation
- Conclusion & future works

# Replace Only Case

Query  $\equiv$  (*wien*, 2R)



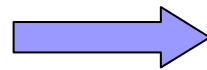
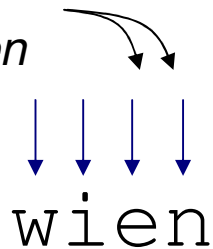
- Start with a restricted version of the problem
  - Only allow replace
- Want to estimate  $|\text{Ans}|$ 
  - The # of strings in the DB that can be converted to *wien* with at most 2 replaces



# Representing A Replace with ?

Strings in Ans (wien, 2R)  
can be acquired by  
replacing up to 2  
characters from *wien*

wien

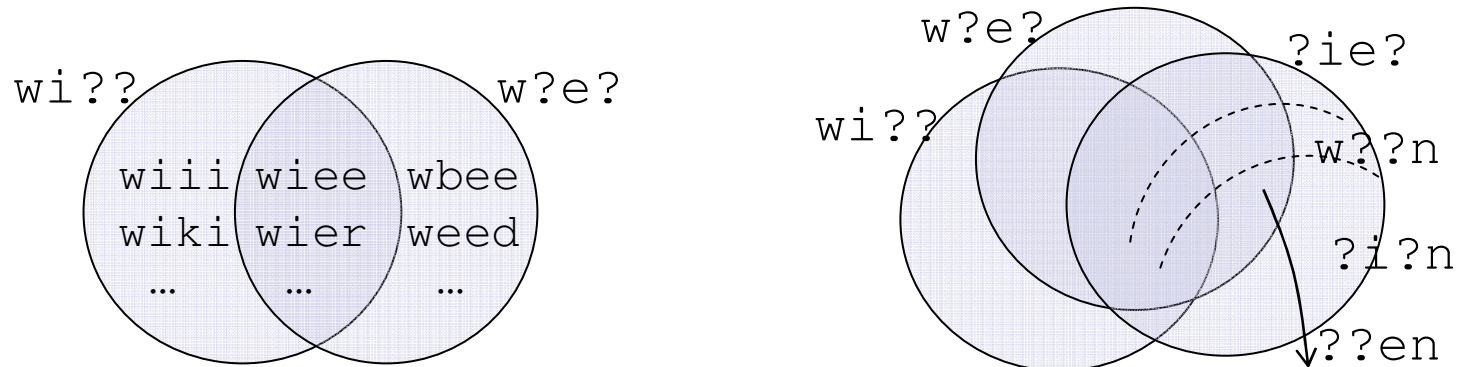


wi??  
w?e?  
?ie?  
w??n  
?i?n  
??en

$\binom{4}{2} = 6$  possible cases

- The wildcard ? represents a replacement (or an insertion)
- Any string in the Ans is in at least one of the above 6 forms
  - E.g., `wiki`  $\subset$  `wi??`
  - `teen`  $\subset$  `??en`
- $|\text{Ans}(\text{wien}, 2R)| = \#$  of strings in any of the 6 forms

# Finding $|\text{Ans}(wien, 2R)|$



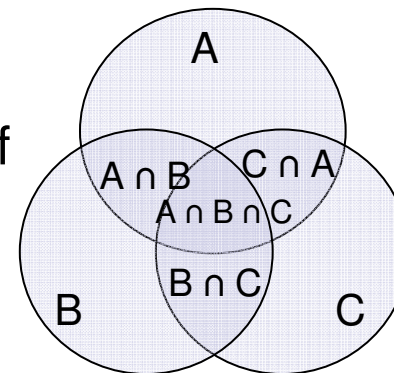
- Note that there are overlaps among the sets
  - E.g.,  $wi?? \cap w?e? = wiew$
- The desired answer is

$$|\text{Ans}(wien, 2R)| = |wi?? \cup w?e? \cup ?ie? \cup w??n \cup ?i?n \cup ??en|$$

# Inclusion-Exclusion Principle

- Inclusion-Exclusion principle

- The size of union of  $n$  sets is the sum of sizes of all possible intersections among  $r$  elements with sign of  $(-1)^{r+1}, 1 \leq r \leq n$



- E.g.,  $|A \cup B \cup C|$

$$= |A| + |B| + |C| - (|A \cap B| + |B \cap C| + |C \cap A|) + |A \cap B \cap C|$$

- $|Ans(wien, 2R)| =$

$$|w_i?? \cup w?e? \cup ?ie? \cup w??n \cup ?i?n \cup ??en|$$

$$= |w_i??|$$

$$- (|w_i??|$$

$$+ (|w_i??|$$

$$- (|w_i??|$$

Exponential # of

- computing intersections (character level)

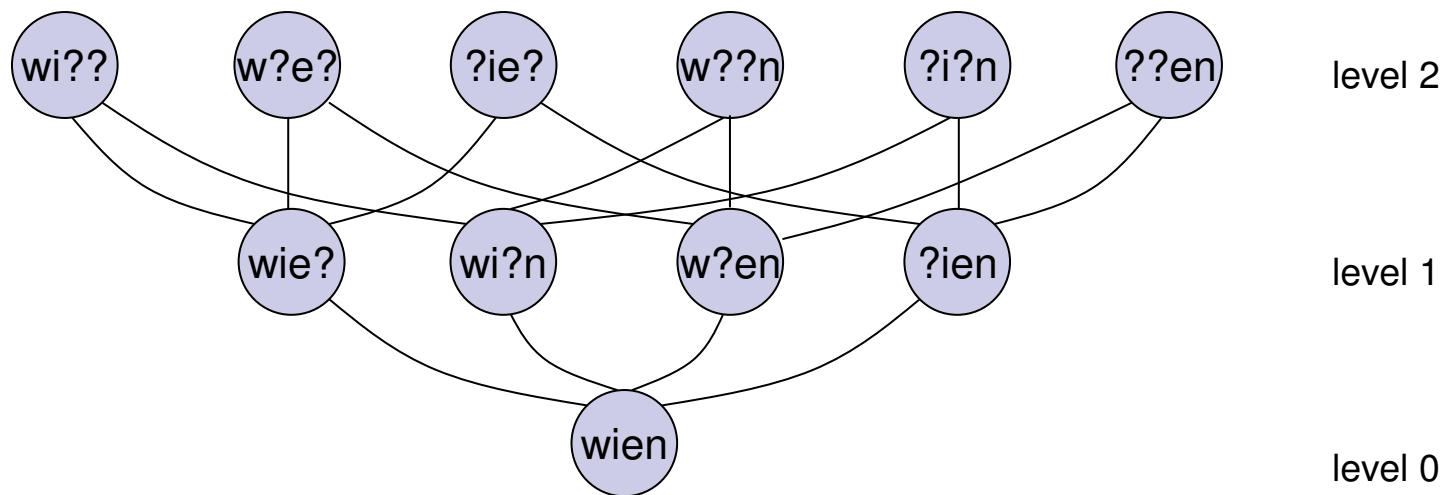
e.g.,  $w_i?? \cap w?e? = w_i e?$

- getting frequency from the summary structure

e.g.,  $|w_i e?| = ?$

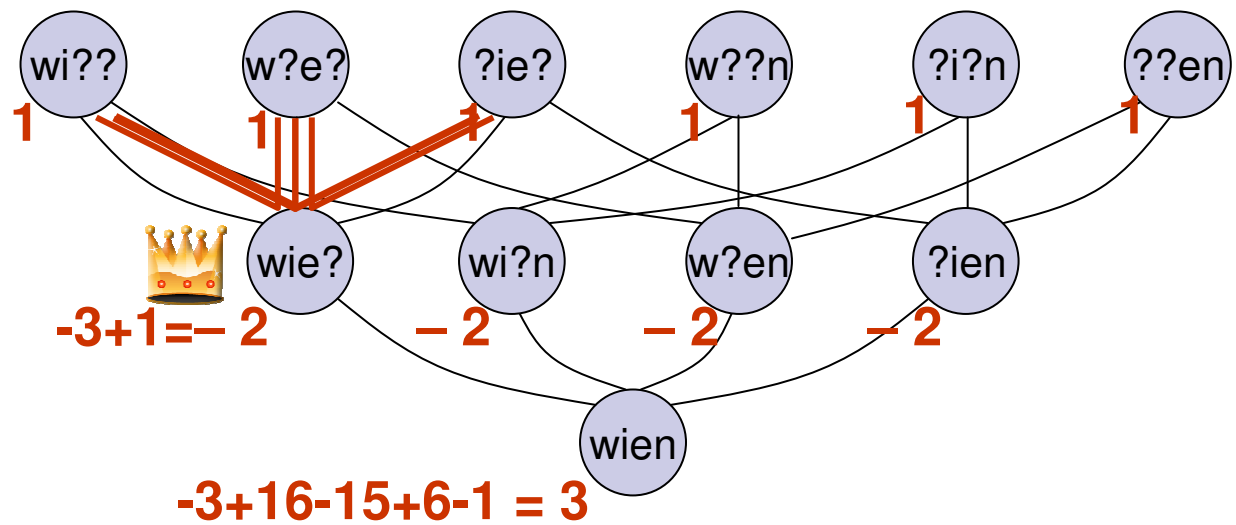


# Solution: Using A Semi-Lattice



- A Node represents the set of strings in DB in that form
- Start with leaf nodes of all possible 6 forms
- Generate nodes from intersections
- Layer nodes according to the # of wildcards (level)
- Draw edges for inclusion relationship

# Using A Semi-Lattice (cont.)



- $|wi?? \cup w?e? \cup ?ie? \cup w??n \cup ?i?n \cup ??en|$   
 $= |wi??| + |w?e?| + \dots + |??en|$   
 $- (|wie?| + |wie?| + |wie?| + \dots)$   
 $+ (|wie?| + \dots)$   
 $\dots$   
 $- |wi?? \cap w?e? \cap \dots \cap ??en|$
- $- 3|wie?| + 1|wie?| = -2|wie?|$



# Using A Semi-Lattice (cont.)

- Key observations

- Many intersections may result in the same node
- Regularity exists in the semi-lattice structure

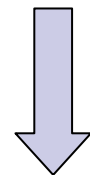
- Key approach

- Substitute an intersection with its result
- Only need to count how many times a node participates in the I-E (inclusion-exclusion) formula
- The coefficient of a node
  - # of times a node participates in the I-E formula
  - Minus sign if appears more in minus part in the I-E formula

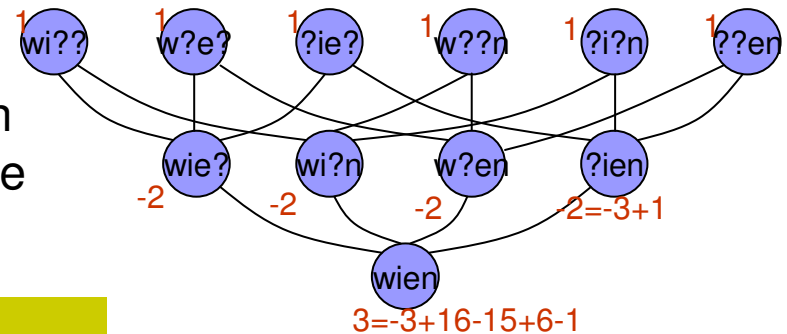
# Using A Semi-Lattice (cont.)

Original Inclusion-Exclusion process

$$\begin{aligned}
 & |wi?? \cup w?e? \cup ?ie? \cup w??n \cup ?i?n \cup ??en| \\
 &= |wi??| + |w?e?| + \dots + |??en| \\
 &- (|wi?? \cap w?e?| + |wi?? \cap ?ie?| + |w?e? \cap ?ie?| + \dots) \\
 &+ (|wi?? \cap w?e? \cap ?ie?| + \dots) \\
 &\dots \\
 &- |wi?? \cap w?e? \cap \dots \cap ??ne|
 \end{aligned}$$



Simplify the equation  
Using the semi-lattice



$$\begin{aligned}
 &= |wi??| + |w?e?| + \dots + |??ne| \\
 &+ (-3 + 1) (|wie?| + |wi?n| + |w?en| + |?ien|) \\
 &+ (-3 + 16 - 15 + 6 - 1) |wien|
 \end{aligned}$$

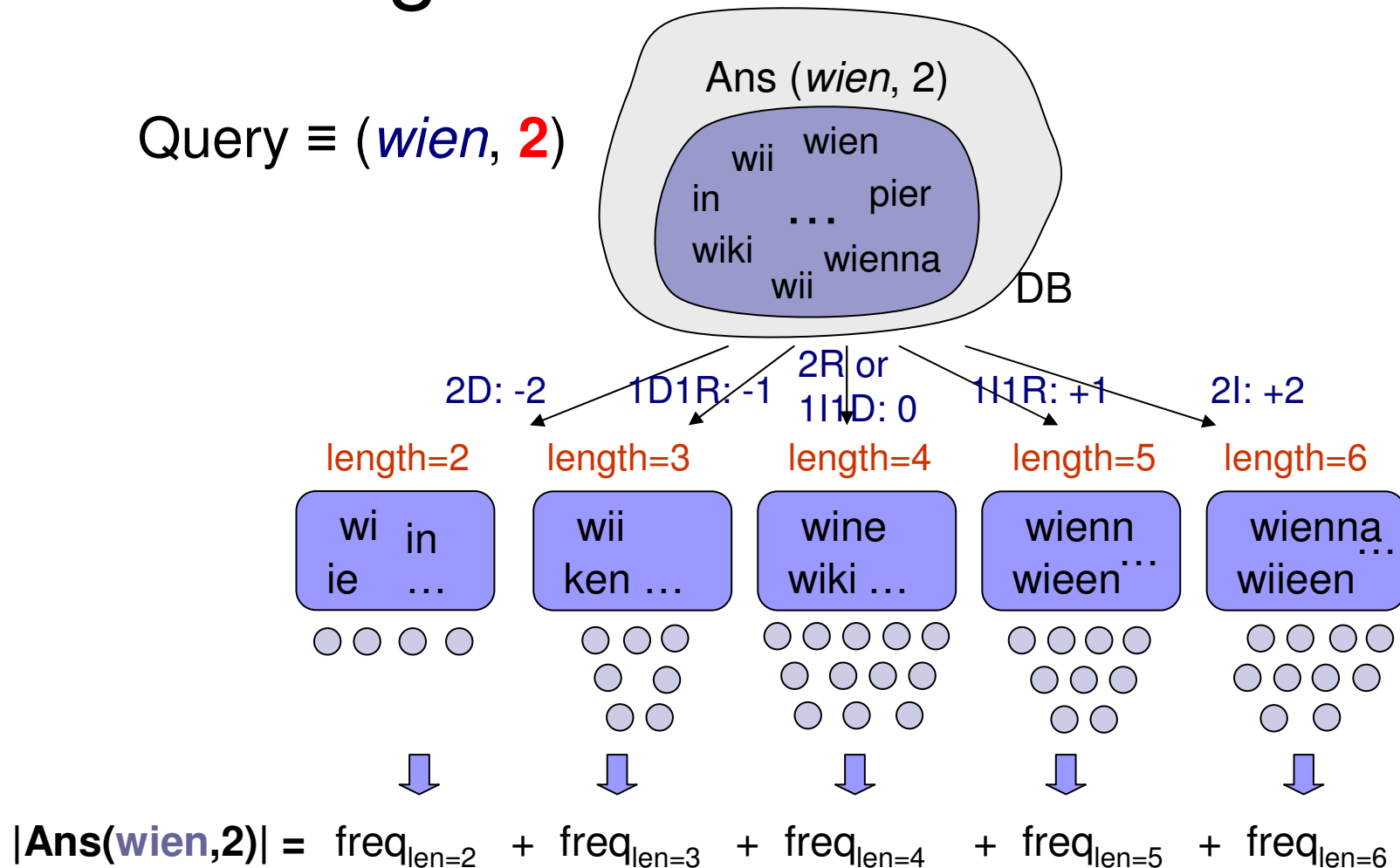


# Overview

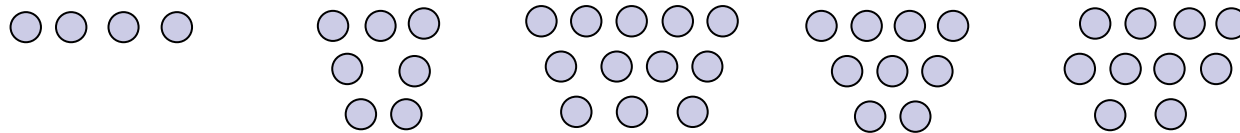
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  - Formulas for special cases
  - **BasicEQ Algorithm**
  - Optimizations
  - Extended Q-grams
- Empirical evaluation
- Conclusion & future works



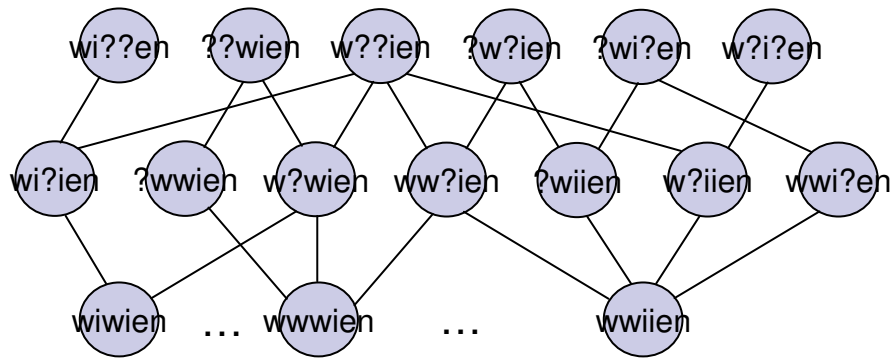
# The BasicEQ Algorithm: Returning to the General Problem



# String Hierarchies




Do not have the formulas for all string hierarchies!  
 E.g.) 1I1R, 2I1D + 1I2R



An example of  
 general  
 string hierarchy

- General string hierarchy: not so regular (closed form fomular is hard)
- Need a general algorithm to handle arbitrary combinations of edit operations. e.g.)1I1R



# Computing Frequency from A String Hierarchy

Answer set cardinality = sum of the frequencies of nodes multiplied by the coefficients

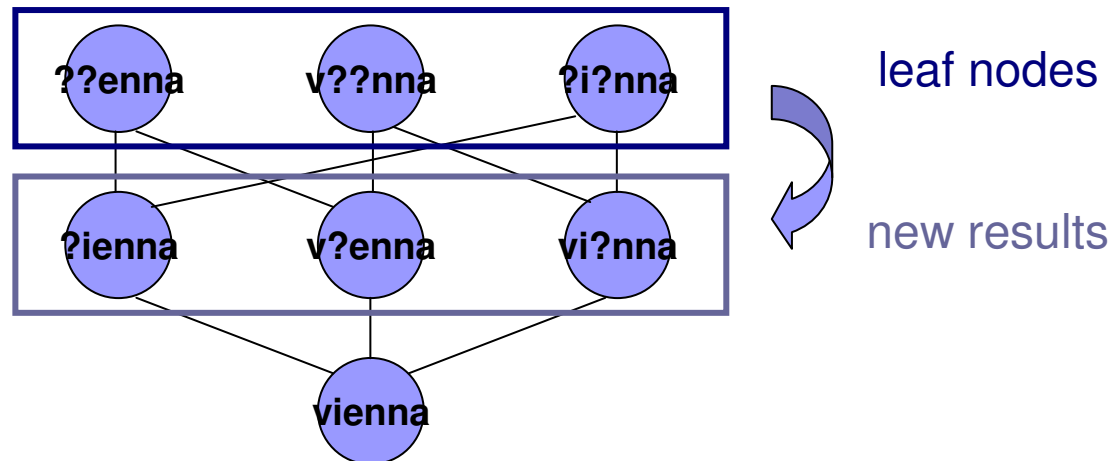
## Key steps

1. Build the string hierarchy
2. Compute the coefficients of nodes
3. Estimate selectivity of each node and compute the simplified inclusion-exclusion formula

# BasicEQ

## Step 1: Building The String Hierarchy

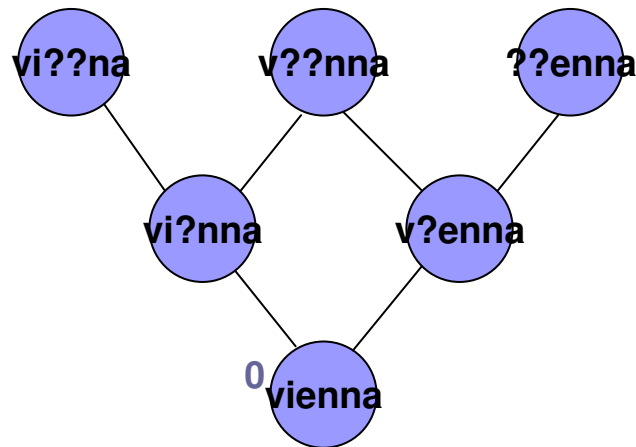
- An Apriori-Style algorithm
  - Start from leaf nodes
  - Generate an intersection of r nodes by extending intersection of (r-1) nodes
  - Two observations are crucial
    - **Only newly formed results** need to be considered at each round
    - **Only** the nodes with **at least one wildcard** need to be considered



# BasicEQ

## Step 2: Computing Coefficients of Nodes

- For each node, add the number of intersections among  $r$  nodes that result in that node with the sign of  $(-1)^{r+1}$



# of 2-intersection results in vienna:  $1 \rightarrow -1$

# of 3-intersection results in vienna:  $1 \rightarrow +1$

The coefficient of vienna  $\rightarrow -1+1=0$



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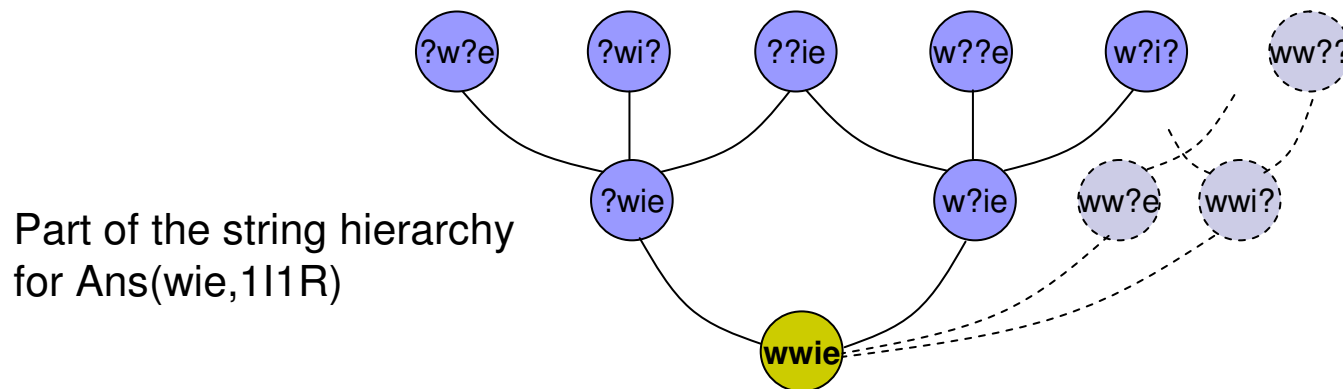


# Three Optimizations

- BasicEQ is not scalable
  - Coefficient computation step is a major bottleneck
- 1. Node partitioning
  - Compute coefficients just once for each partition
- 2. Coefficient approximation
  - Use replace-only formula to approximate coefficients
- 3. Fast intersection test by grouping
  - Avoid test of intersections that are guaranteed to produce the empty result

# Coefficient Approximation

- Approximate coefficients using the replace-only formula
  - Motivation is that we have a formula for coefficients



- Complete the lattice to the full replacement lattice
- Scale terms in the formula assuming everything is proportional to the possible choices





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# Estimating Selectivity of Each Node

$$|\text{Ans}(\text{wien}, 2R)| = 1(|\text{wi??}| + \dots + |\text{??ne}|) - 2(|\text{wie?}| + |\text{wi?n}| + |\text{w?en}| + |\text{?ien}|) + 3|\text{wien}|$$

$|\text{wien}| = \text{freq}(\text{wien}) = \#$  of *wien* in the database

- Q-grams

- Any string of length  $q$  in  $\Sigma$
- *vienna*  $\rightarrow$  3-grams: *vie, ien, enn, nna*

- Q-gram table [Chaudhuri, Ganti & Gravano 04]

- N-grams of length  $q$  or less
- with their frequency

Q-gram	Frequency
<b>wien</b>	<b>9</b>
wie	12
ien	10
ein	56
ei	1,205
e	24,503
...	...

# Extended Q-Gram Table

- Extended q-grams
  - *Extend* q-gram with wildcard ? (not in  $\Sigma$ )
  - Speed up the frequency computation of string forms
    - Example using just simple q-gram tables
      - $|wie?| = |wiew| + |wien| + |wies| + \dots$

Q-gram	Frequency
wien	9
<b>wie?</b>	<b>89</b>
wiew	1
wien	10
<b>i??</b>	<b>4,213</b>
...	...



# Overview

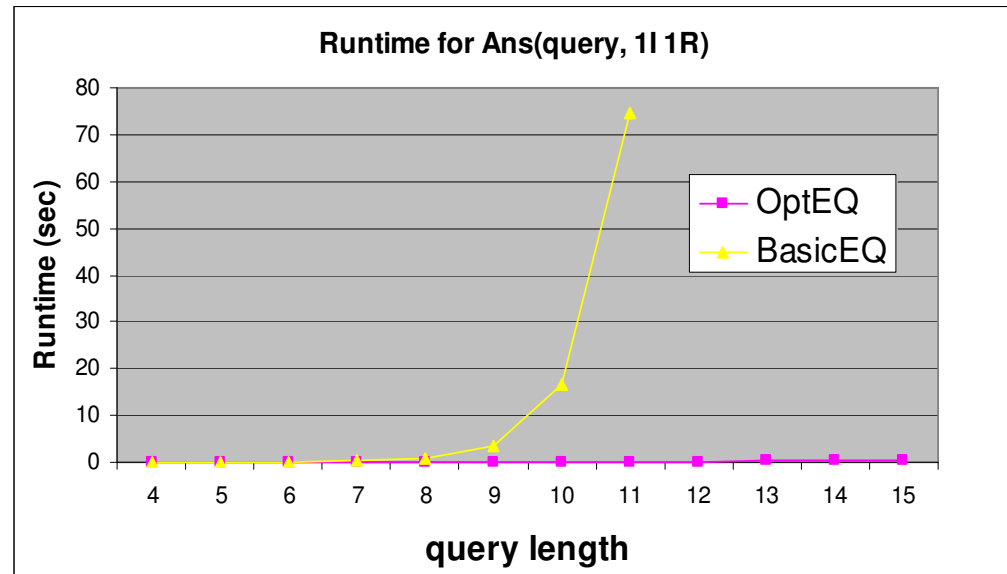
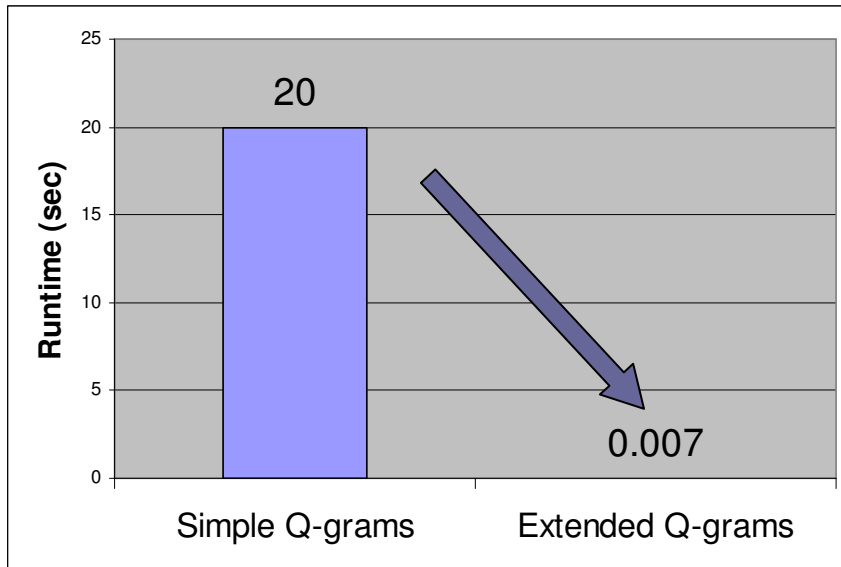
- Introduction
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  - Formulas for special cases
  - Algorithm BasicEQ
  - 3 Optimizations
  - Extended Q-grams
- **Empirical evaluation**
  - **Settings**
  - **Effectiveness of optimizations**
  - **Estimation accuracy**
- Conclusion & future works



# Empirical Evaluation

- Data set
  - 392,132 IMDB actresses' last names
  - 699,198 DBLP Authors full names
  - 53,365 DBLP Paper titles
- Compared technique
  - SEPIA [Jin & Li 05]
- Settings
  - SEPIA: 2000 clusters, 5% sampling
  - OptEQ: BasicEQ + optimizations
  - Coefficients are pre-computed (not data dependent)
  - Intel P4 3GHz PC with 1 GB Memory

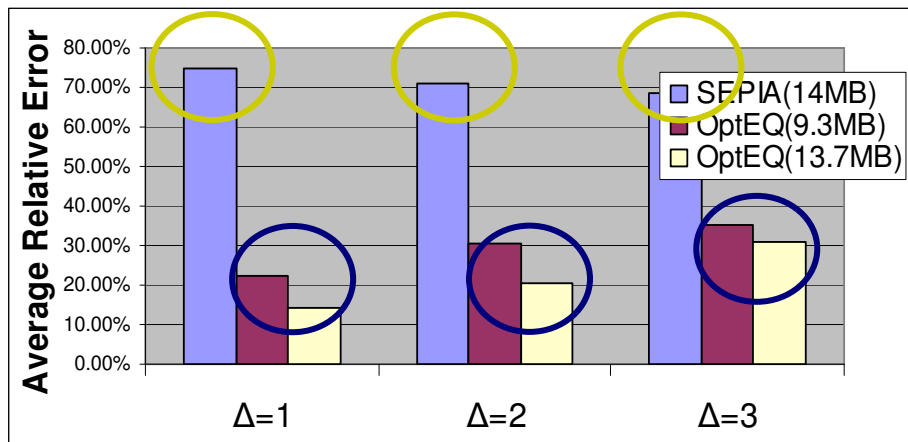
# Effectiveness of Optimizations



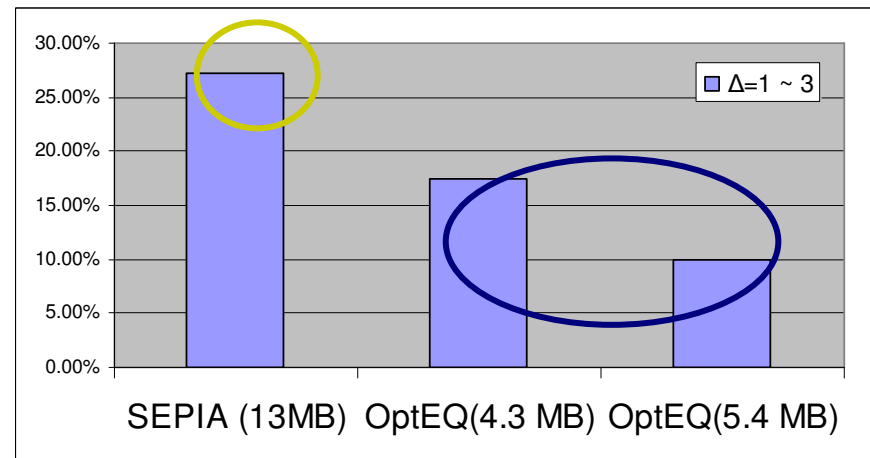
Extended q-gram vs. simple q-gram    BasicEQ vs. OptEQ

- Extended q-grams enable faster computation
- OptEQ's optimizations improve the performance of BasicEQ by orders of magnitudes

# Estimation Accuracy



DBLP Author names



DBLP Paper titles

- Relative error:  $|\text{freq}_{\text{est}} - \text{freq}_{\text{real}}| / \text{freq}_{\text{real}}$
- OptEQ delivers more accurate estimation
- OptEQ is able to utilize additional space showing clear trade-off between space and accuracy



# Other Experimental Results

- Error distribution characteristics
  - Scalability
  - Higher edit distance threshold with sampling
- 
- See the paper for details





# Related Work

- Substring selectivity estimation
  - Exact string match
  - MO [Jagadish, Ng & Srivastava 99]
  - CRT [Chaudhuri, Ganti & Gravano 04]
- Approximate string selectivity estimation
  - SEPIA [Jin & Li 05]



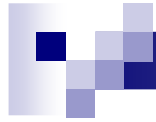
# Conclusion

## ■ Contribution

- Extended q-grams with the wildcard
- New lattice-based algorithm for estimating selectivity of approximate string matching
- Performance study shows that OptEQ delivers accurate selectivity estimation

## ■ Future work

- Handling longer string with higher edit distance threshold as in genomic applications



Any Questions?

Danke schön!

# Node Partitioning

- Coefficients only depend on the lattice structure
- We *partition* nodes according to the local lattice structure to each node and *compute the coefficients just once per each partition*
  - Approximate isomorphism test is developed

