How to Effectively Use Topic Models for Software Engineering Tasks? An Approach Based on Genetic Algorithms


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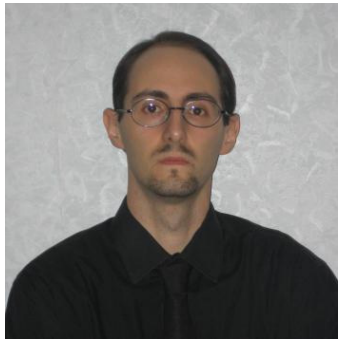
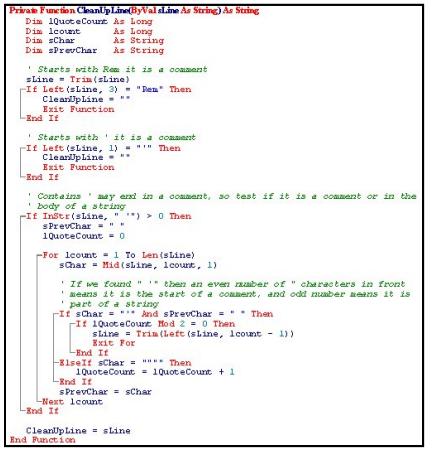

Massimiliano Di Penta


Denys Poshyvanyk


Andrea De Lucia

Source Code



```
Private Function CleanUpLine(ByVal sLine As String) As String
    Dim lQuoteCount As Long
    Dim lcount      As Long
    Dim sChar       As String
    Dim sPrevChar   As String

    ' Starts with Rem it is a comment
    sLine = Trim(sLine)
    If Left(sLine, 3) = "Rem" Then
        CleanUpLine = ""
        Exit Function
    End If

    ' Starts with ' it is a comment
    If Left(sLine, 1) = "'" Then
        CleanUpLine = ""
        Exit Function
    End If

    ' Contains ' may and in a comment, so test if it is a comment or in the
    ' body of a string
    If InStr(sLine, "'") > 0 Then
        sPrevChar = " "
        lQuoteCount = 0

        For lcount = 1 To Len(sLine)
            sChar = Mid(sLine, lcount, 1)

            ' If we found "'" then an even number of " characters in front
            ' means it is the start of a comment, and odd number means it is
            ' part of a string
            If sChar = "'" And sPrevChar = " " Then
                If lQuoteCount Mod 2 = 0 Then
                    sLine = Trim(Left(sLine, lcount - 1))
                    Exit For
                End If
            ElseIf sChar = """" Then
                lQuoteCount = lQuoteCount + 1
            End If
            sPrevChar = sChar
        Next lcount
    End If

    CleanUpLine = sLine
End Function
```

Bug Reports

First Last Prev Next This bug is not in your last search results.

Bug 816298 - Change "-moz-user-select:none" to behave like WebKit, IE, and Opera (and "-moz-user-select:-moz-none") Last Comment

Status: RESOLVED FIXED
Whiteboard:
Keywords: compat, dev-doc-complete

Product: Core (show info)
Component: DOM: CSS Object Model (show info)
Version: Trunk
Platform: All All

Importance: -- normal (vote)
Target Milestone: mozilla21
Assigned To: Chris Peterson (:cpeterson)
QA Contact:

URL: https://developer.mozilla.org/en-US/d...

Depends on: 739396 882644
Blocks: 759029 914274
Show dependency tree / graph

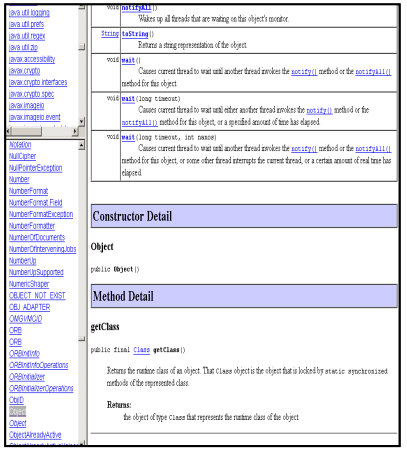
Reported: 2012-11-28 15:03 PST by Chris Peters
Modified: 2013-05-20 00:14 PDT (History)
CC List: 12 users (show)

See Also:

Crash Signature:

Tracking Flags: status-firefox20: wontfix
status-firefox21: fixed
relnote-firefox: 21+

Documentation



java.util.logging
java.util.prefs
java.util.regex
java.util.zip
javax.accessibility
javax.crypto
javax.crypto.interfaces
javax.crypto.spec
javax.imageio
javax.imageio.event
Notation
NullCipher
NullPointerException
Number
NumberFormat
NumberFormat.Field
NumberFormatException
NumberFormatter
NumberOfDocuments
NumberOfInterveningJobs
NumberUp
NumberUpSupported
NumericShaper
OBJECT_NOT_EXIST
OBJ_ADAPTER
OMGVMCID
ORB
ORB
ORBInitInfo
ORBInitInfoOperations
ORBInitializer
ORBInitializerOperations
OrbID
Other
Object
ObjectAlreadyActive

void **notifyAll**()
Wakes up all threads that are waiting on this object's monitor.

String **toString**()
Returns a string representation of the object.

void **wait**()
Causes current thread to wait until another thread invokes the notify() method or the notifyAll() method for this object.

void **wait**(long timeout)
Causes current thread to wait until either another thread invokes the notify() method or the notifyAll() method for this object, or a specified amount of time has elapsed.

void **wait**(long timeout, int nanos)
Causes current thread to wait until another thread invokes the notify() method or the notifyAll() method for this object, or some other thread interrupts the current thread, or a certain amount of real time has elapsed.

Constructor Detail

Object

public **Object**()

Method Detail

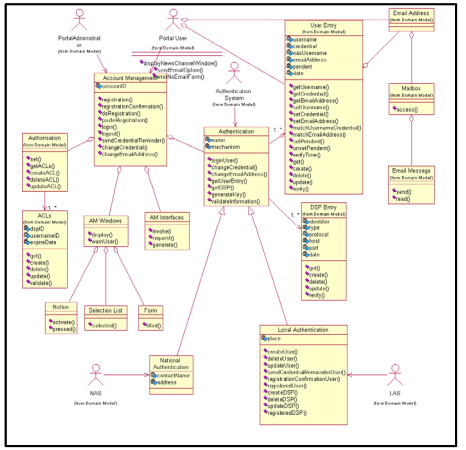
getClass

public final Class **getClass**()

Returns the runtime class of an object. That Class object is the object that is locked by static synchronized methods of the represented class.

Returns:
the object of type Class that represents the runtime class of the object.

Design documents



Information Retrieval Techniques

Maintenance Tasks

Information Retrieval Techniques

Maintenance Tasks

Vector Space Model
Latent Semantic Indexing
Latent Dirichlet Allocation
Relational Topic Model

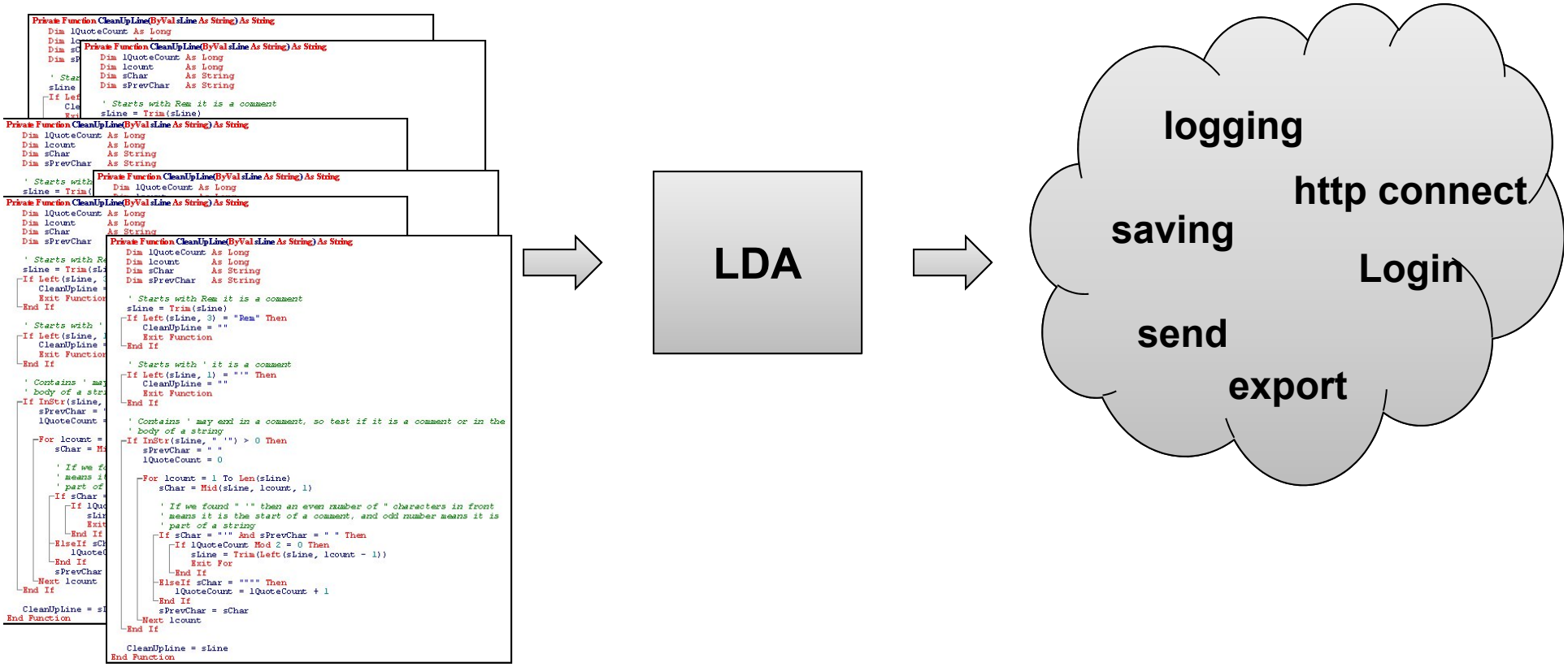
What is LDA?

Latent **D**irichlet **A**llocation (LDA)

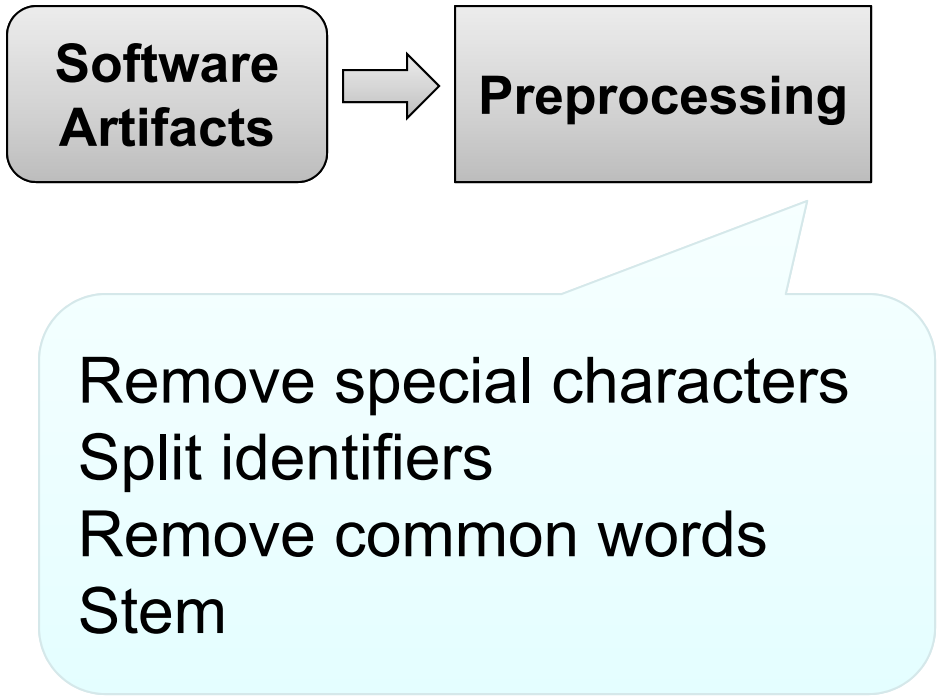
- Topic model that generates the distribution of latent topics from textual documents

Latent Dirichlet Allocation (LDA)

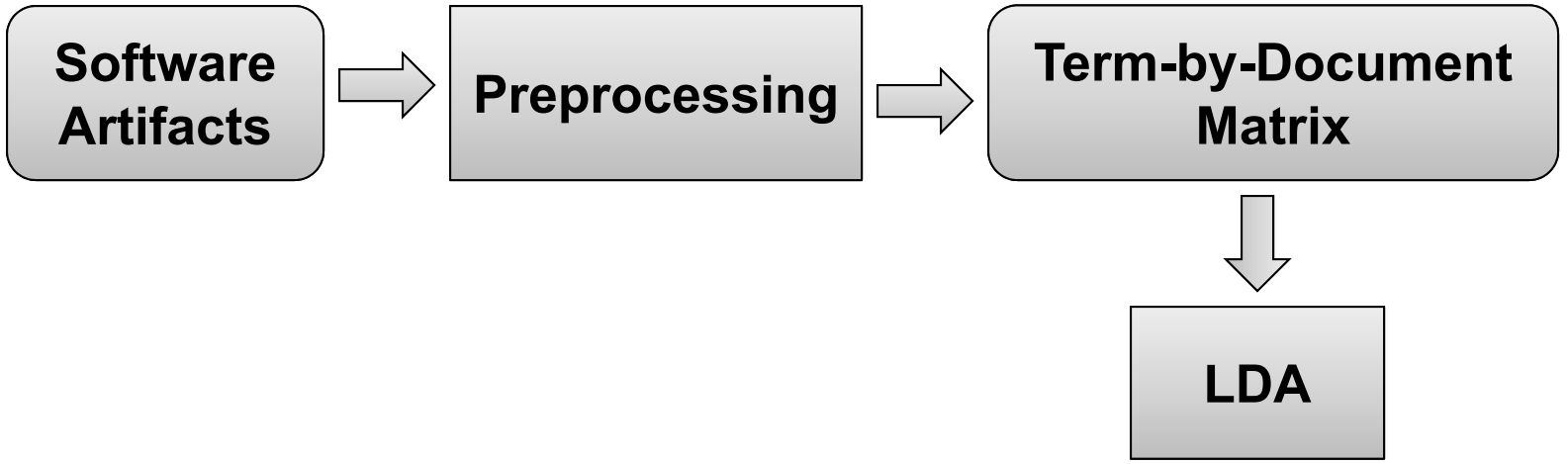
- Topic model that generates the distribution of latent topics from textual documents

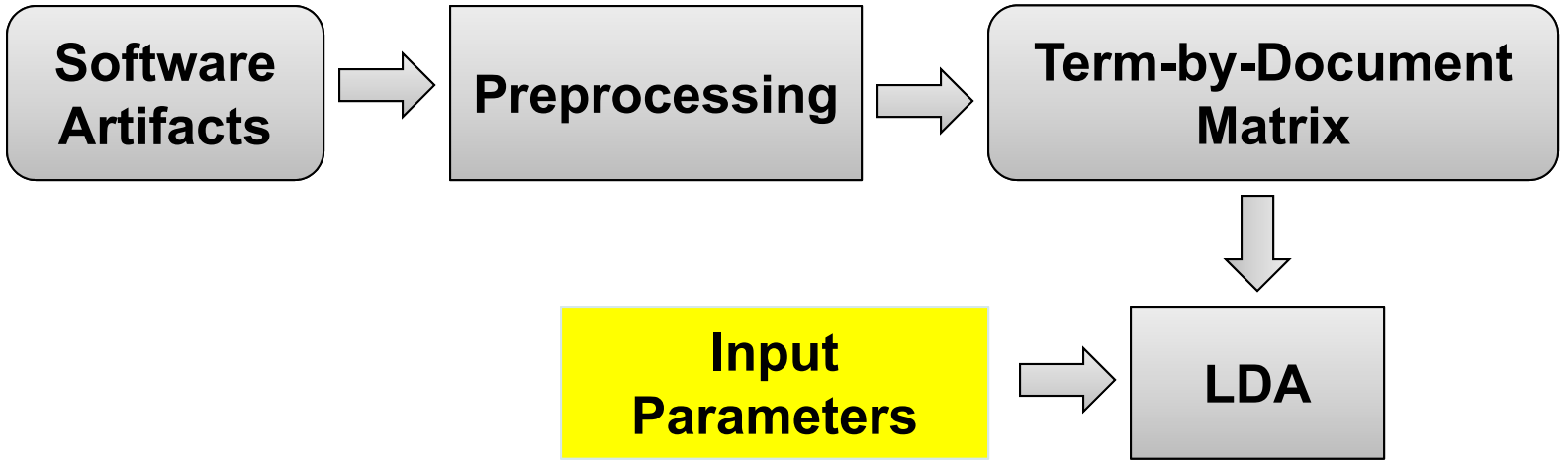


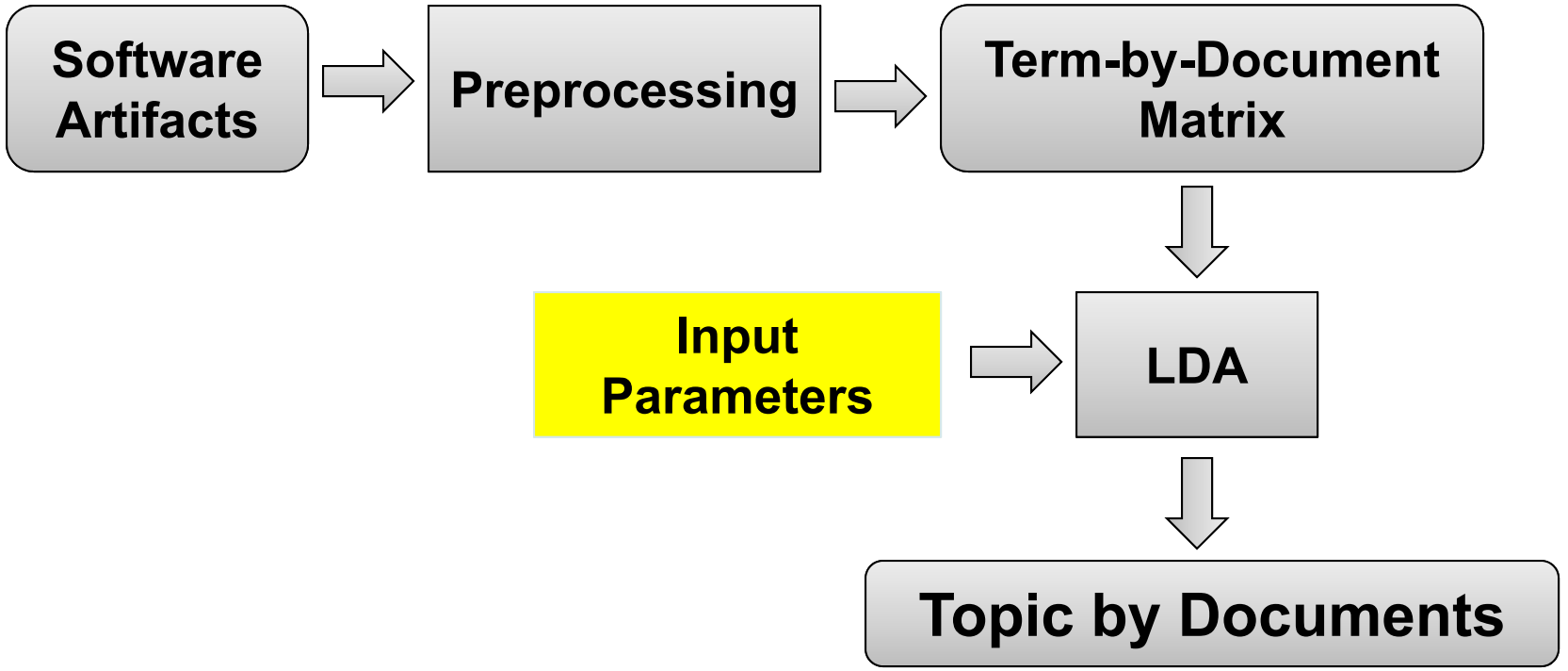

Software
Artifacts

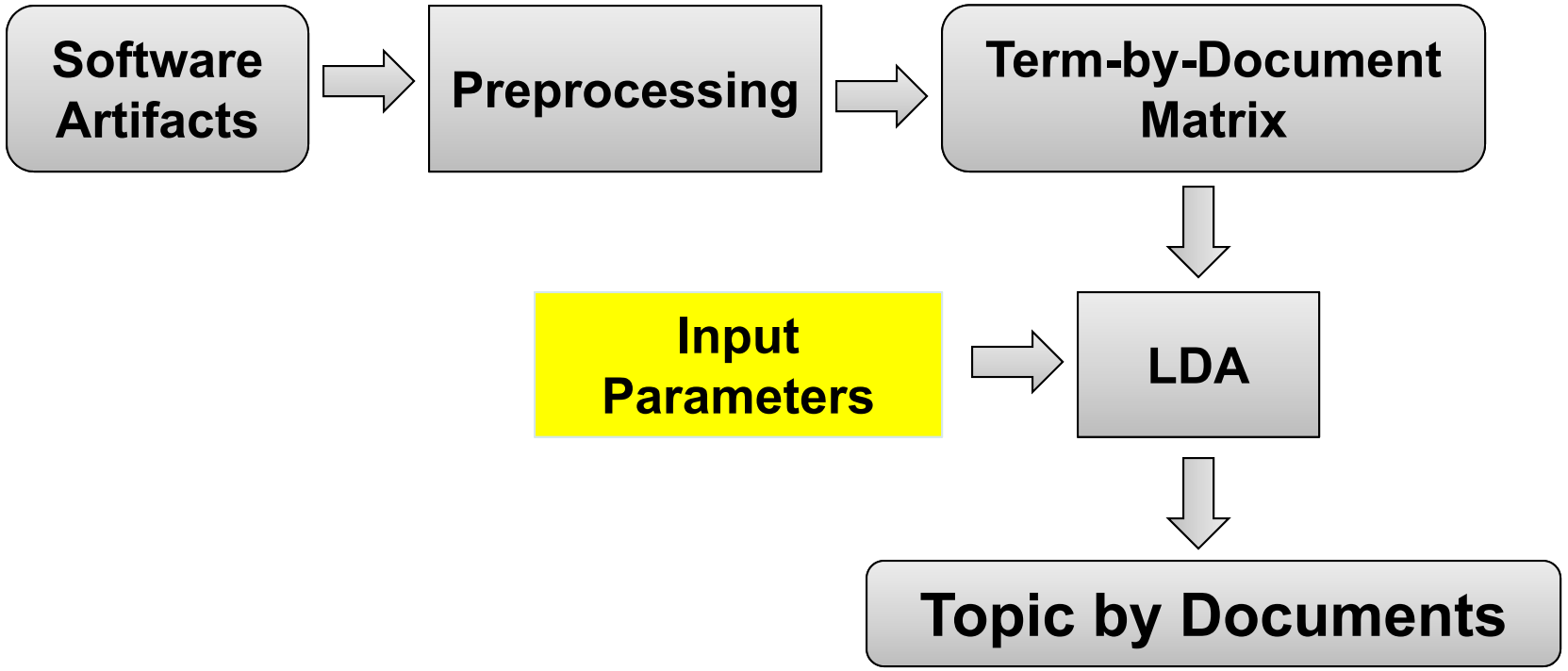

Software Artifacts
Preprocessing
Remove special characters
Split identifiers
Remove common words
Stem


Software Artifacts
Preprocessing
Term-by-Document Matrix

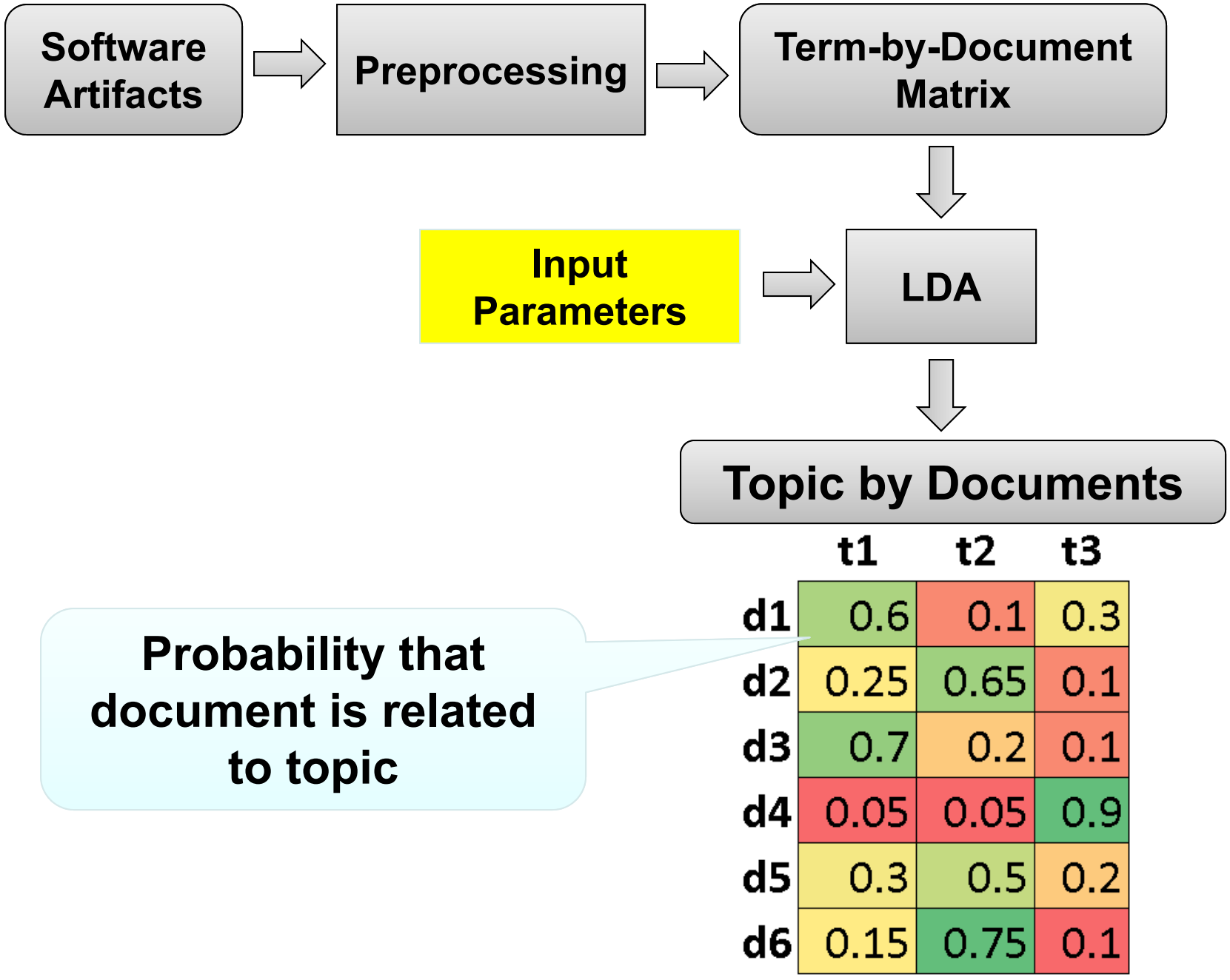

Software Artifacts
Preprocessing
Term-by-Document Matrix
LDA

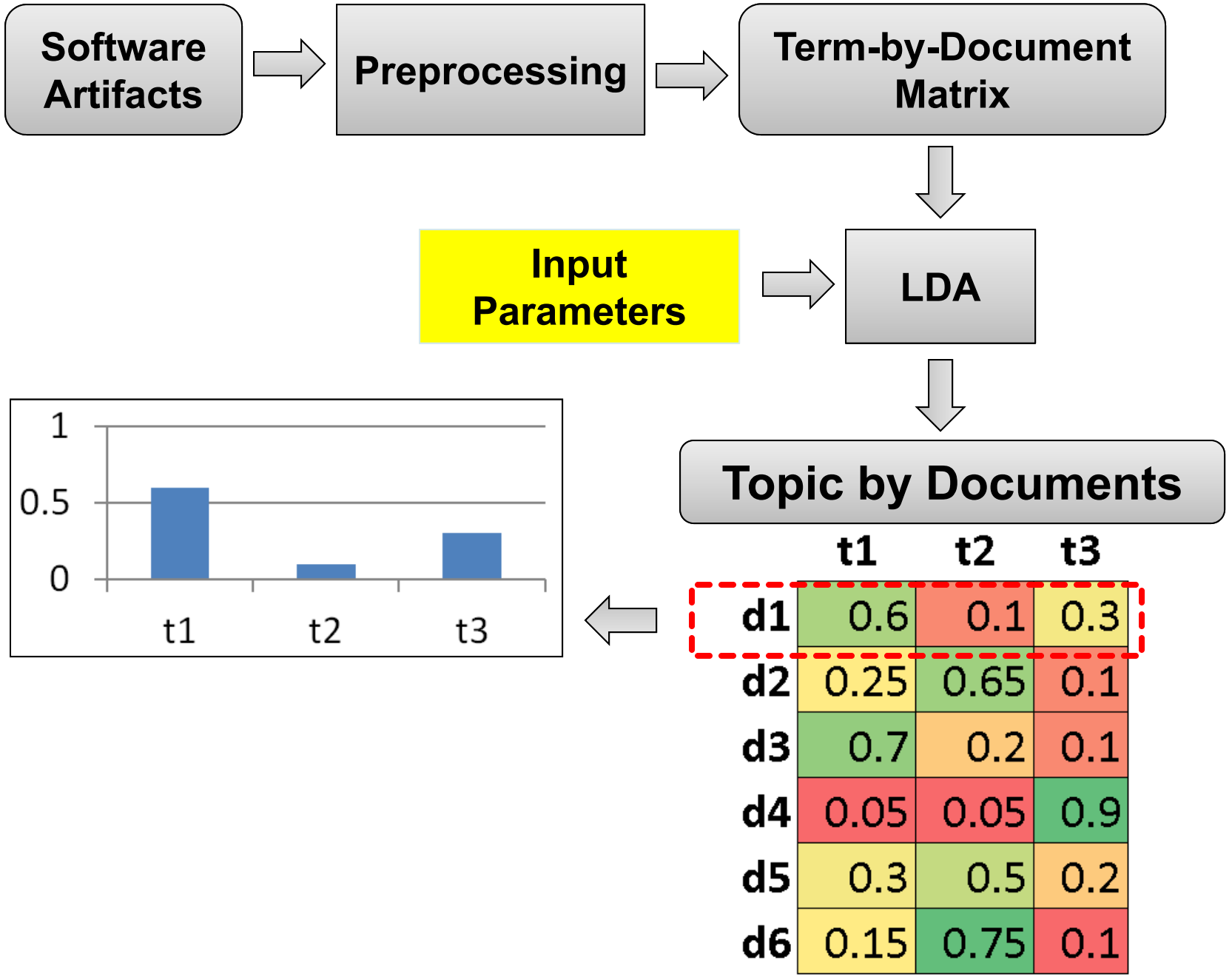

Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA

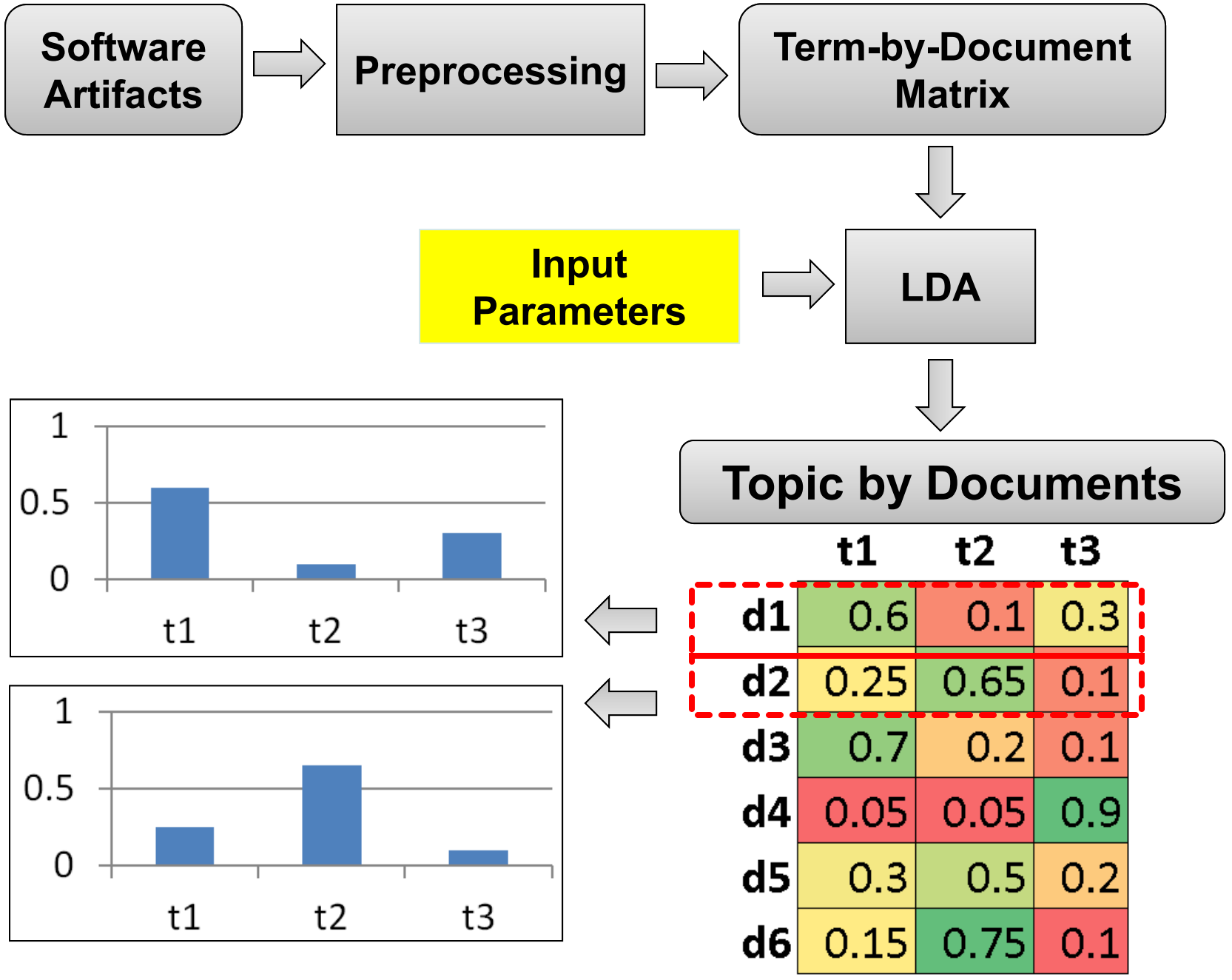

Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Topic by Documents

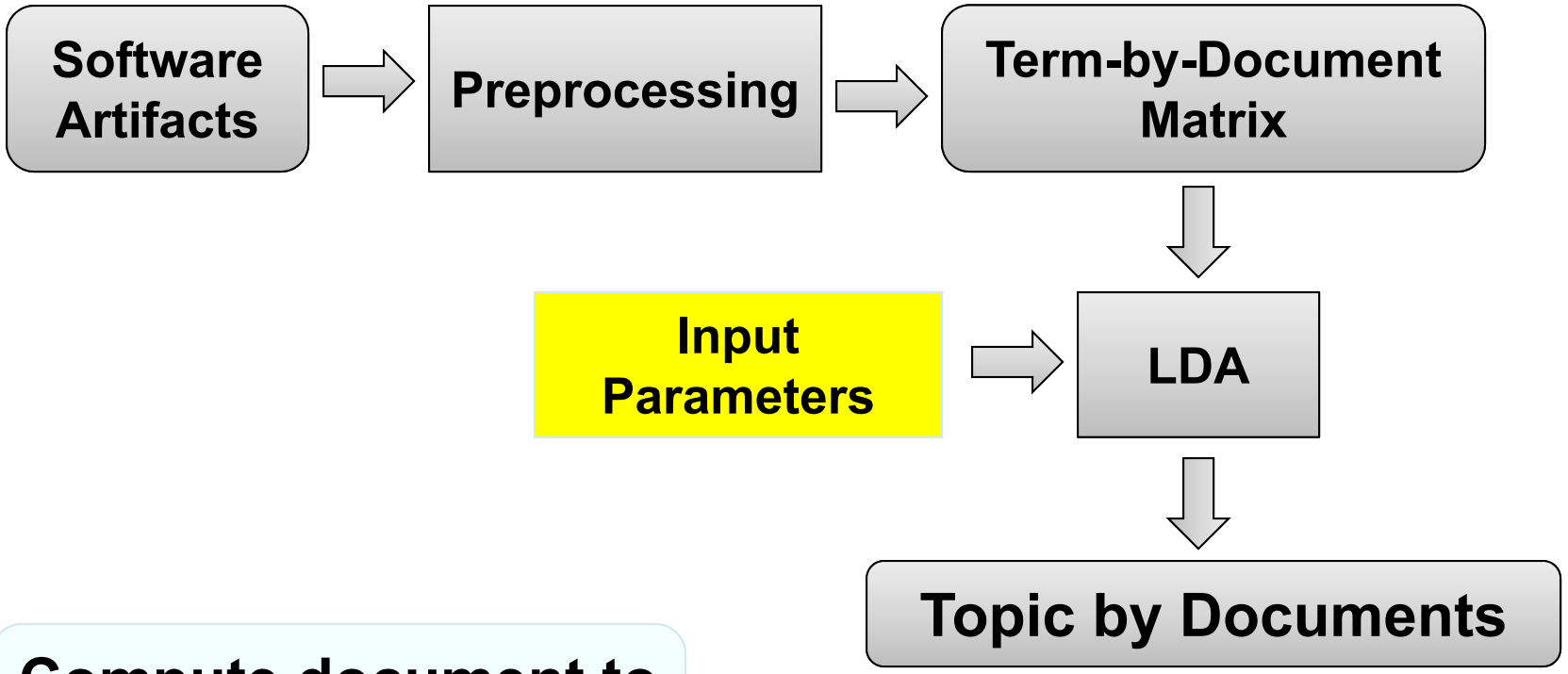


	t1	t2	t3
d1	0.6	0.1	0.3
d2	0.25	0.65	0.1
d3	0.7	0.2	0.1
d4	0.05	0.05	0.9
d5	0.3	0.5	0.2
d6	0.15	0.75	0.1


Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Topic by Documents
Probability that document is related to topic
t1 t2 t3
d1 0.6 0.1 0.3
d2 0.25 0.65 0.1
d3 0.7 0.2 0.1
d4 0.05 0.05 0.9
d5 0.3 0.5 0.2
d6 0.15 0.75 0.1


Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Topic by Documents
1
0.5
0
t1
t2
t3
t1 t2 t3
d1 0.6 0.1 0.3
d2 0.25 0.65 0.1
d3 0.7 0.2 0.1
d4 0.05 0.05 0.9
d5 0.3 0.5 0.2
d6 0.15 0.75 0.1


Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Topic by Documents
t1 t2 t3
d1 0.6 0.1 0.3
d2 0.25 0.65 0.1
d3 0.7 0.2 0.1
d4 0.05 0.05 0.9
d5 0.3 0.5 0.2
d6 0.15 0.75 0.1
1
0.5
0
t1 t2 t3
1
0.5
0
t1 t2 t3

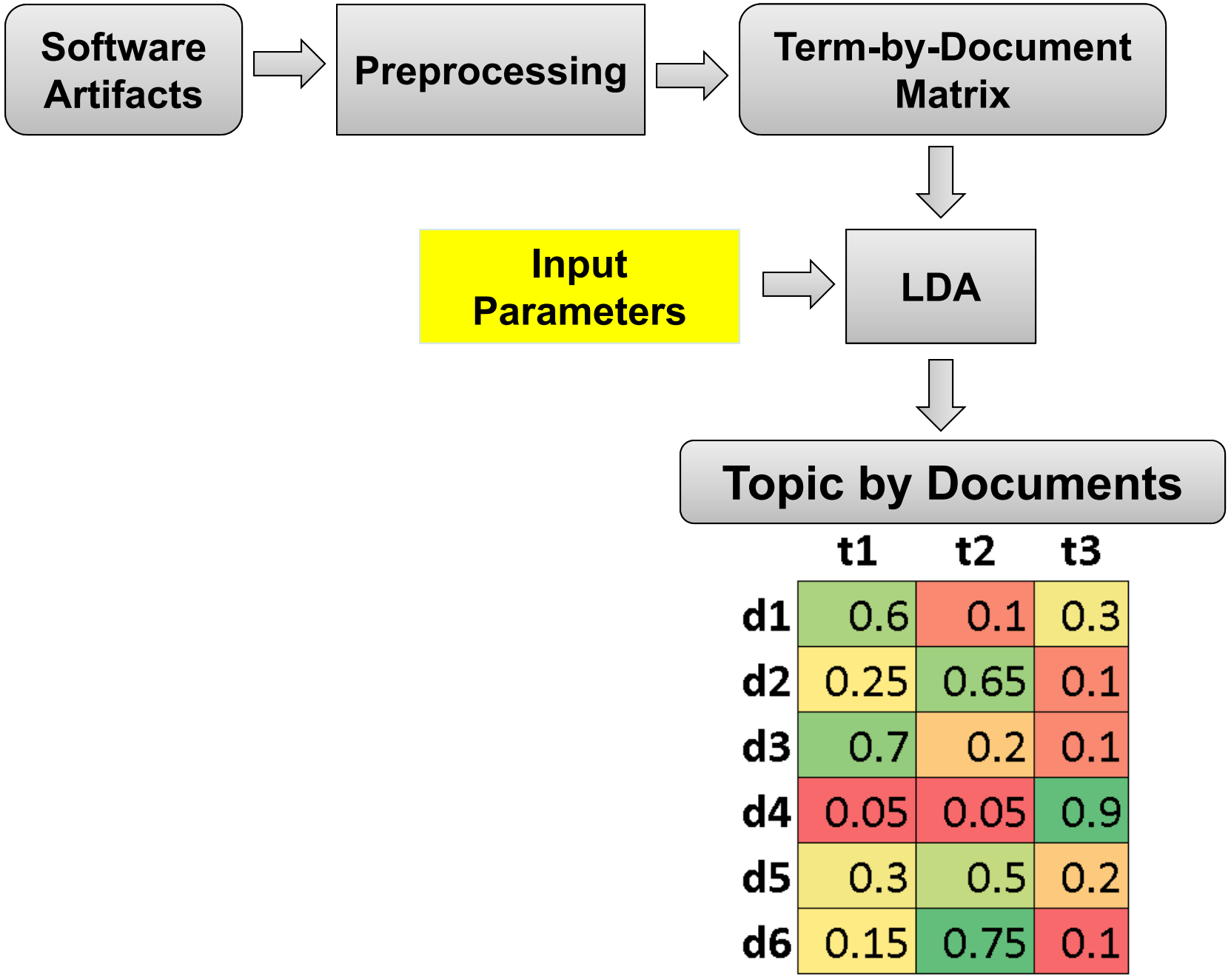


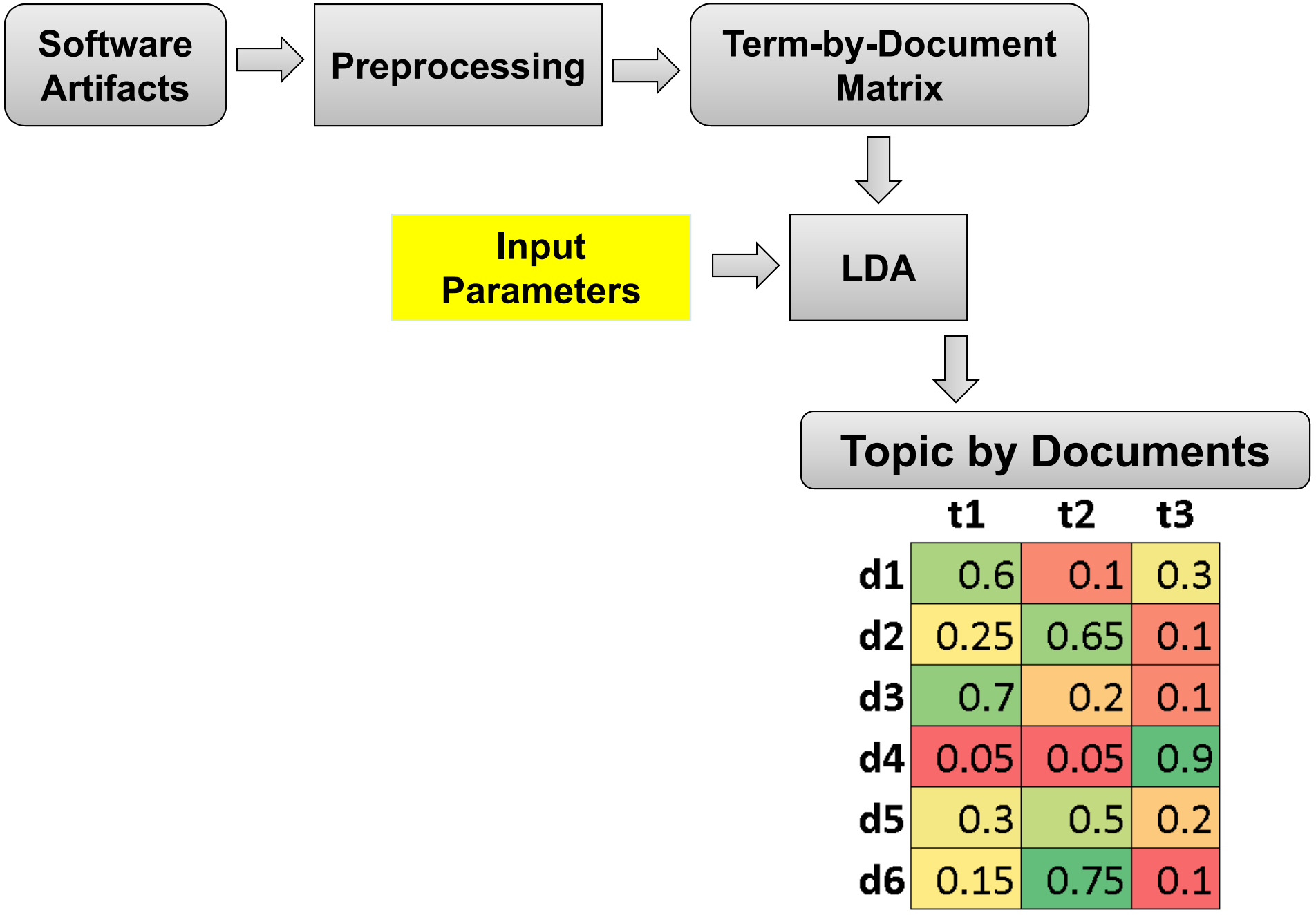
Compute document to document similarity

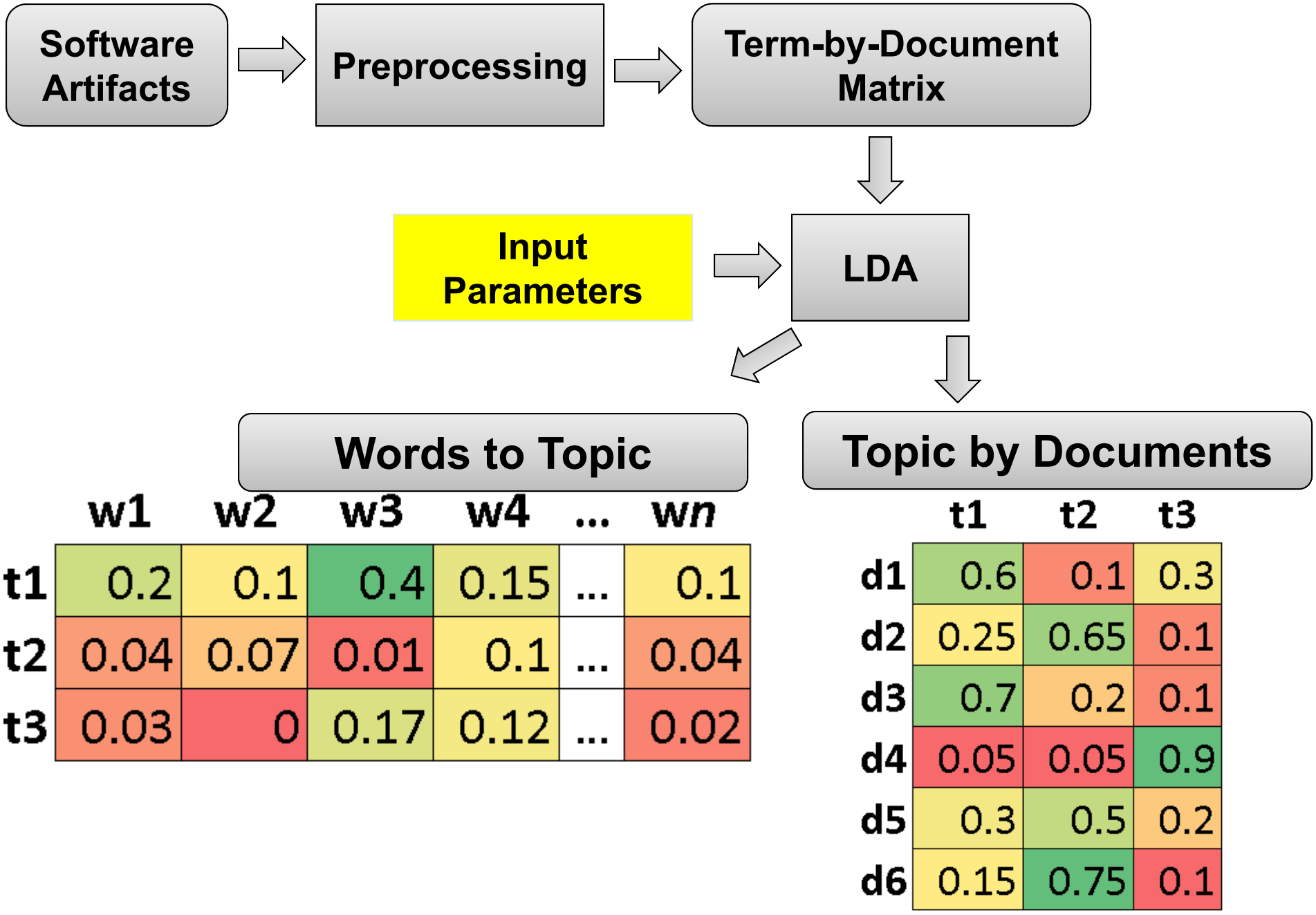
Compute query to document similarity

"Cluster" documents by topics

	t1	t2	t3
d1	0.6	0.1	0.3
d2	0.25	0.65	0.1
d3	0.7	0.2	0.1
d4	0.05	0.05	0.9
d5	0.3	0.5	0.2
d6	0.15	0.75	0.1

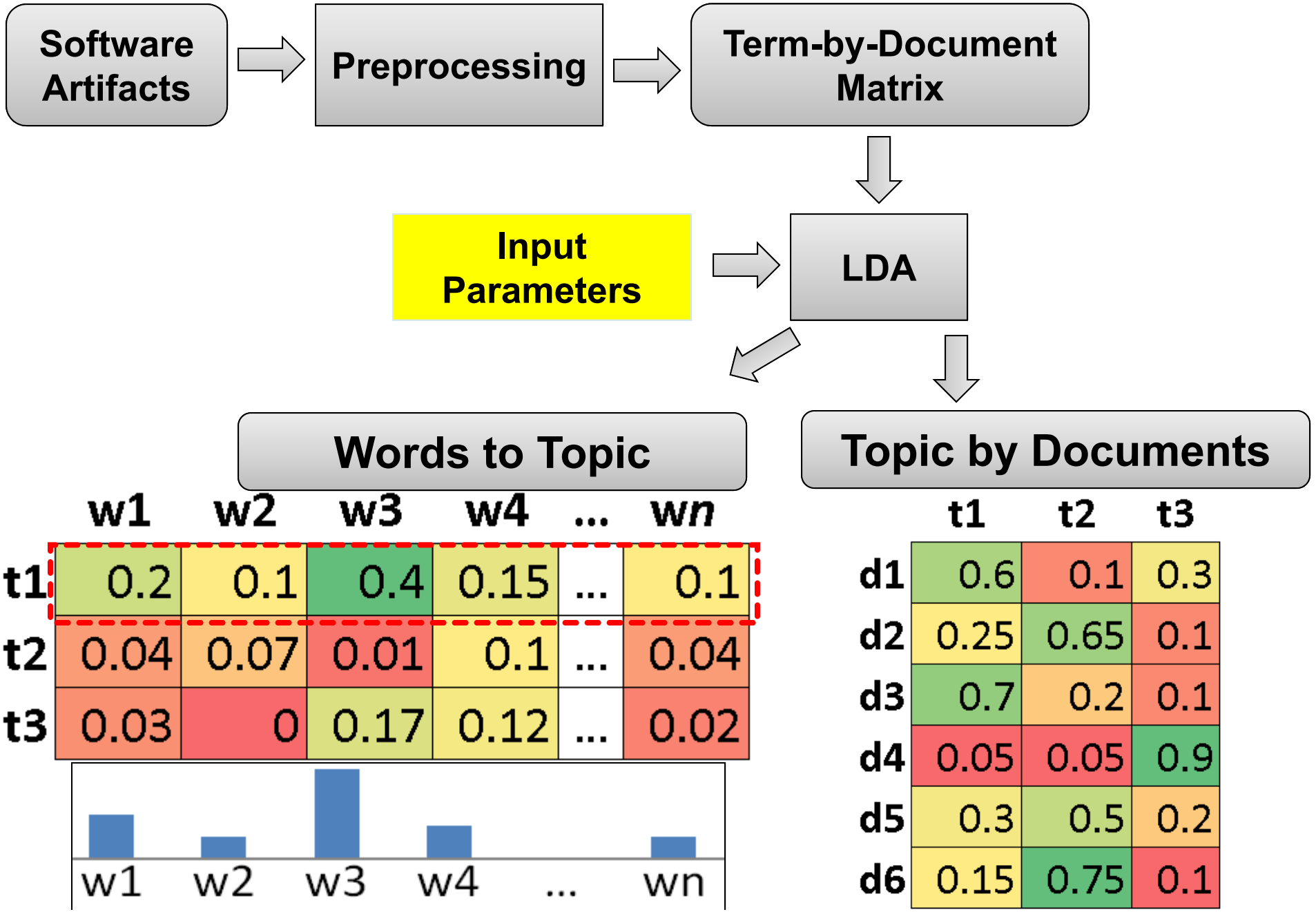

Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Topic by Documents
t1 t2 t3
d1 0.6 0.1 0.3
d2 0.25 0.65 0.1
d3 0.7 0.2 0.1
d4 0.05 0.05 0.9
d5 0.3 0.5 0.2
d6 0.15 0.75 0.1

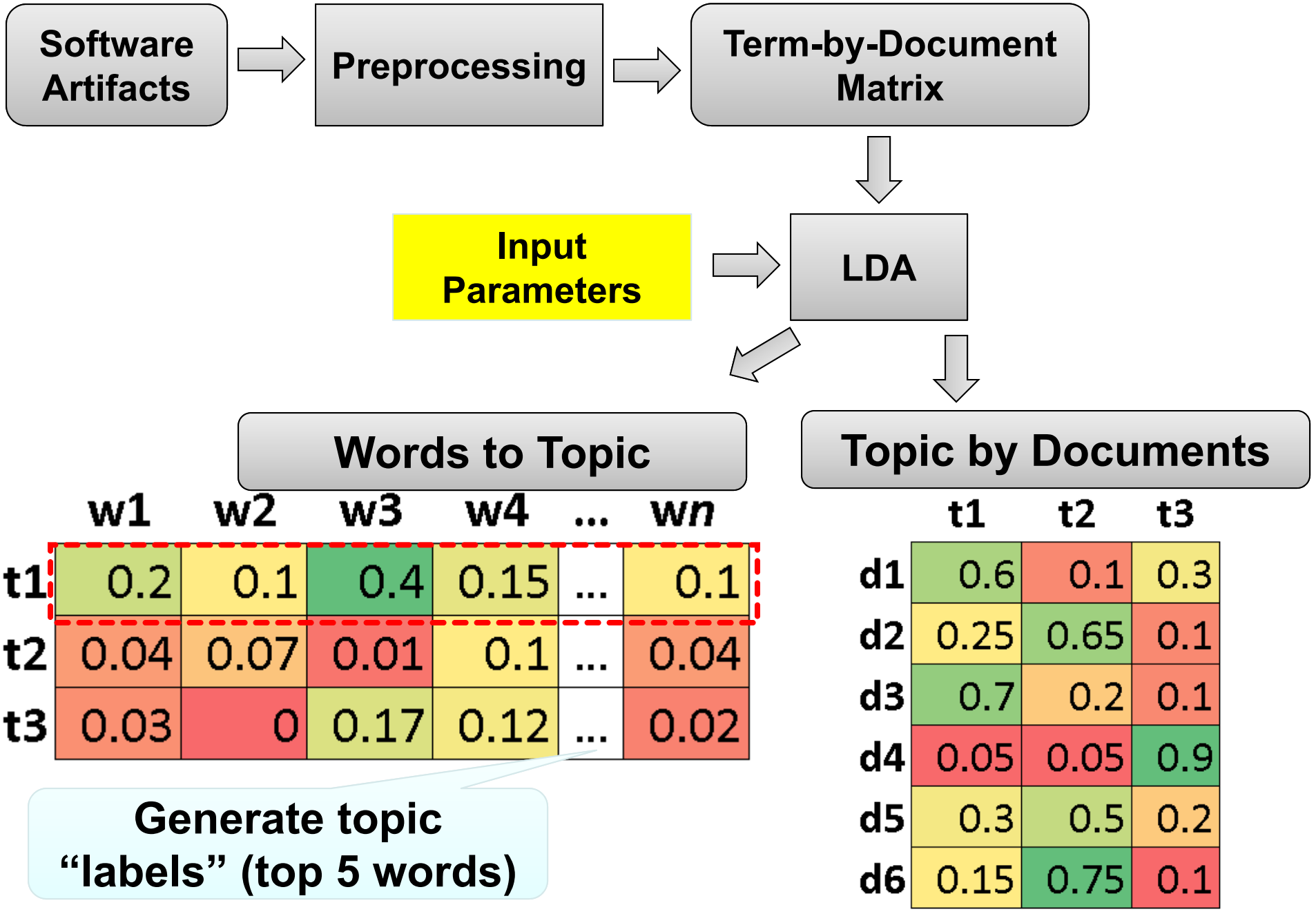

Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Topic by Documents
t1 t2 t3
d1 0.6 0.1 0.3
d2 0.25 0.65 0.1
d3 0.7 0.2 0.1
d4 0.05 0.05 0.9
d5 0.3 0.5 0.2
d6 0.15 0.75 0.1

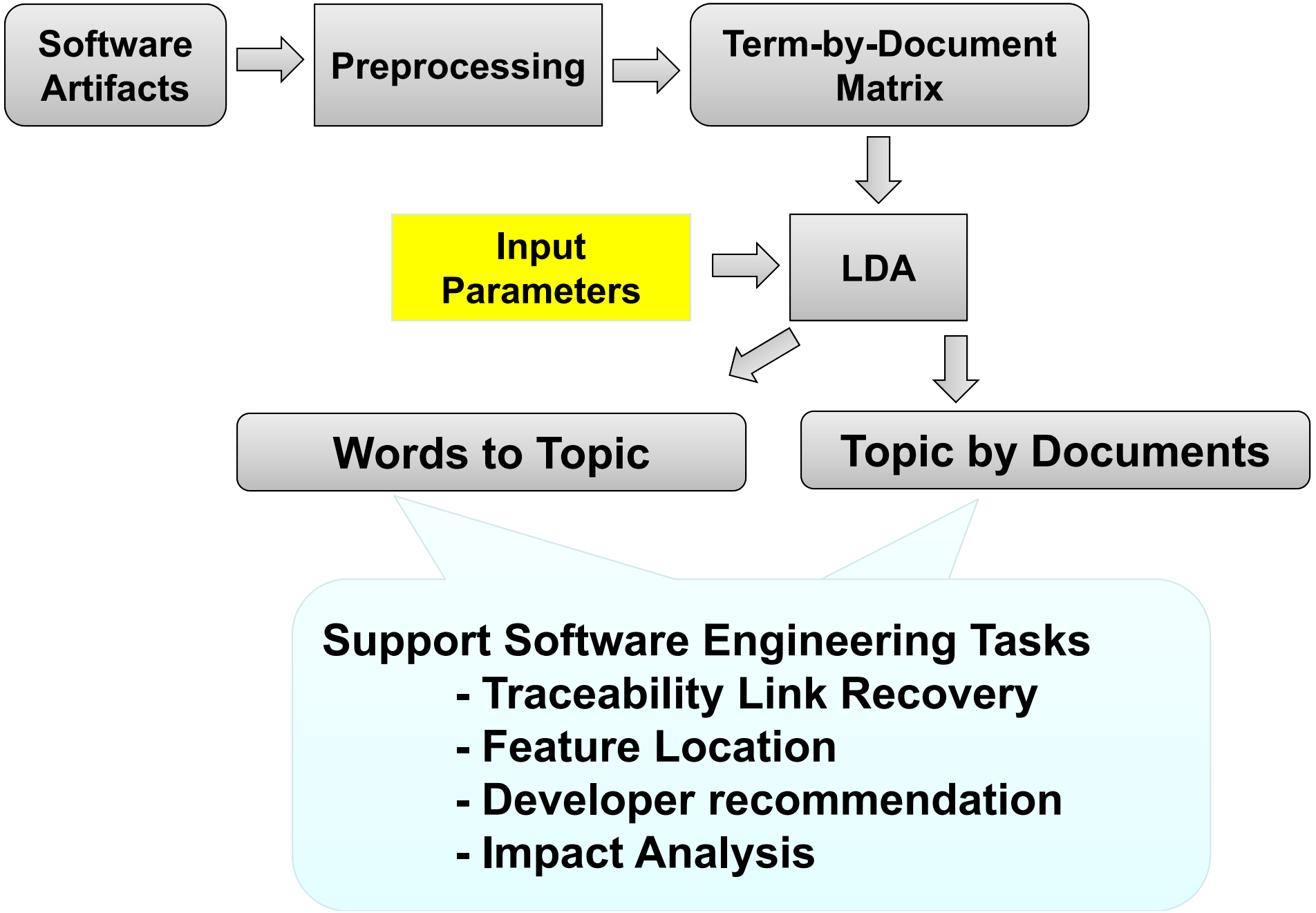


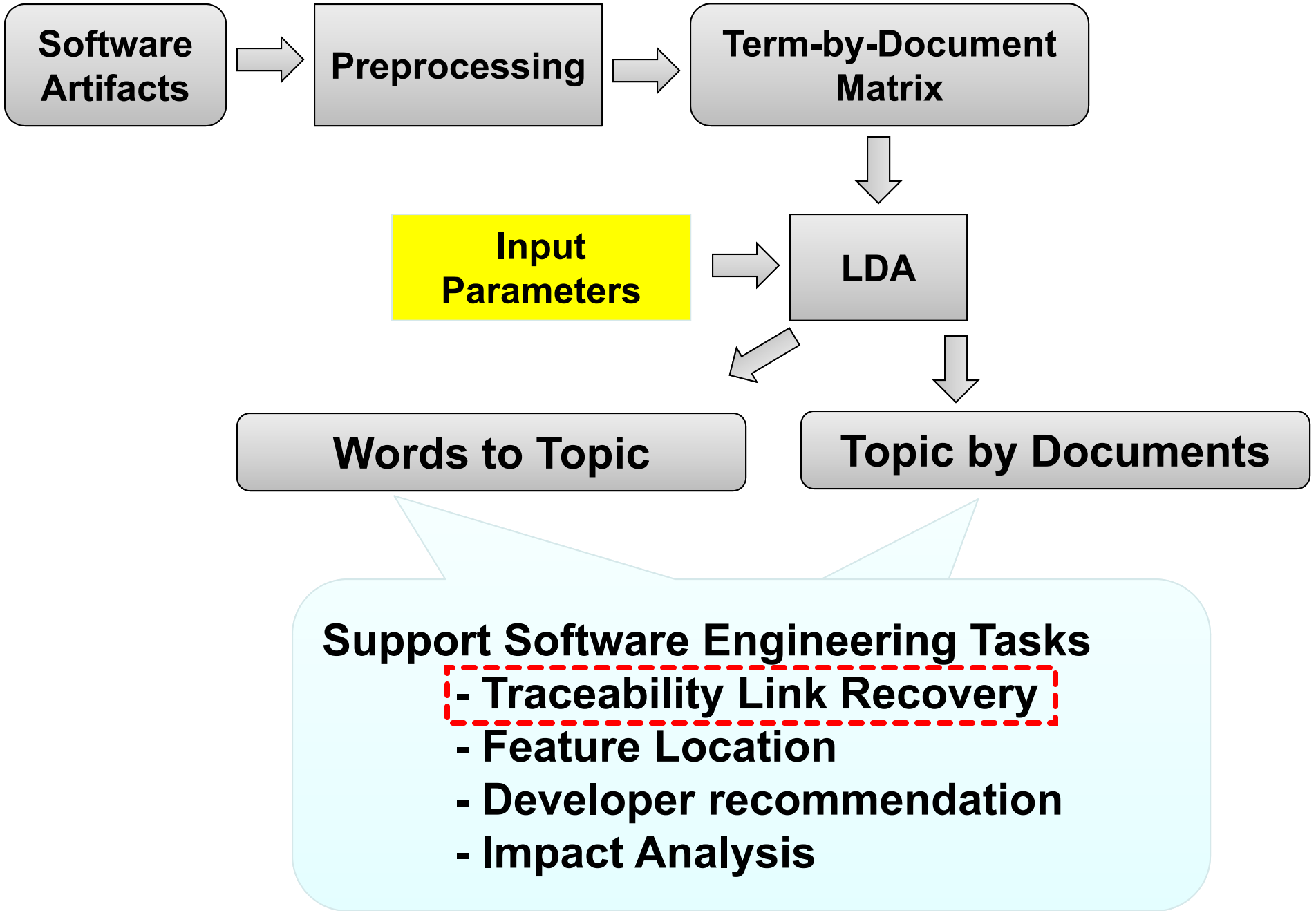
	w1	w2	w3	w4	...	wn
t1	0.2	0.1	0.4	0.15	...	0.1
t2	0.04	0.07	0.01	0.1	...	0.04
t3	0.03	0	0.17	0.12	...	0.02

	t1	t2	t3
d1	0.6	0.1	0.3
d2	0.25	0.65	0.1
d3	0.7	0.2	0.1
d4	0.05	0.05	0.9
d5	0.3	0.5	0.2
d6	0.15	0.75	0.1


Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Words to Topic
Topic by Documents
w1 w2 w3 w4 ... wn
t1 0.2 0.1 0.4 0.15 ... 0.1
t2 0.04 0.07 0.01 0.1 ... 0.04
t3 0.03 0 0.17 0.12 ... 0.02
w1 w2 w3 w4 ... wn
t1 t2 t3
d1 0.6 0.1 0.3
d2 0.25 0.65 0.1
d3 0.7 0.2 0.1
d4 0.05 0.05 0.9
d5 0.3 0.5 0.2
d6 0.15 0.75 0.1


Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Words to Topic
Topic by Documents
w1 w2 w3 w4 ... wn
t1 0.2 0.1 0.4 0.15 ... 0.1
t2 0.04 0.07 0.01 0.1 ... 0.04
t3 0.03 0 0.17 0.12 ... 0.02
t1 t2 t3
d1 0.6 0.1 0.3
d2 0.25 0.65 0.1
d3 0.7 0.2 0.1
d4 0.05 0.05 0.9
d5 0.3 0.5 0.2
d6 0.15 0.75 0.1
Generate topic "labels" (top 5 words)


Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Words to Topic
Topic by Documents
Support Software Engineering Tasks
- Traceability Link Recovery
- Feature Location
- Developer recommendation
- Impact Analysis


Software Artifacts
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Term-by-Document Matrix
Input Parameters
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Words to Topic
Topic by Documents
Support Software Engineering Tasks
- Traceability Link Recovery
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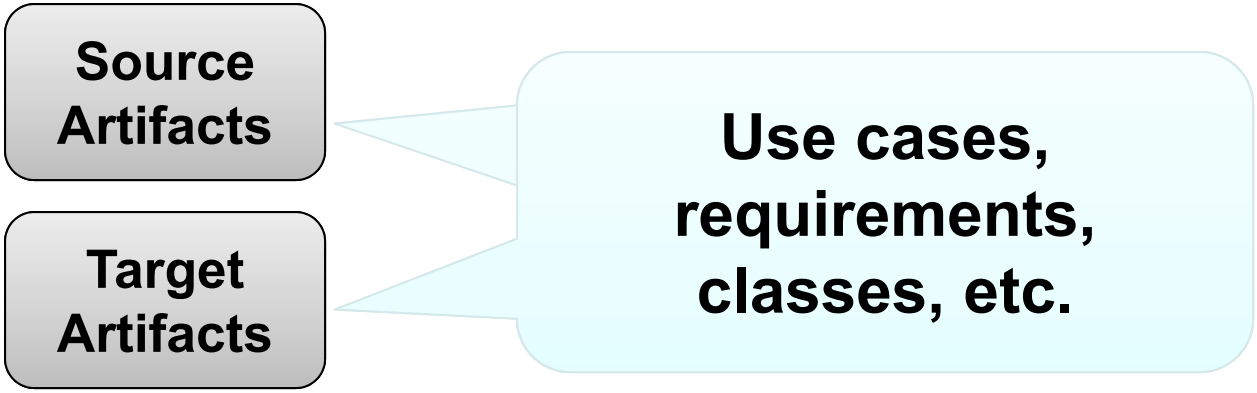
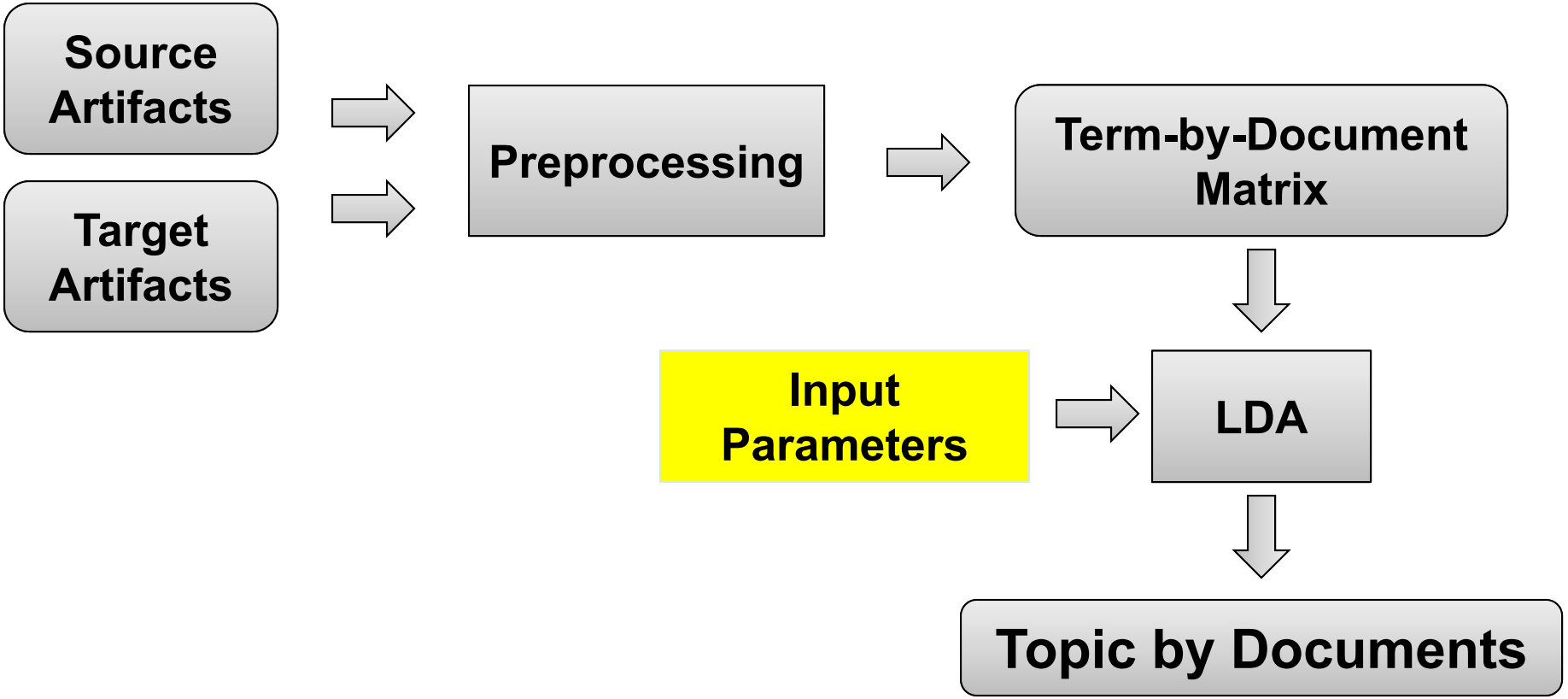
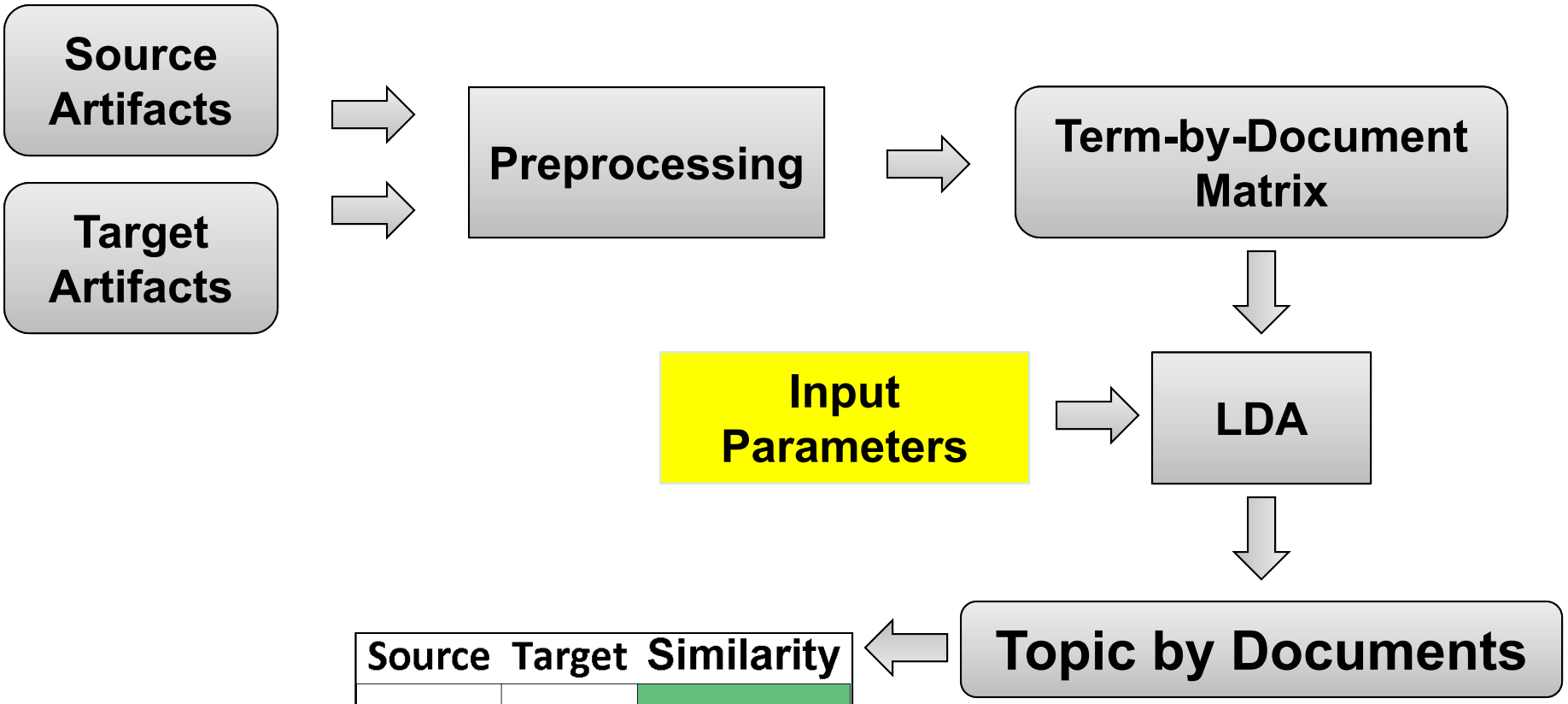
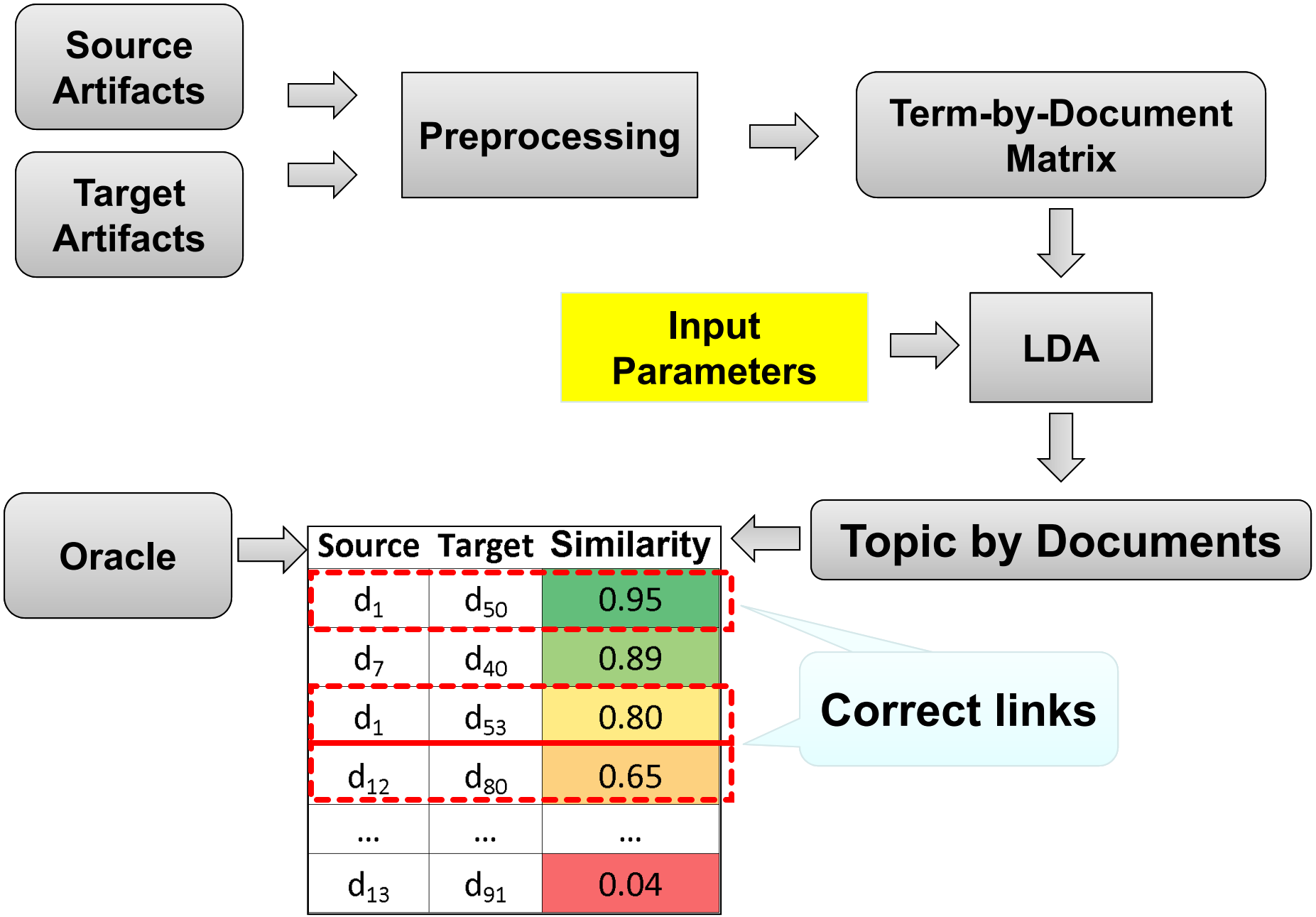
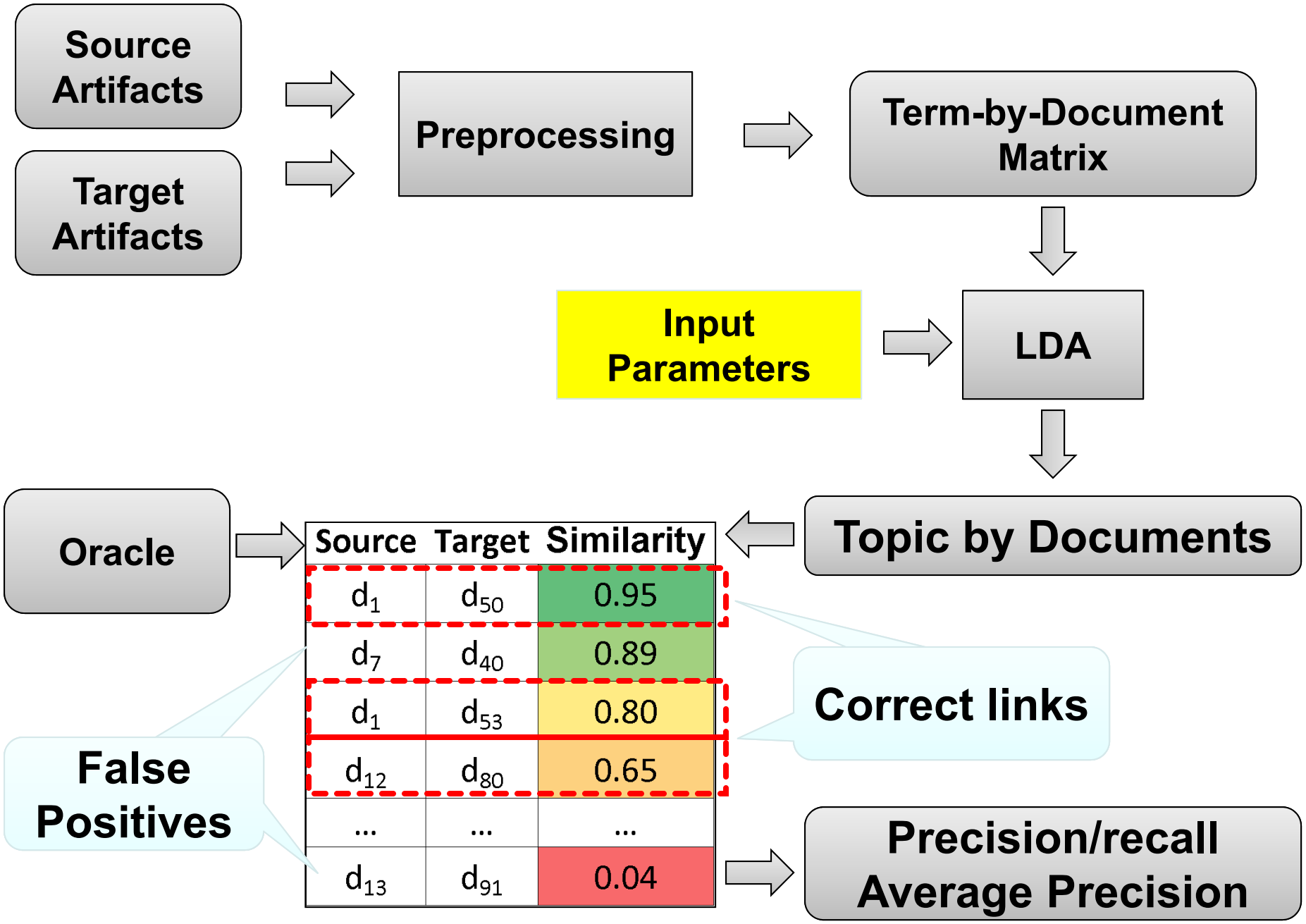

Source Artifacts
Target Artifacts
Use cases, requirements, classes, etc.


Source Artifacts
Target Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Topic by Documents

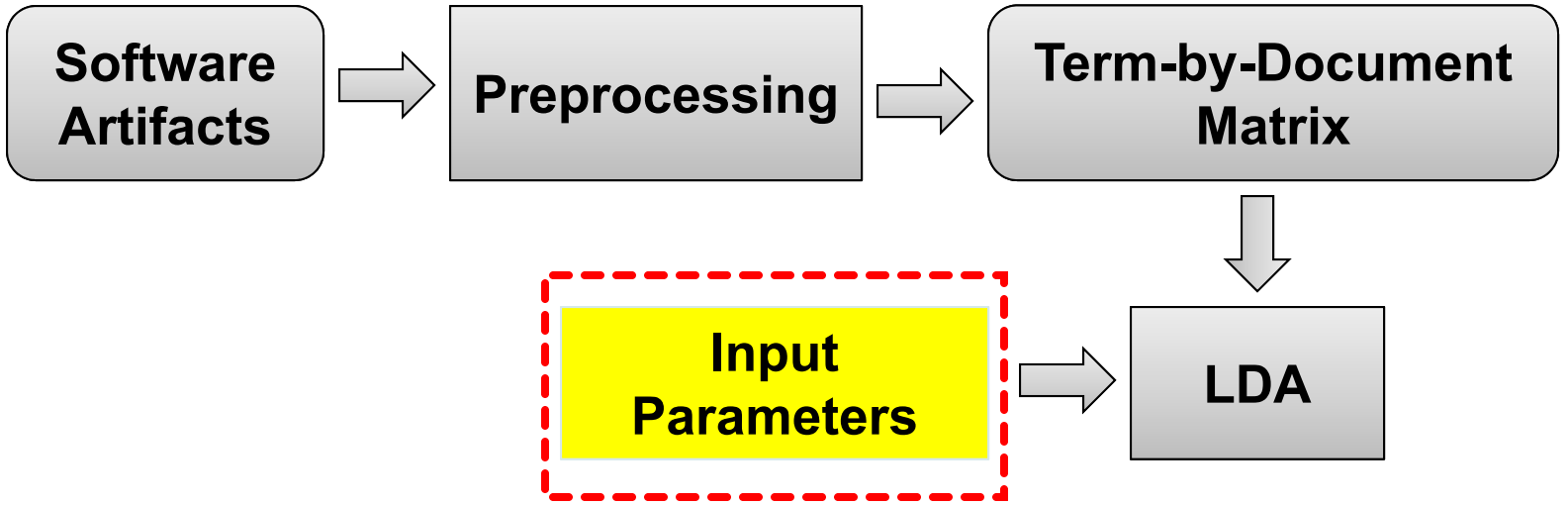


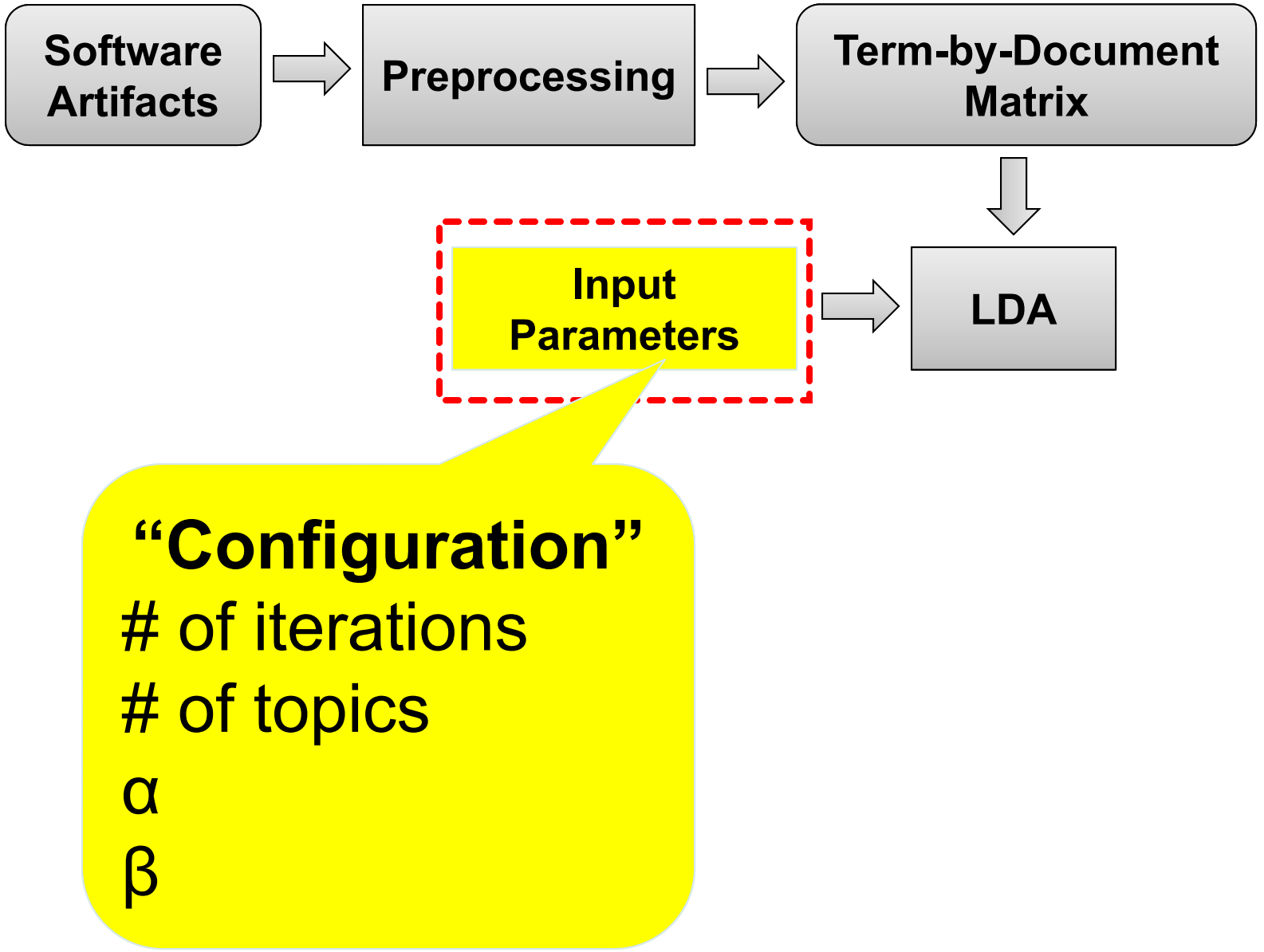
Source	Target	Similarity
d_1	d_{50}	0.95
d_7	d_{40}	0.89
d_1	d_{53}	0.80
d_{12}	d_{80}	0.65
...	...	...
d_{13}	d_{91}	0.04

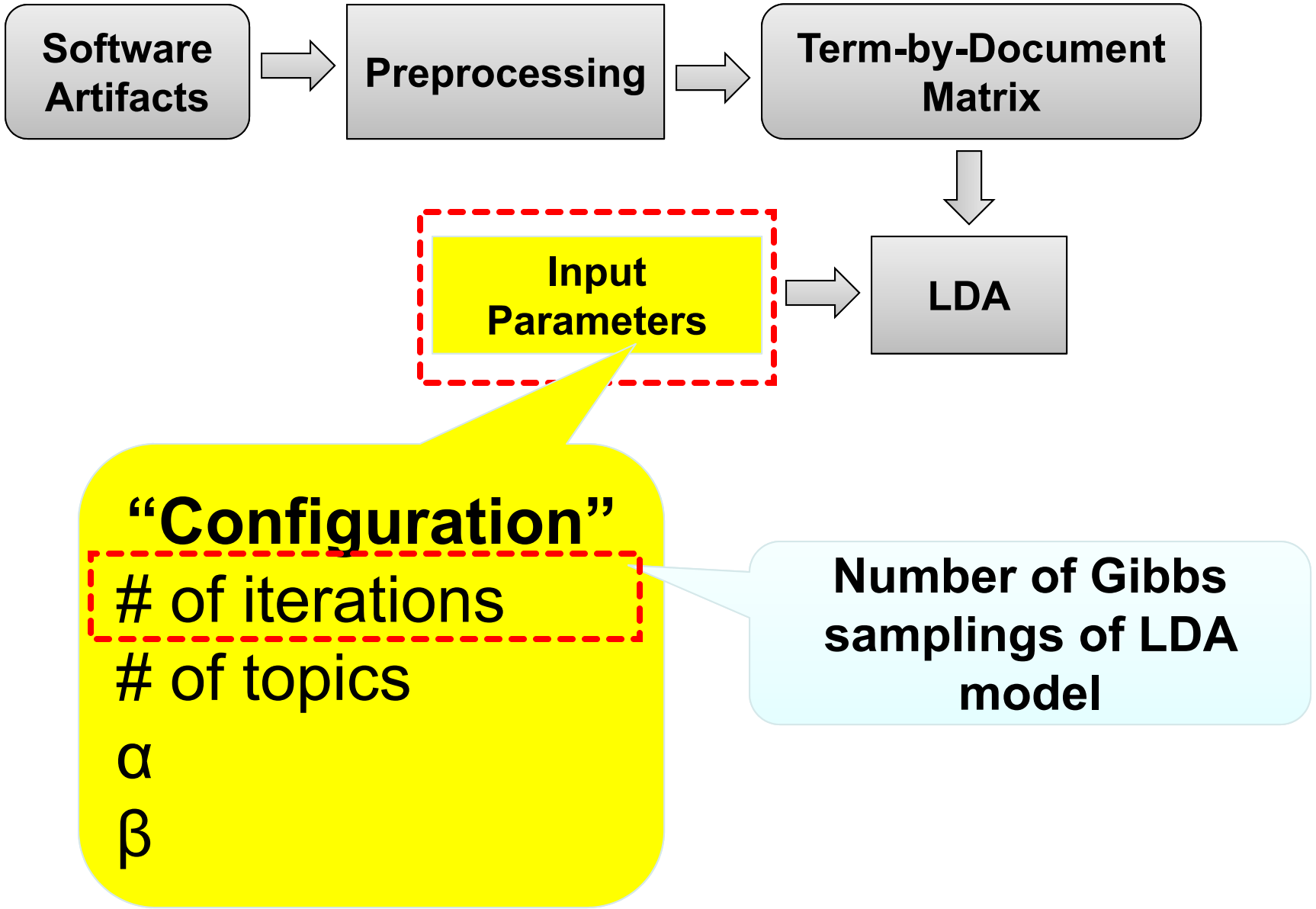

Source Artifacts
Target Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Topic by Documents
Oracle
Source Target Similarity
d1 d50 0.95
d7 d40 0.89
d1 d53 0.80
d12 d80 0.65
... ...
d13 d91 0.04
Correct links


Source Artifacts
Target Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Topic by Documents
Oracle
Source Target Similarity
d1 d50 0.95
d7 d40 0.89
d1 d53 0.80
d12 d80 0.65
... ...
d13 d91 0.04
Correct links
False Positives
Precision/recall Average Precision

Let’s examine the LDA input parameters in more details

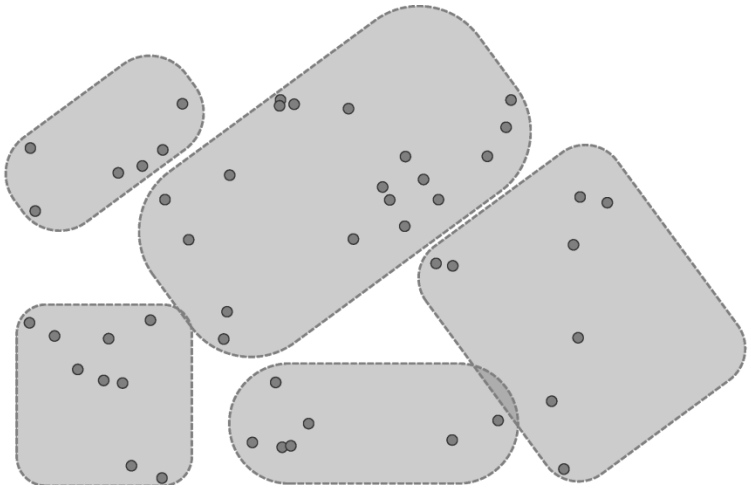

Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA


Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
"Configuration"
# of iterations
# of topics
α
β


Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
"Configuration"
# of iterations
# of topics
α
β
Number of Gibbs samplings of LDA model

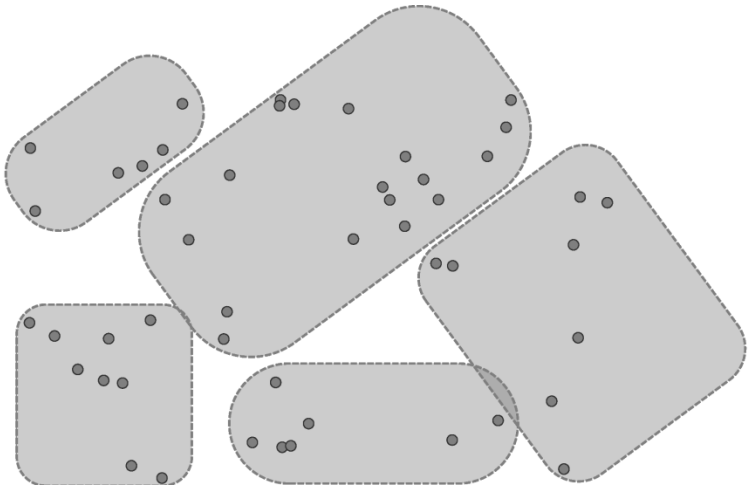
Number of topics…

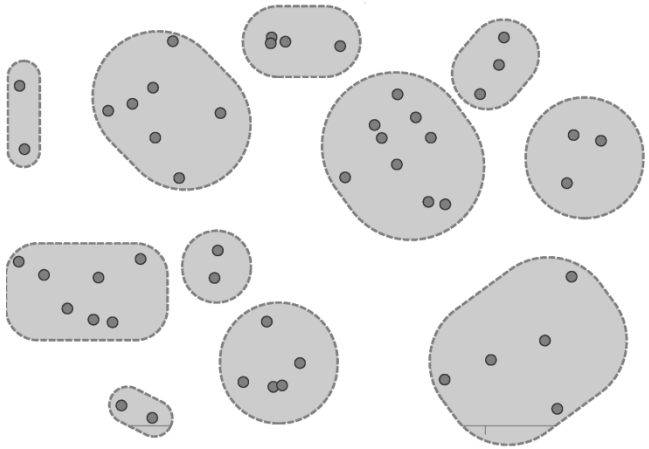
Number of topics…



General topics

Number of topics…





General topics

Specific topics

α, influences the "smoothness" of documents to topics distribution

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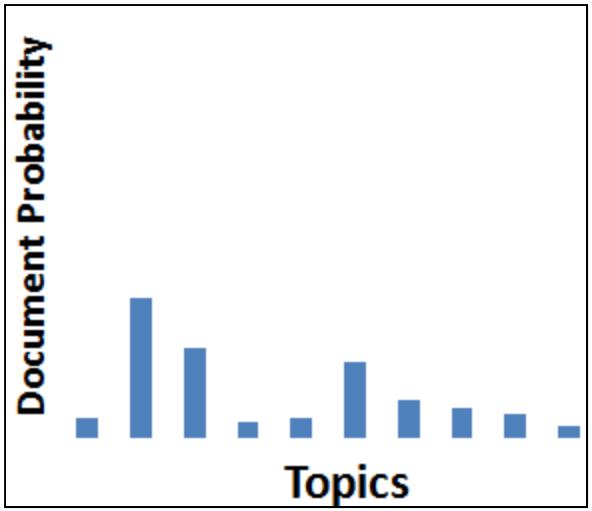

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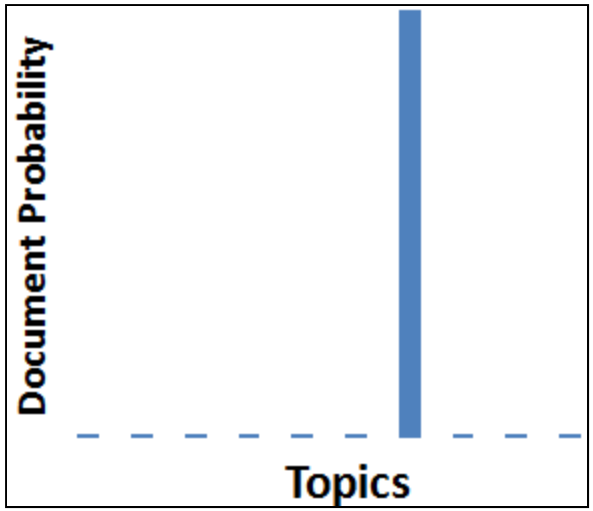

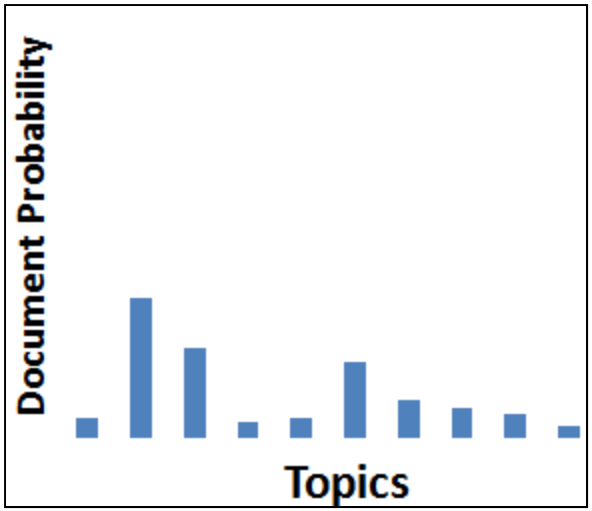

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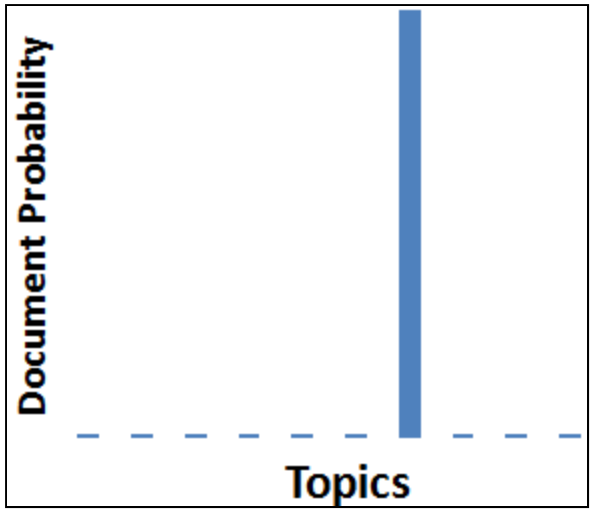

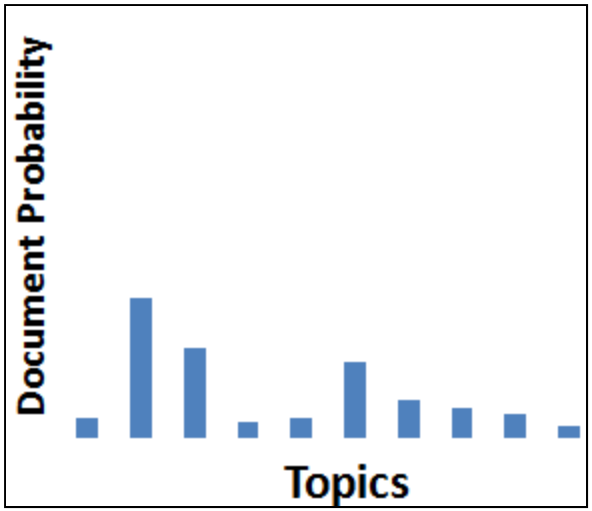

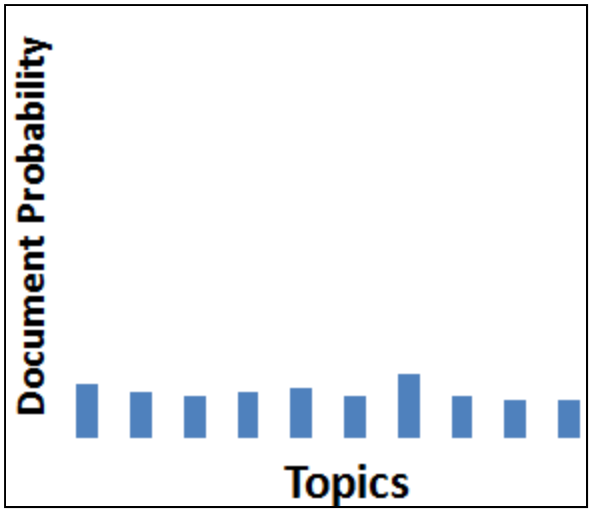

β, influences the "smoothness" of topics to words distribution

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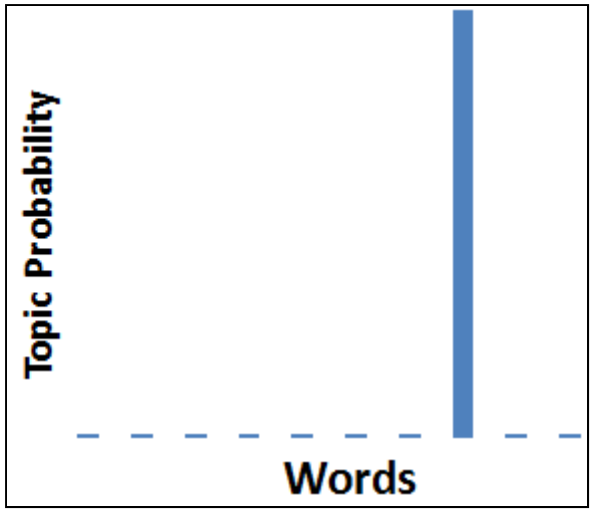

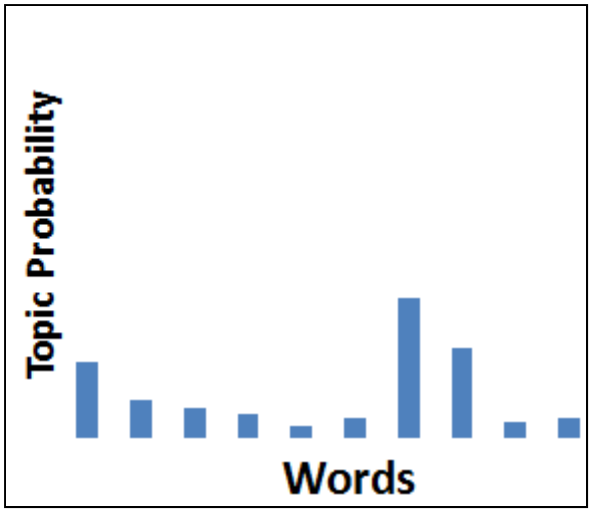

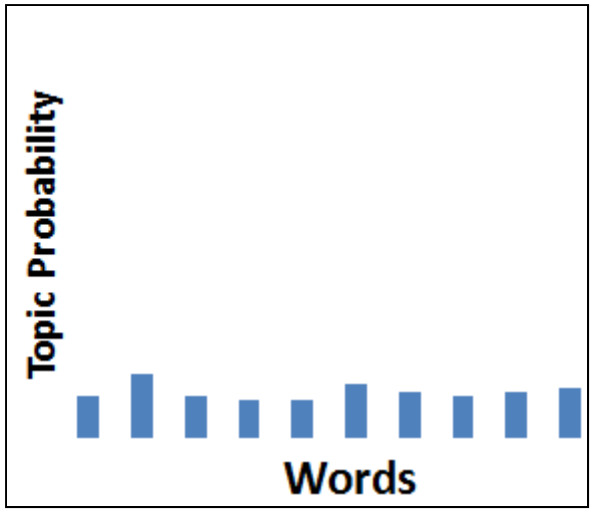

LDA parameters significantly influence the results

- Traceability Link Recovery
- 1,000 different configurations of LDA parameters
  - Evaluate the Average Precision on EasyClinic

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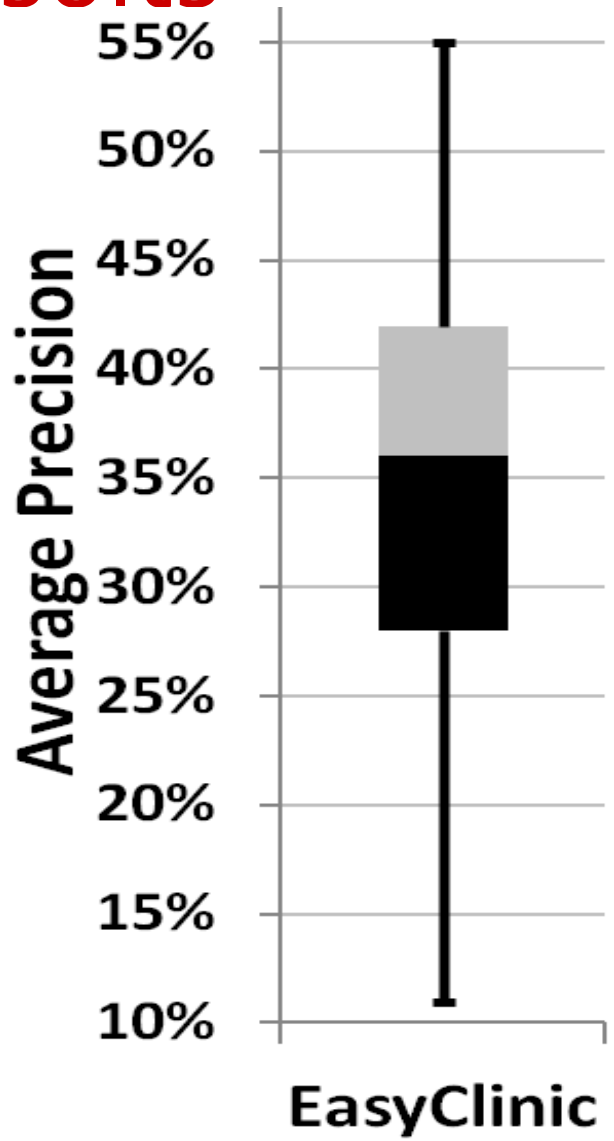
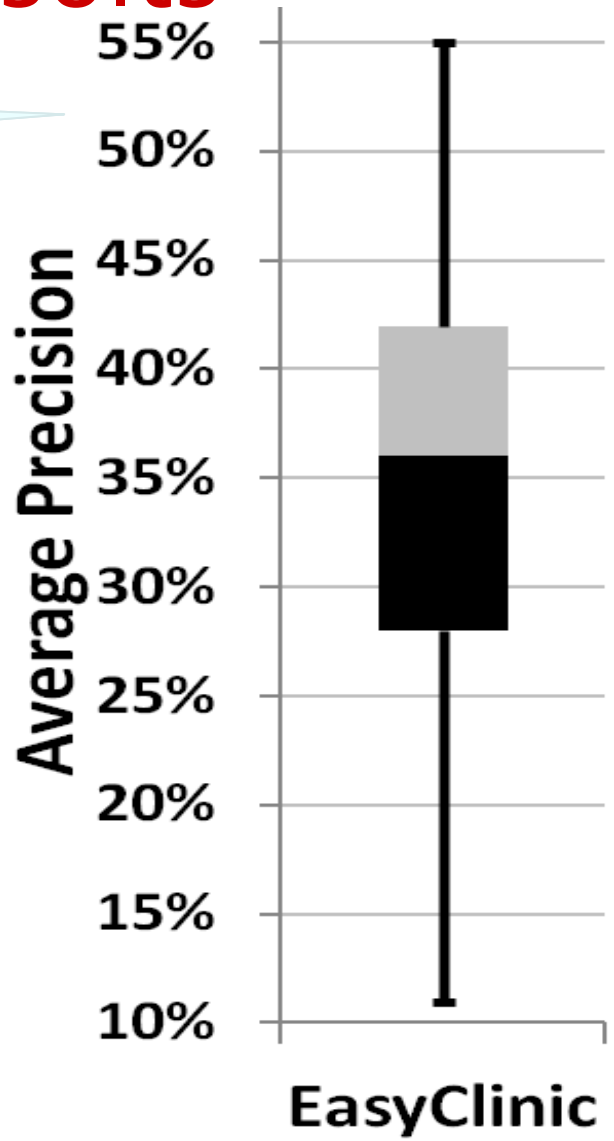


LDA parameters significantly influence the results

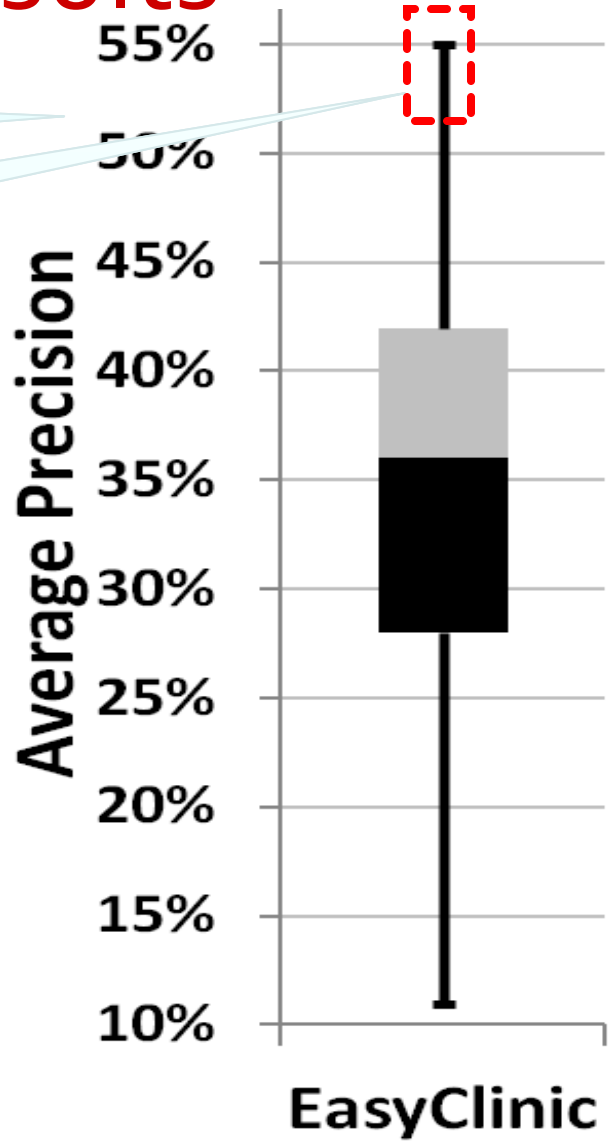
High variability in results



LDA parameters significantly influence the results

High variability in results

Few configurations produce good results



What kind of LDA configurations were used for software?

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“ad-hoc” configurations

Parameters “imported” from natural language community

Assumption:

source code
has the same characteristics as
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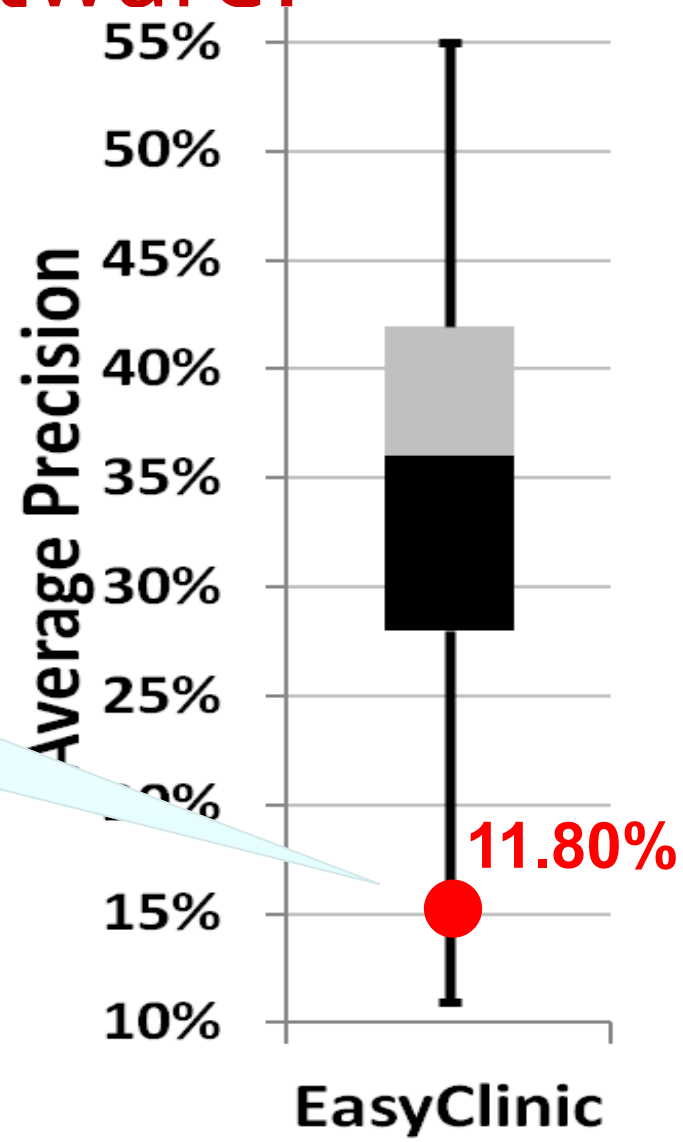

What kind of LDA configurations were used for software?

[Hindle et al. @ ICSE'12]:

source code
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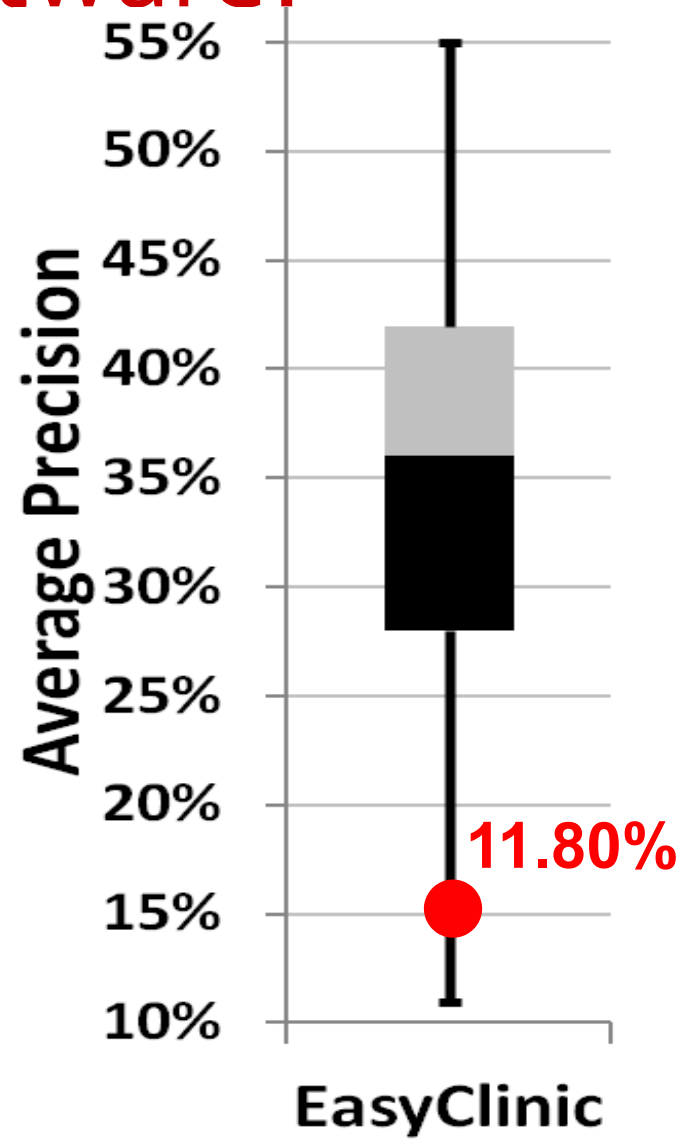

What kind of LDA configurations were used for software?

We need new techniques to find these configurations

[Hindle et al. @ ICSE'12]:

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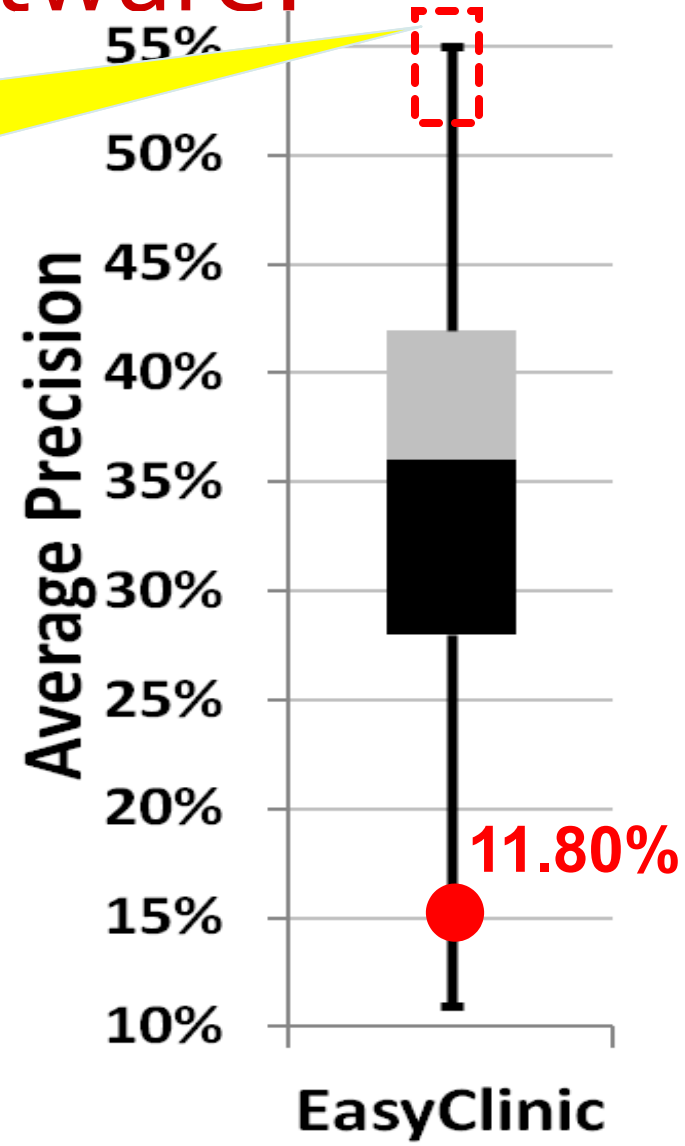

Our contribution…**LDA-GA**

LDA-GA: automatically calibrate the input parameters of LDA using a genetic algorithm

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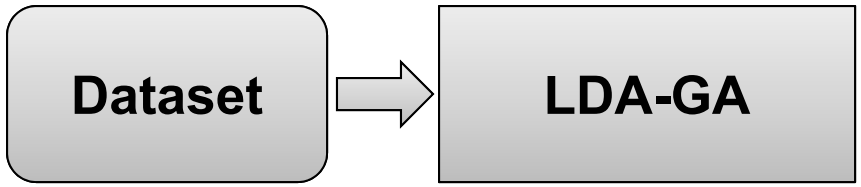
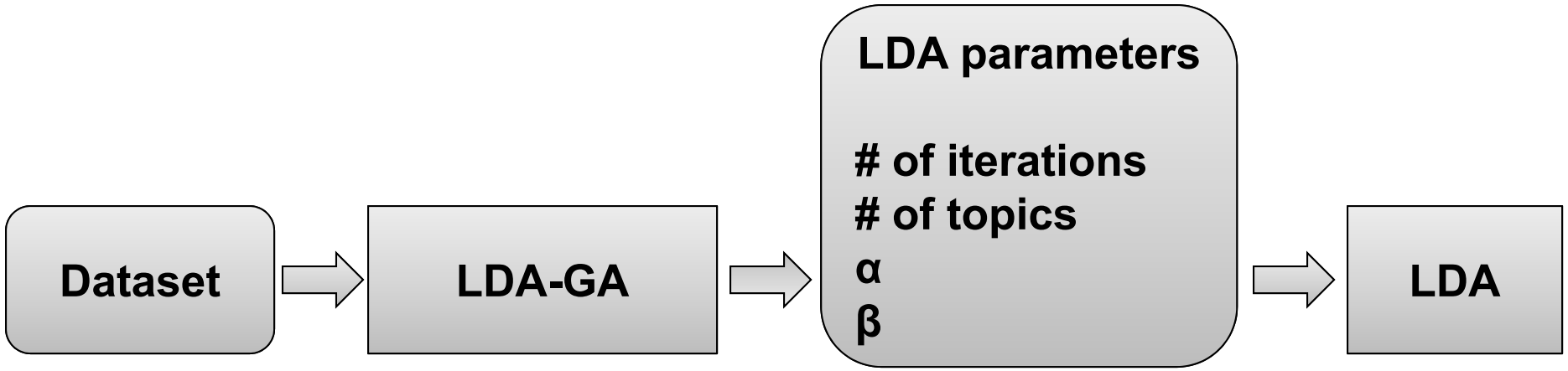


LDA-GA: automatically calibrate the input parameters of LDA using a genetic algorithm



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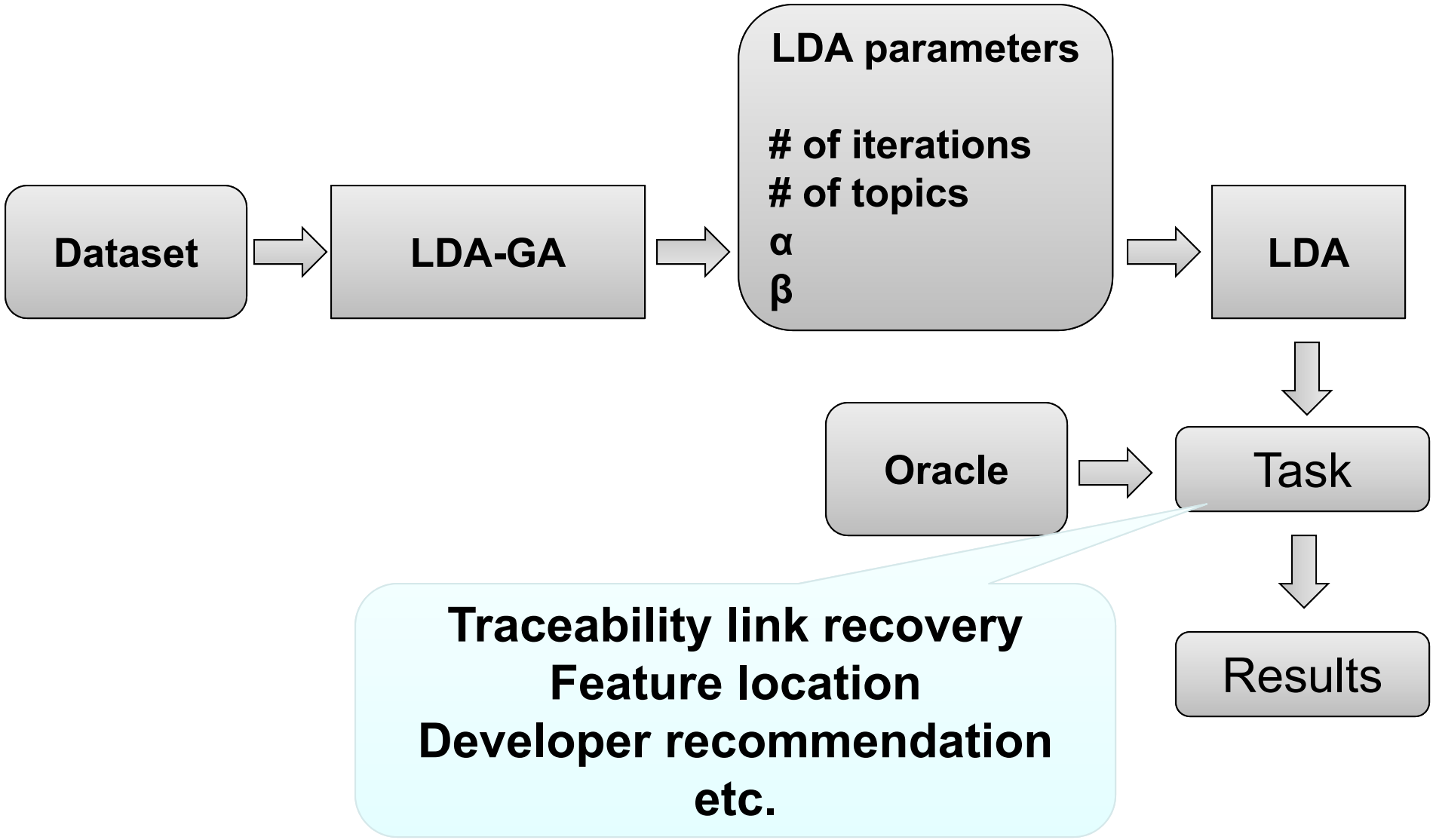

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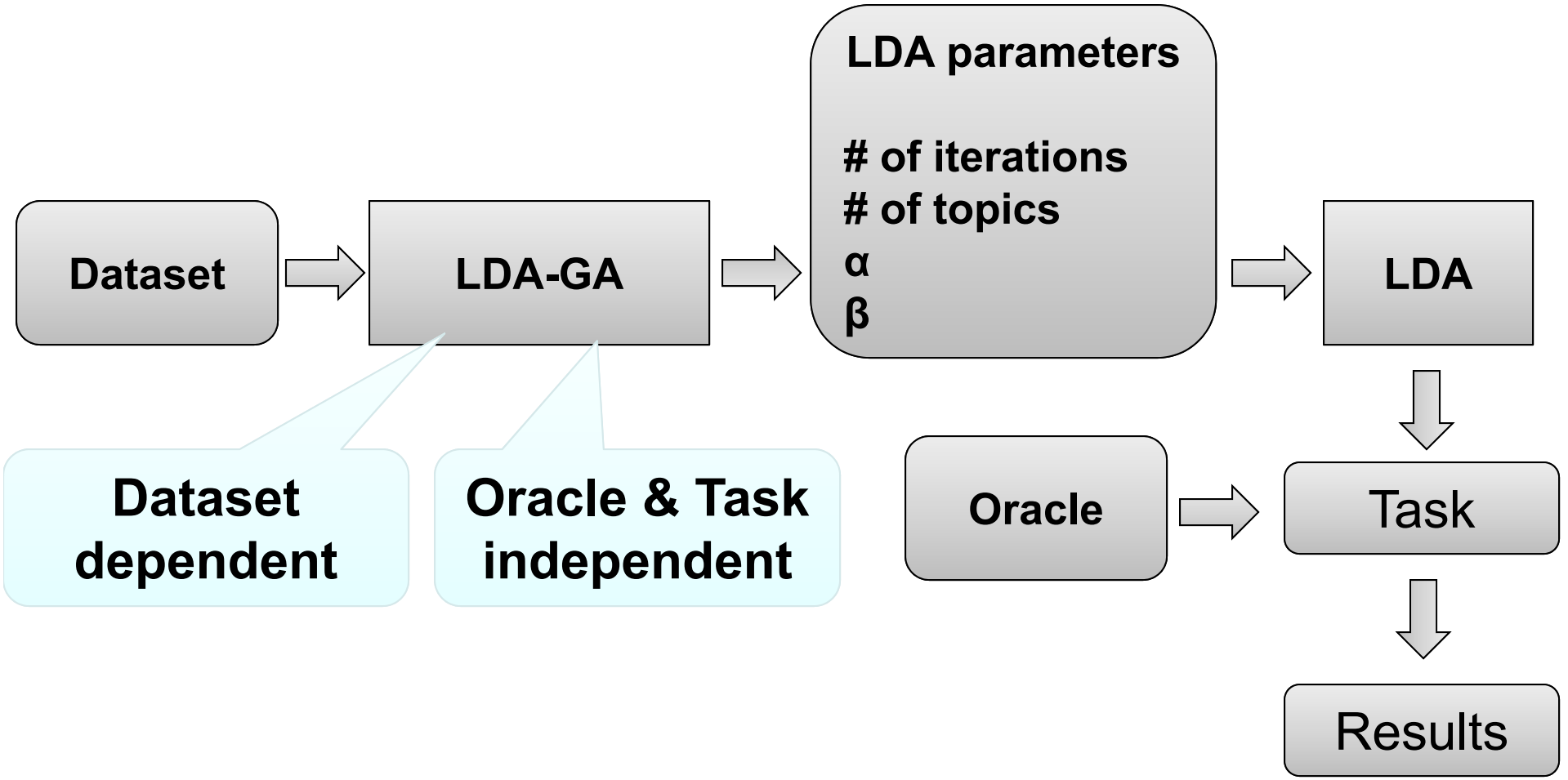
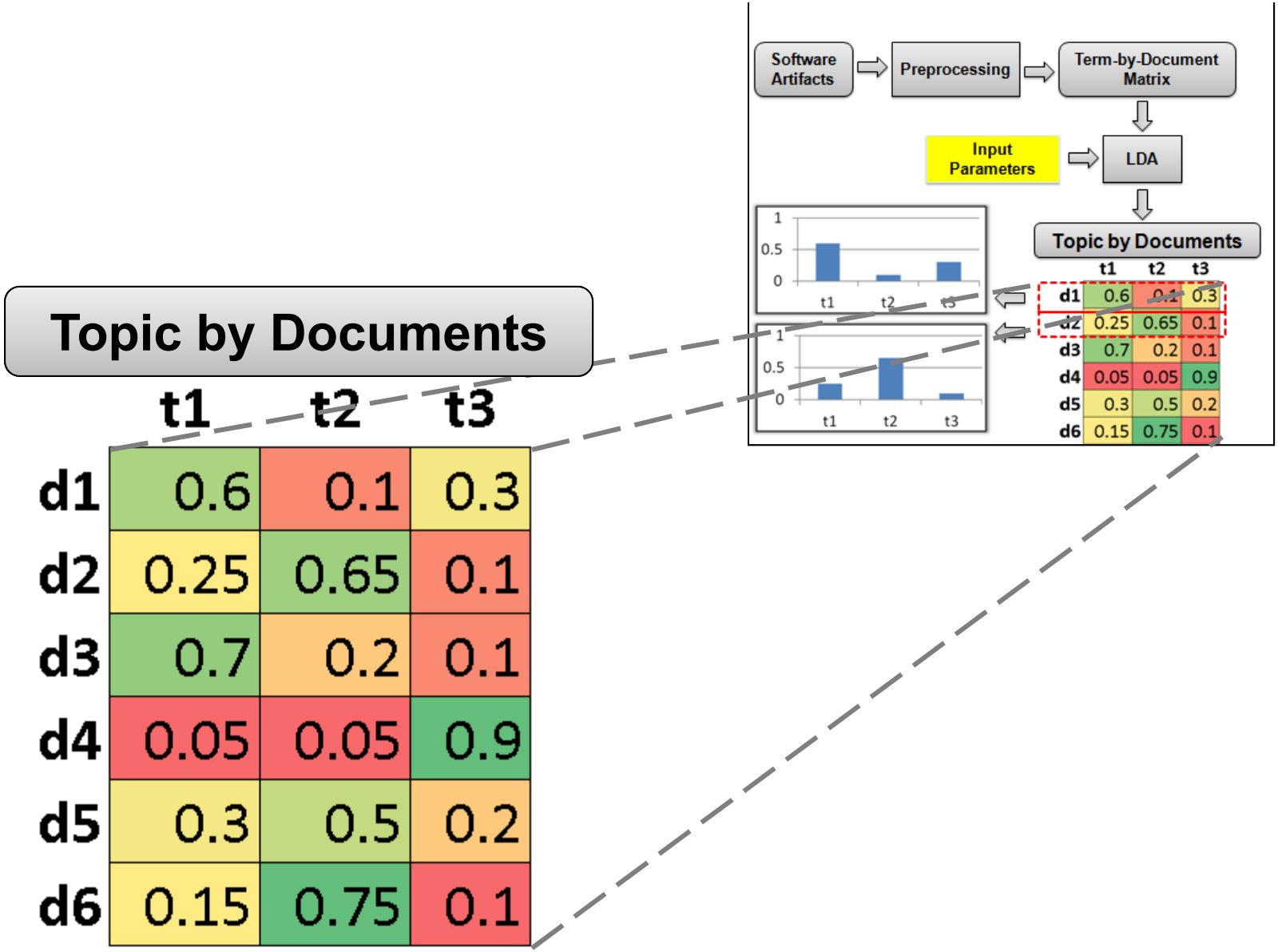


How to **evaluate** how "good" an LDA configuration is?


Software Artifacts
Preprocessing
Term-by-Document Matrix
Input Parameters
LDA
Topic by Documents
t1 t2 t3
d1 0.6 0.1 0.3
d2 0.25 0.65 0.1
d3 0.7 0.2 0.1
d4 0.05 0.05 0.9
d5 0.3 0.5 0.2
d6 0.15 0.75 0.1
Topic by Documents
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Dominant Topics

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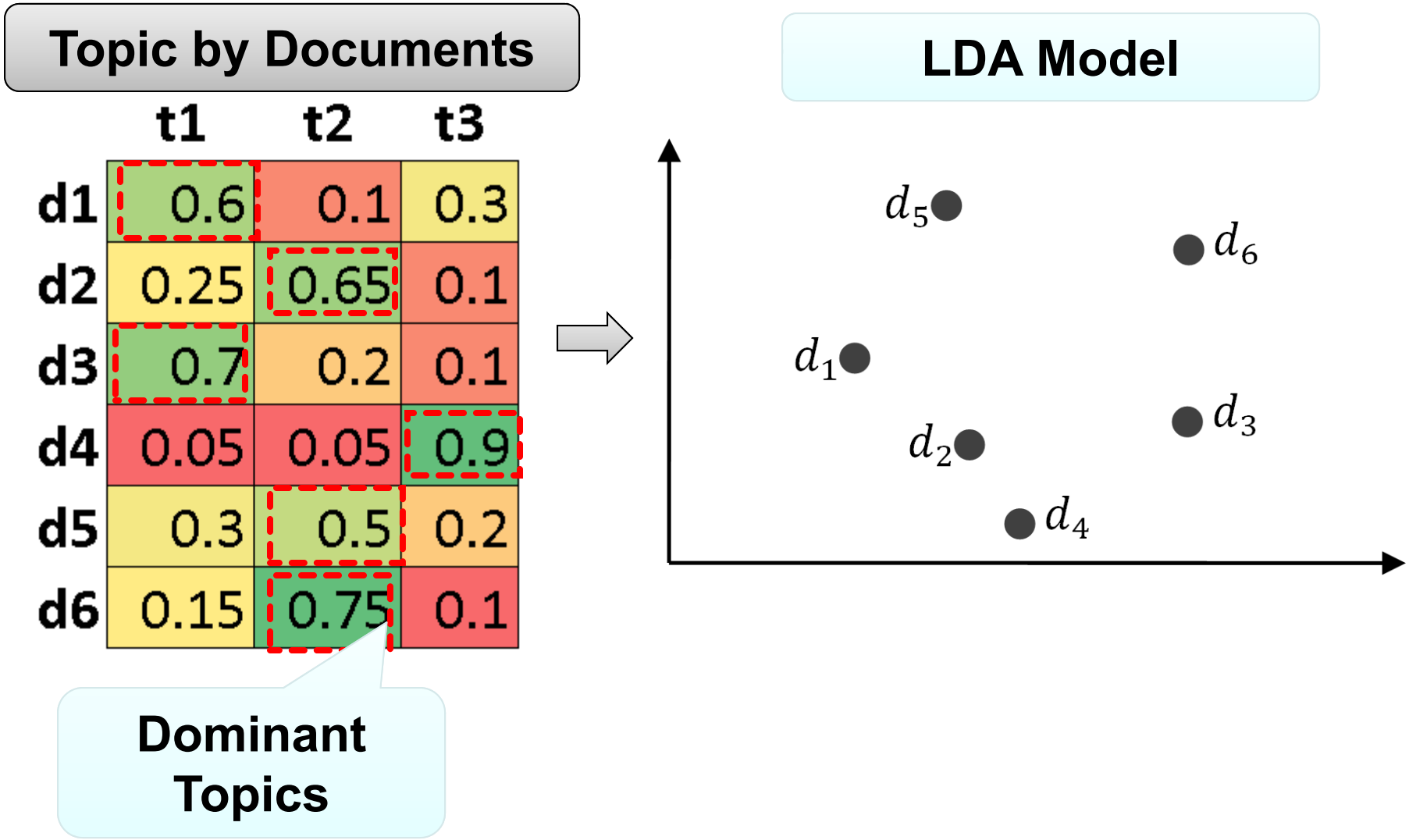
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Dominant Topics
LDA Model
d_5
d_6
d_1
d_3
d_2
d_4

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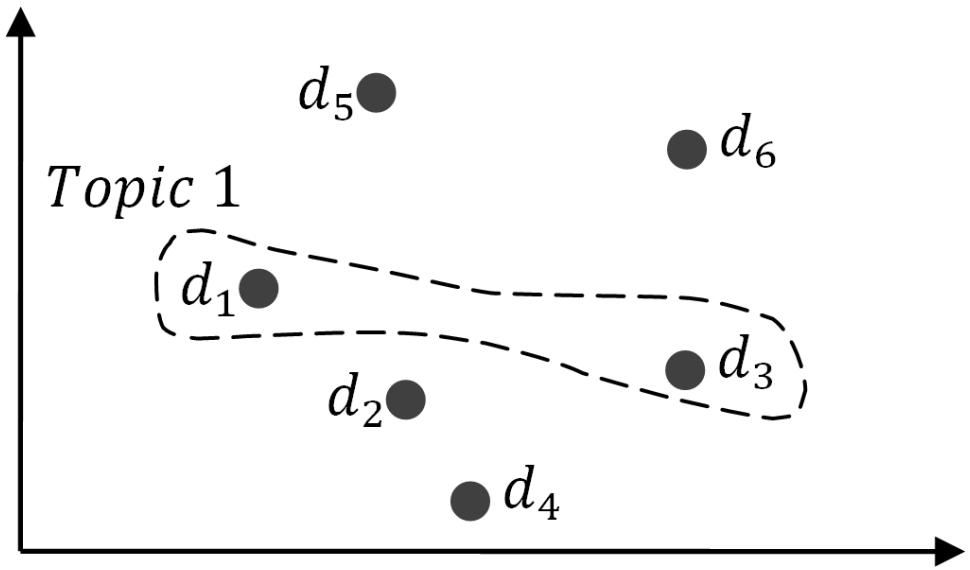
LDA Model



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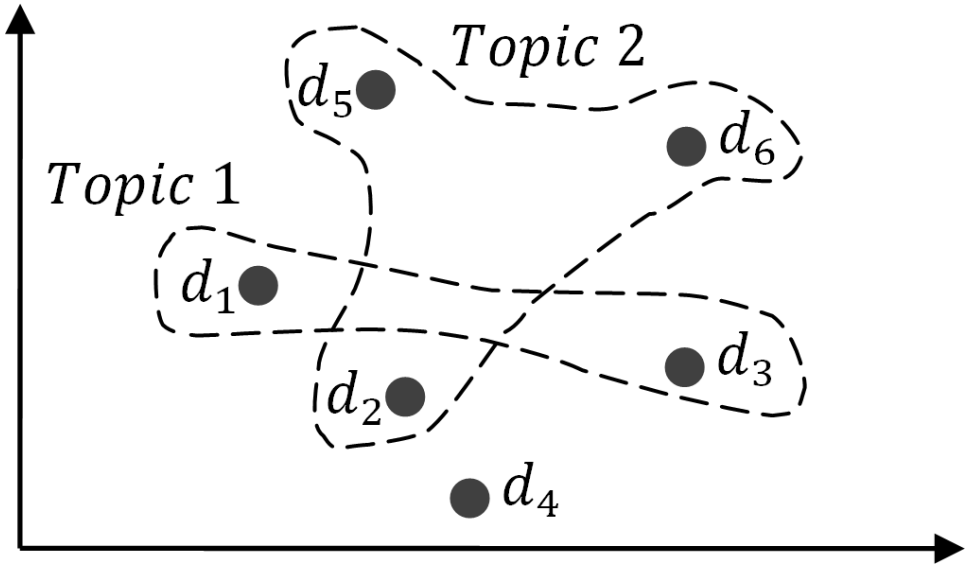

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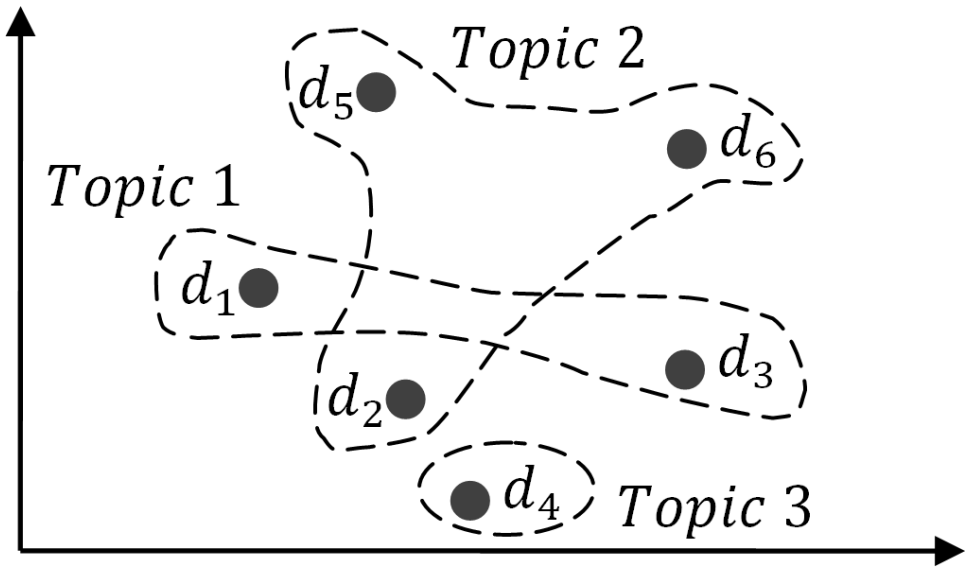

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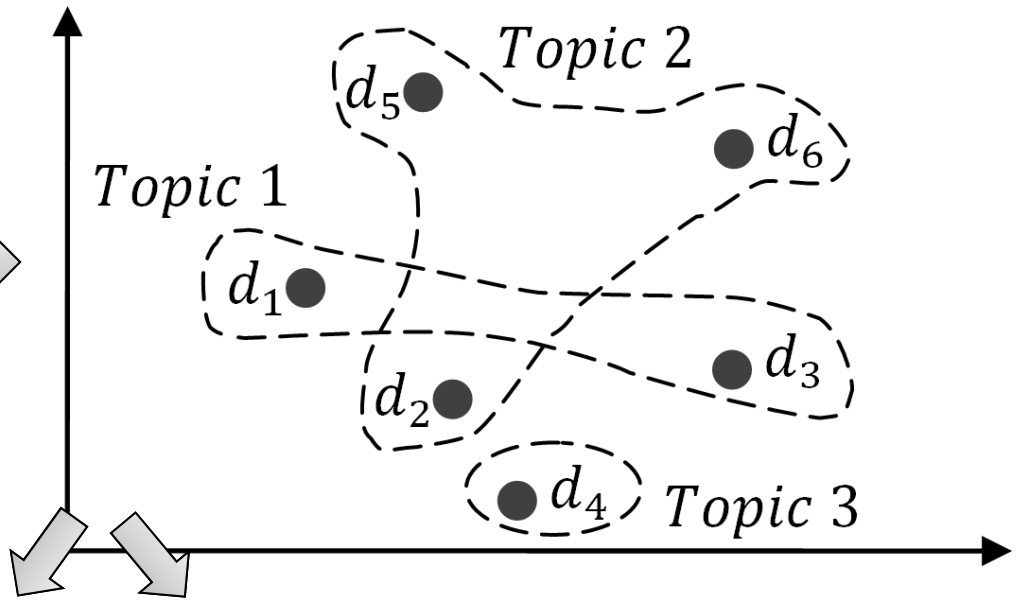
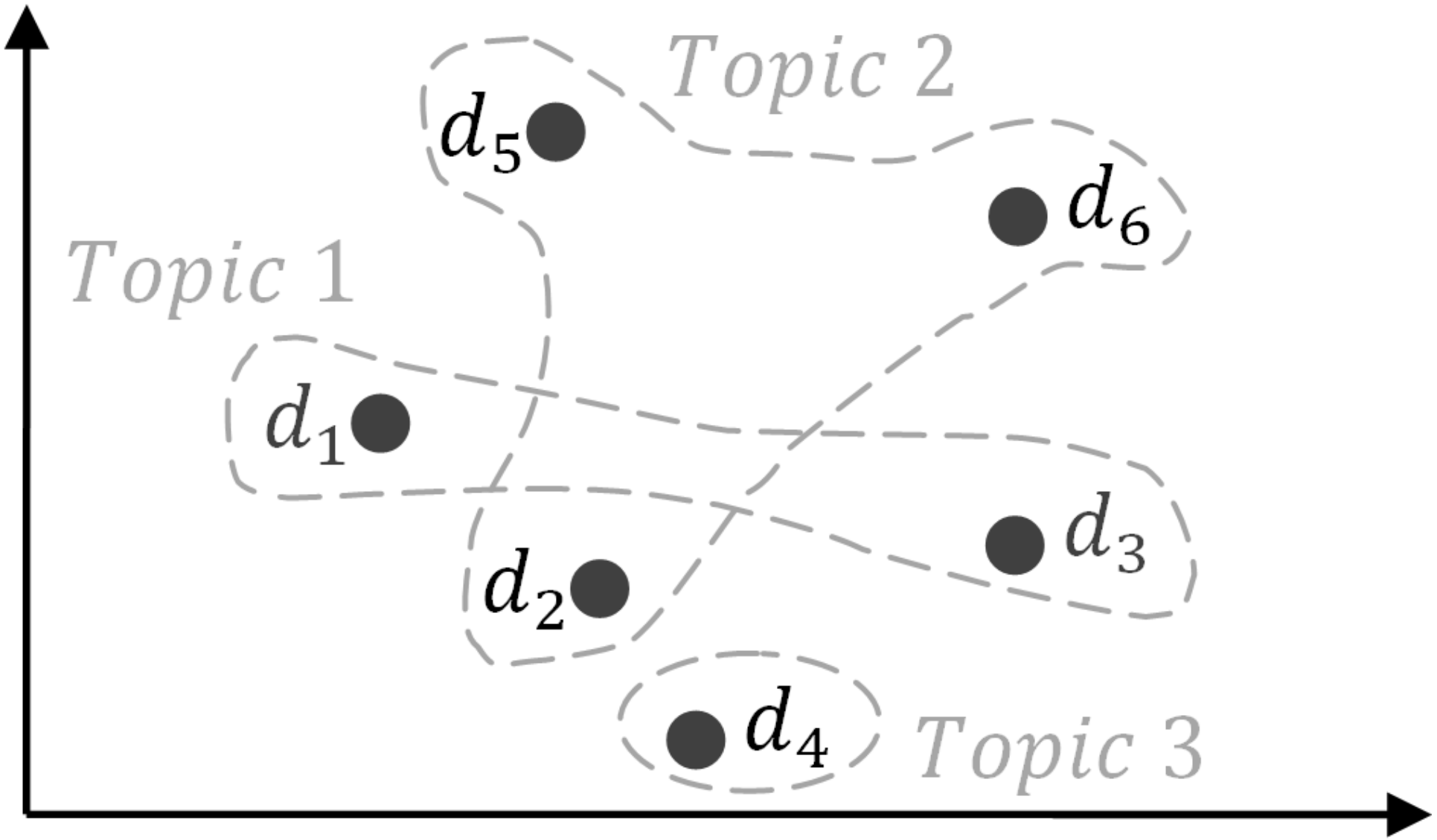
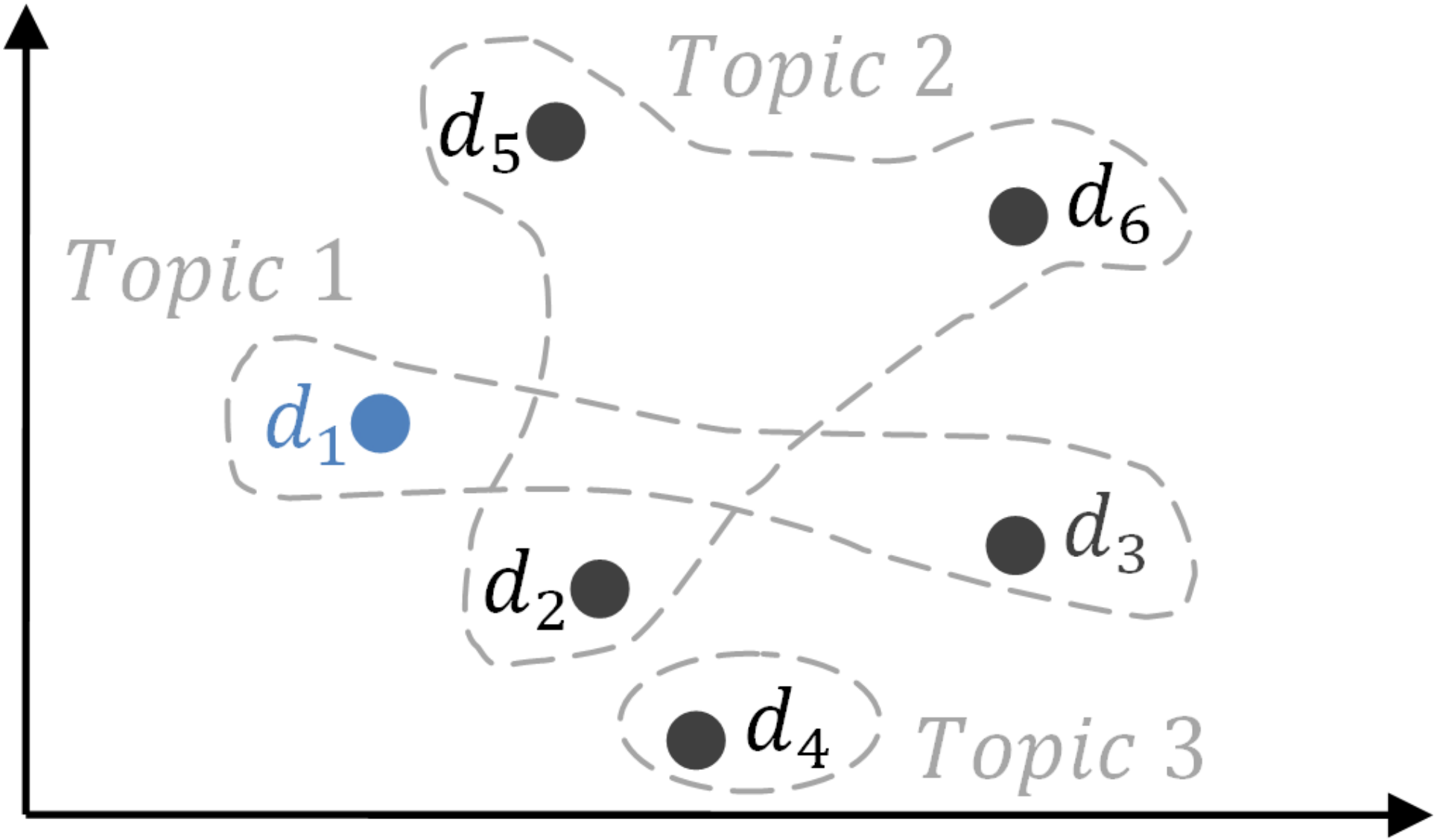


Cohesion (similarity): how related the documents in the same clusters are

Separation (dissimilarity): how distinct a cluster is from other clusters


Topic 2
d_5
d_6
Topic 1
d_1
d_3
d_2
d_4
Topic 3


Topic 2
d_5
d_6
Topic 1
d_1
d_3
d_2
d_4
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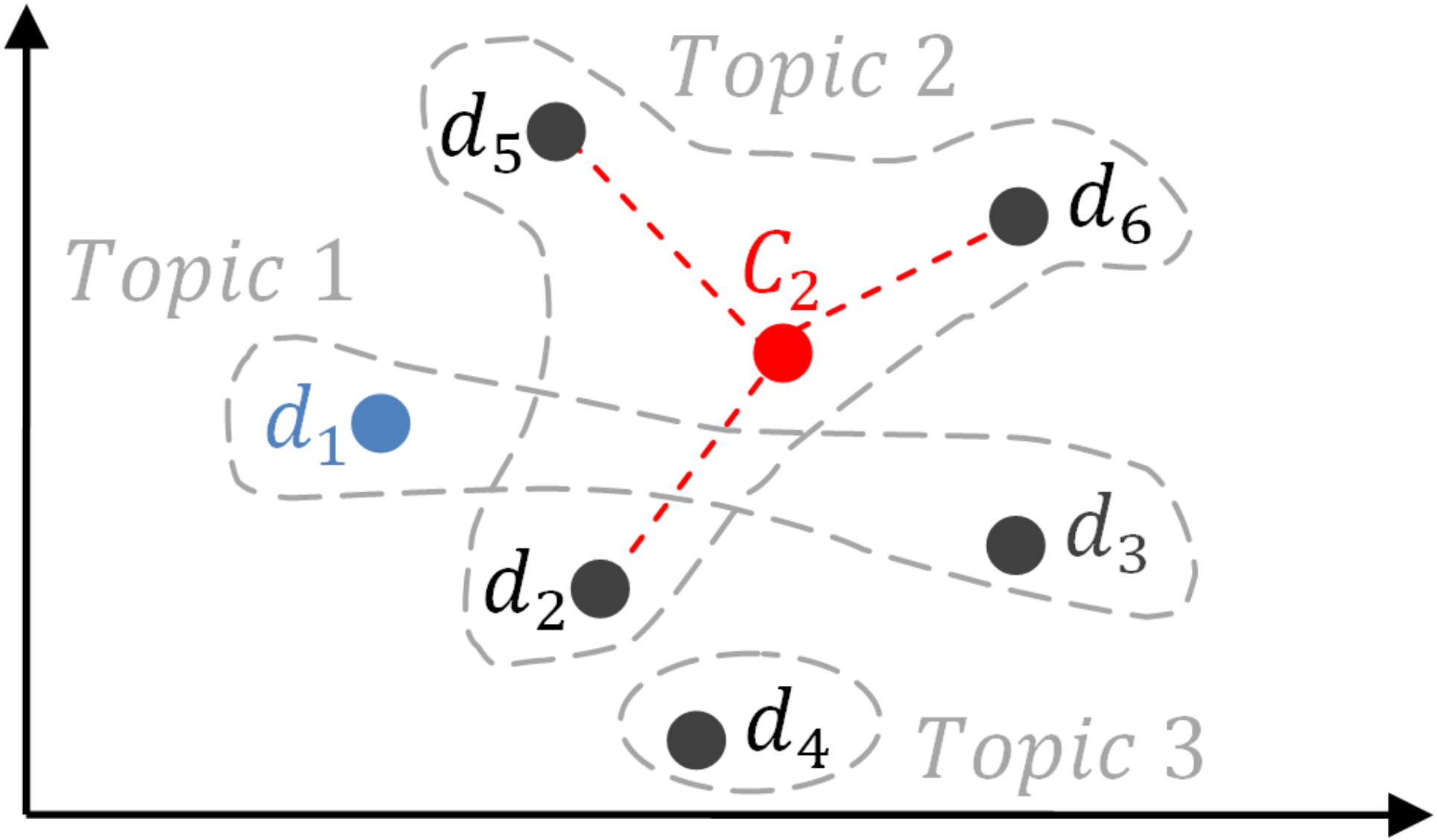
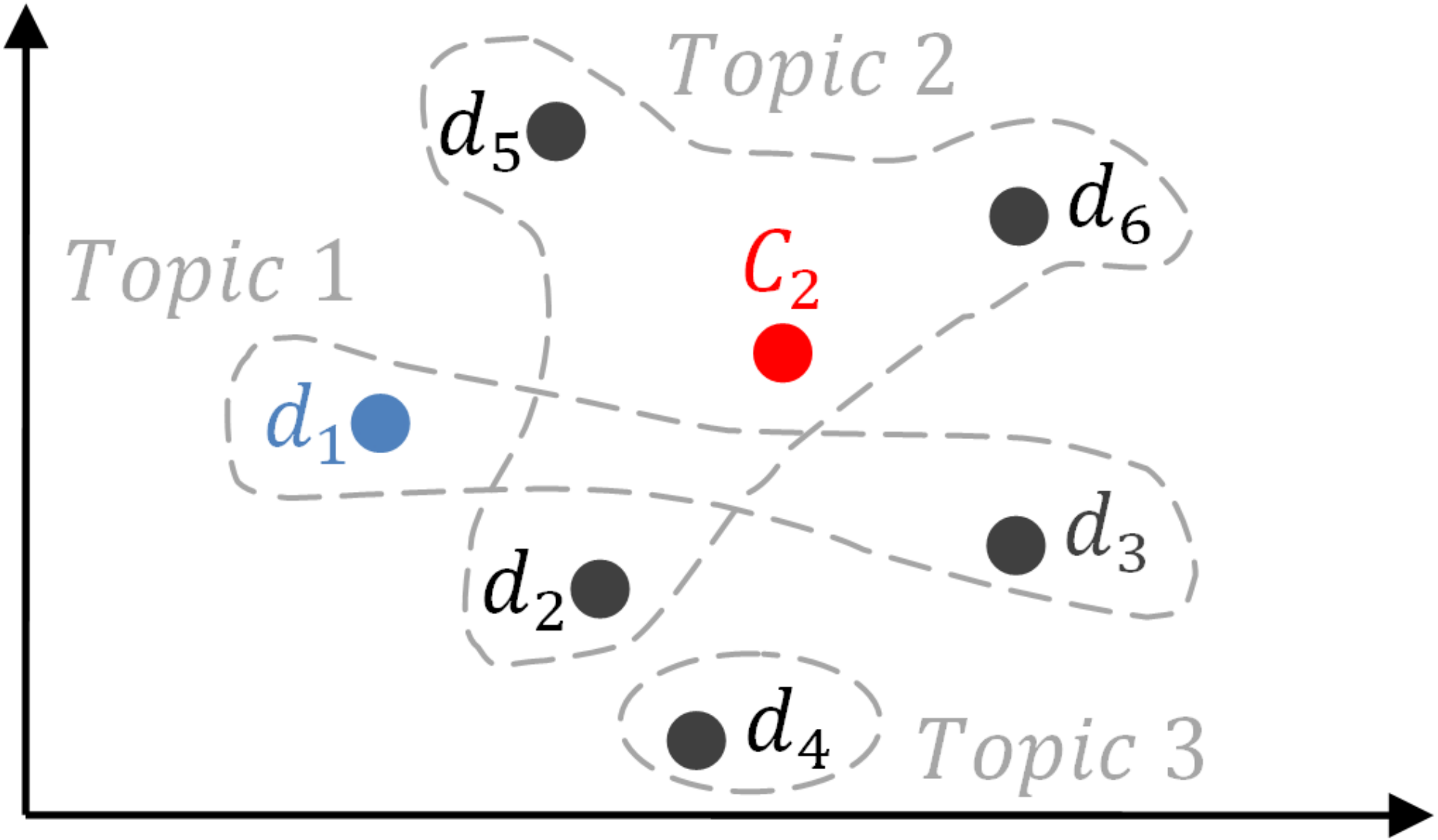

Topic 2
d_5
d_6
C_2
Topic 1
d_1
d_3
d_2
d_4
Topic 3


Topic 2
d_5
d_6
Topic 1
C_2
d_1
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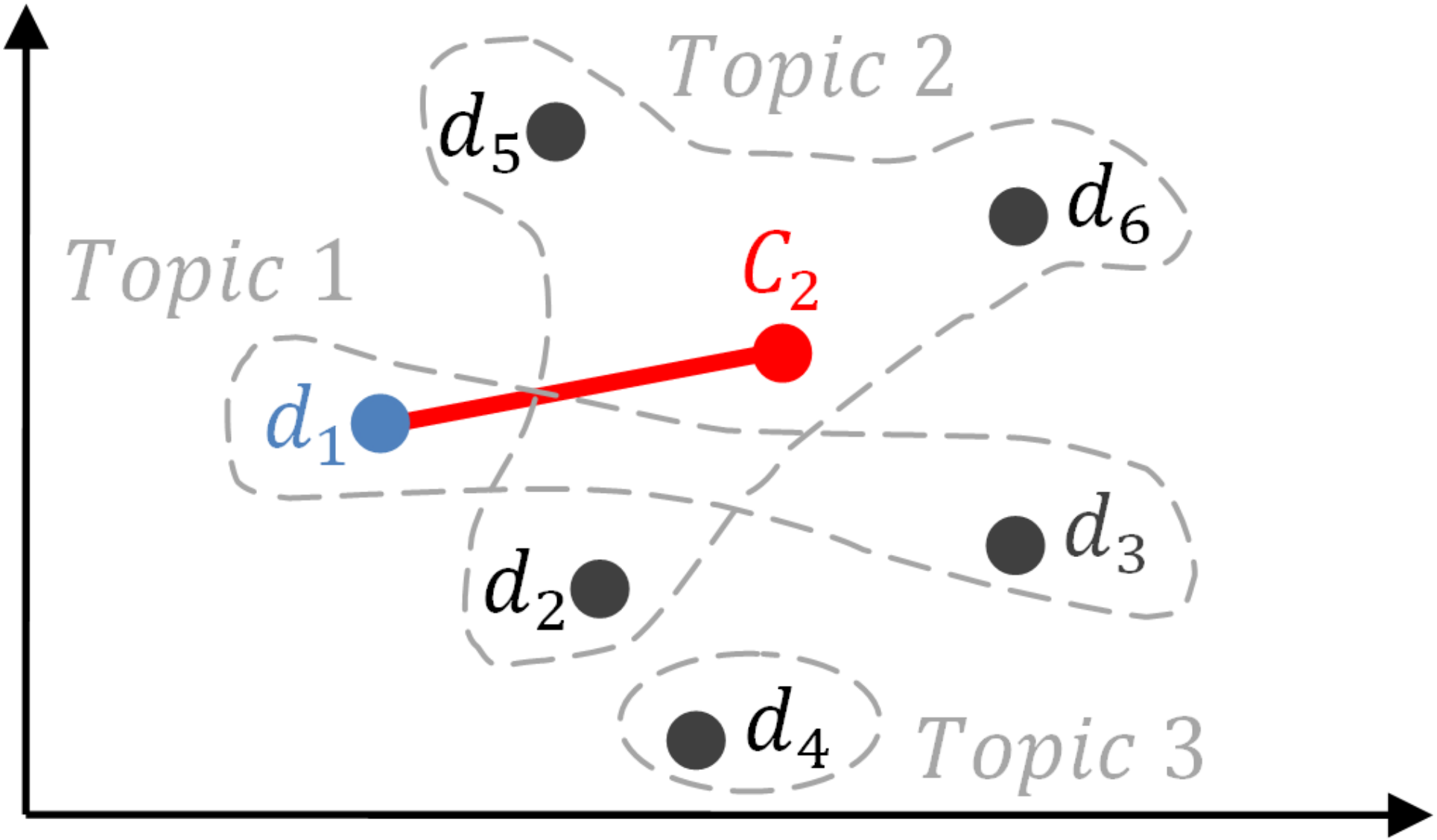
Topic 2
d_5
d_6
Topic 1
C_2
d_1
d_3
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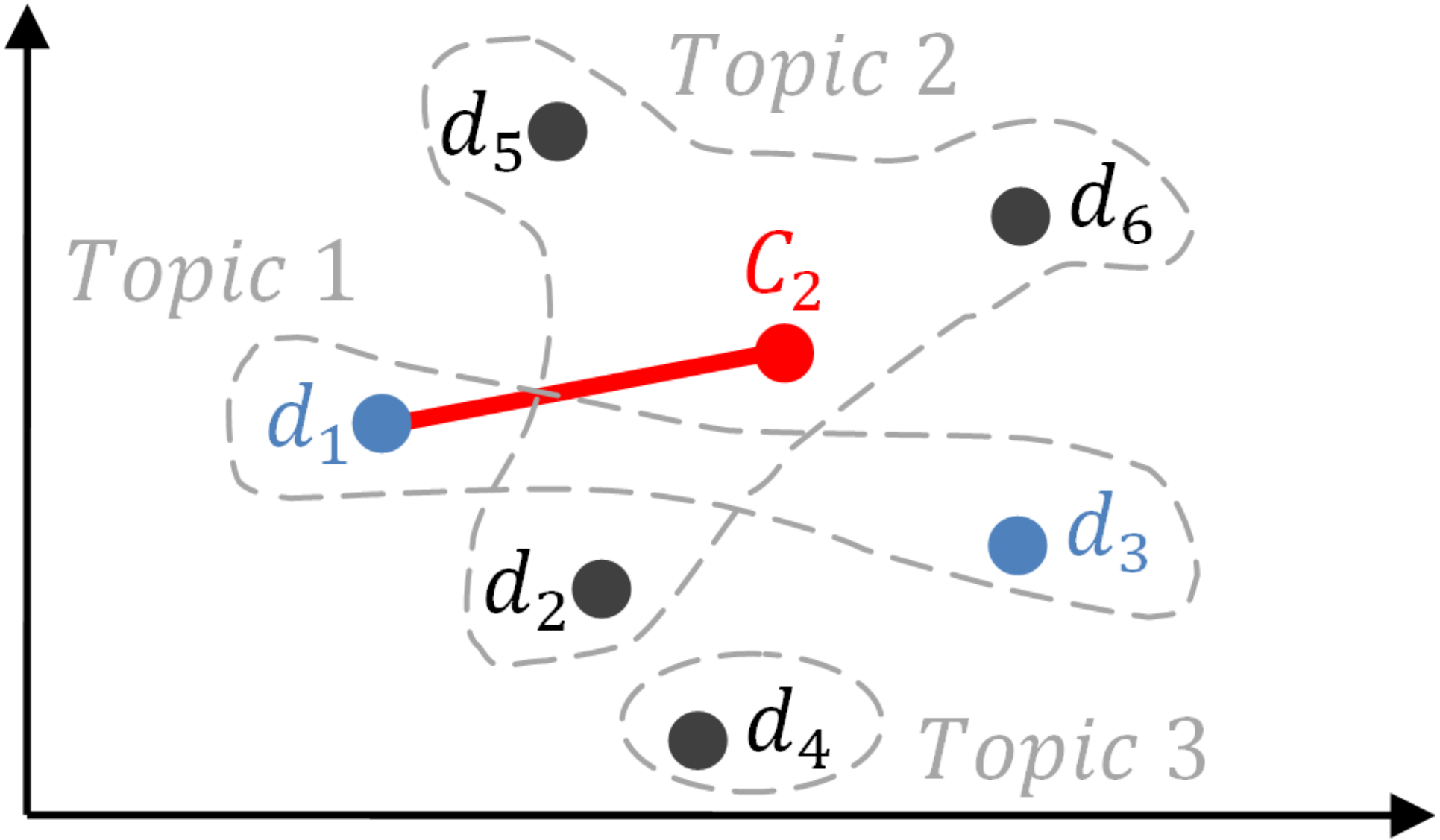
Topic 3


Topic 2
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C_2
d_1
d_3
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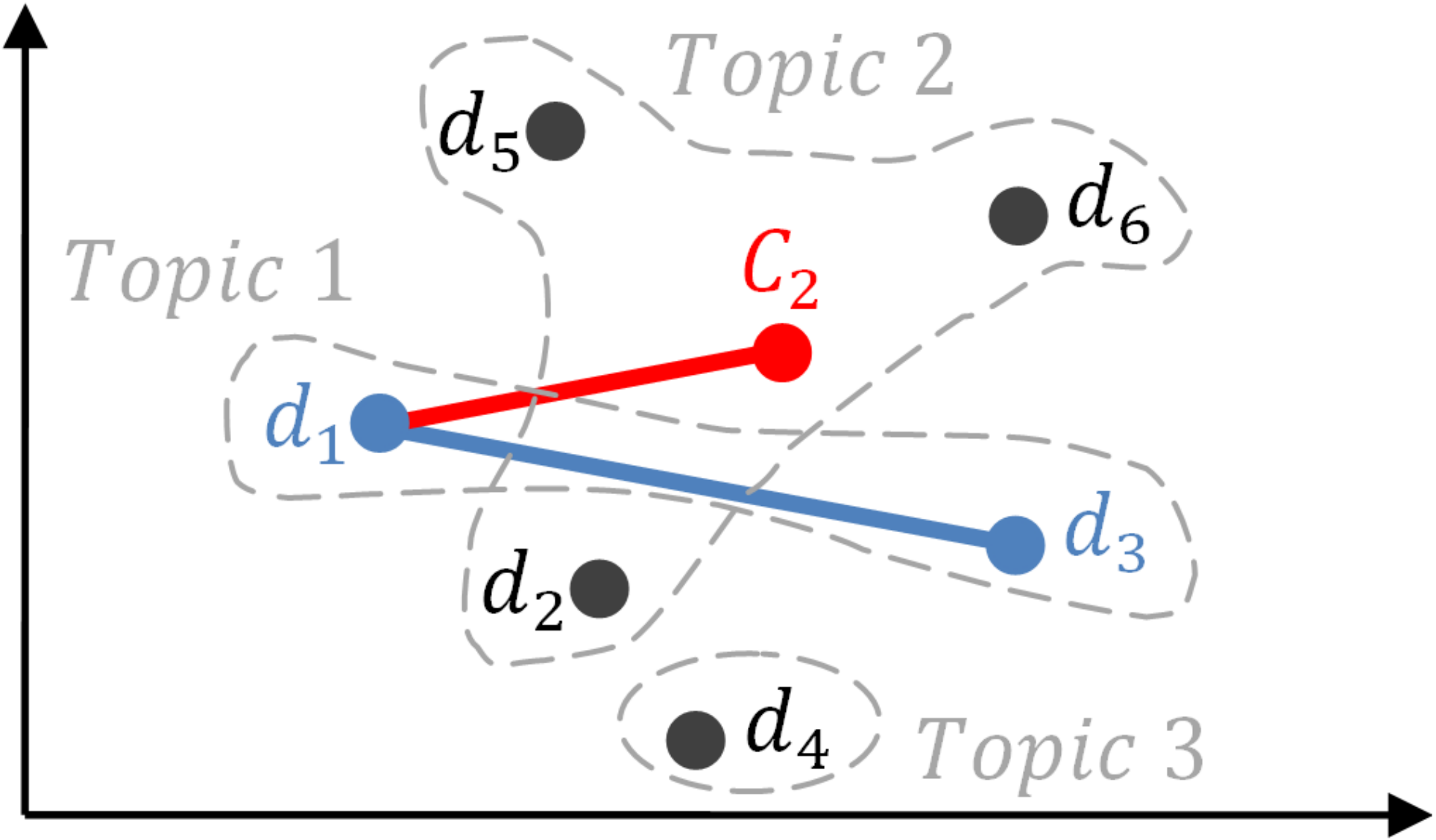
d_4
Topic 3


Topic 2
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d_6
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C_2
d_1
d_3
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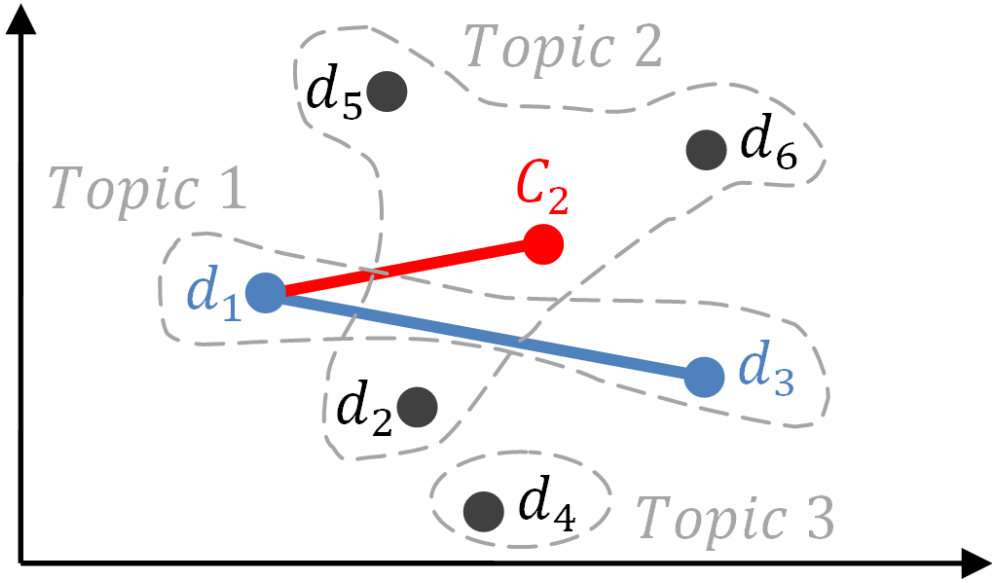
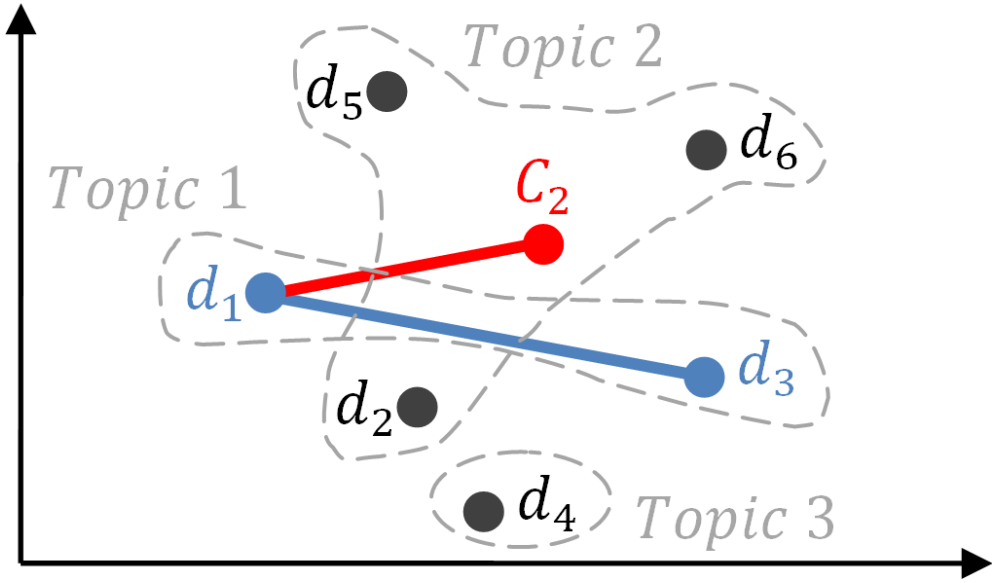
d_4
Topic 3



$$silhouette(doc) = \frac{red - blue}{\max(red, blue)}$$



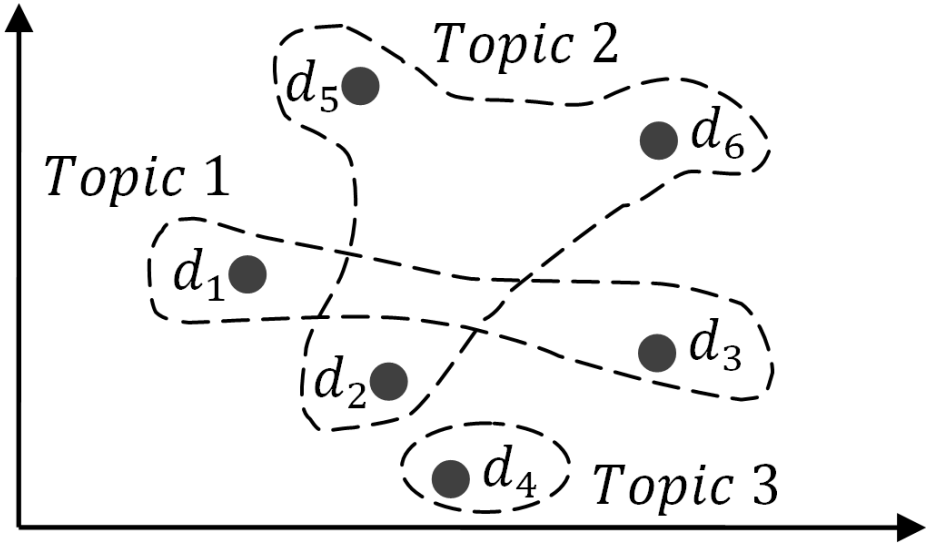
$$silhouette(doc) = \frac{red - blue}{\max(red, blue)}$$

$$silhouette(LDA\ model) = \frac{silhouette(doc_1) + \cdots + silhouette(doc_n)}{number\ of\ documents}$$

Higher silhouette coefficients are better

LDA Model 1

#Iterations$_1$; #topics$_1$; α_1; β_1



LDA Model 1

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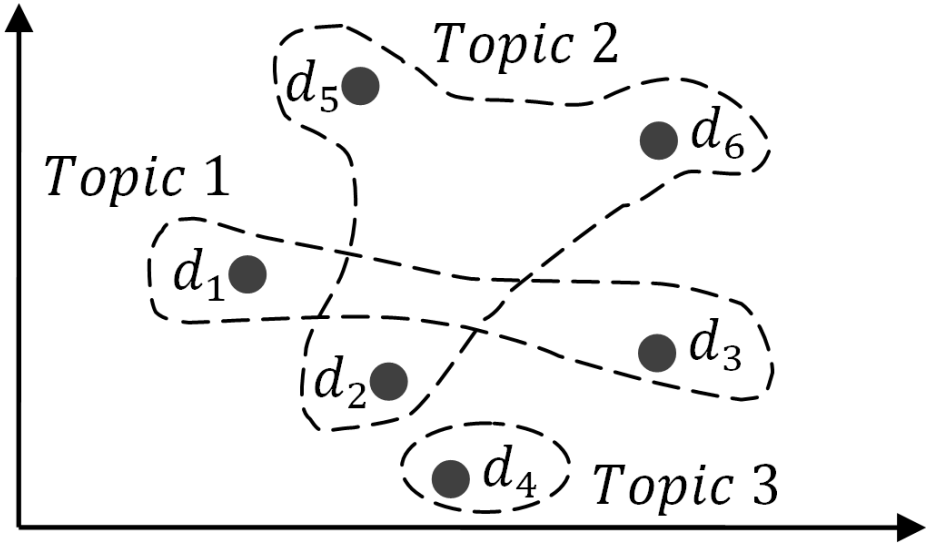
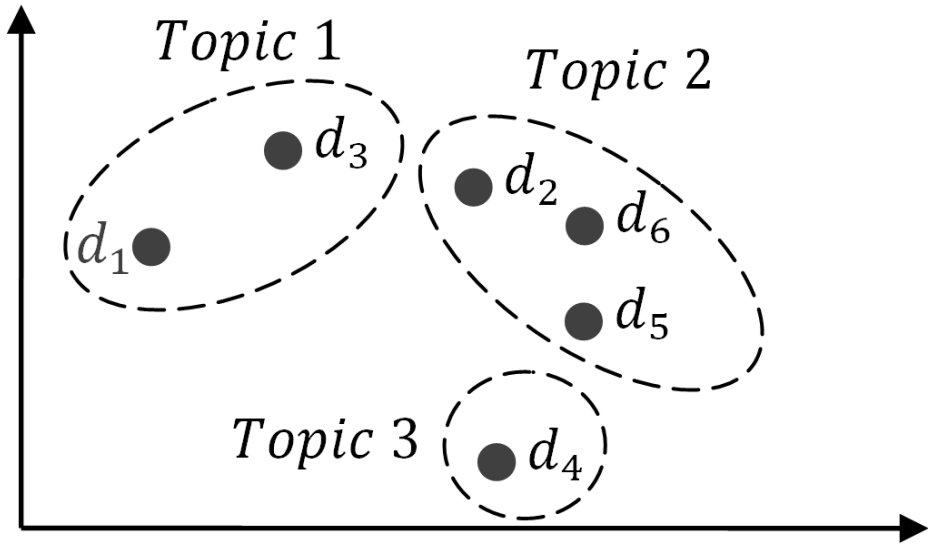


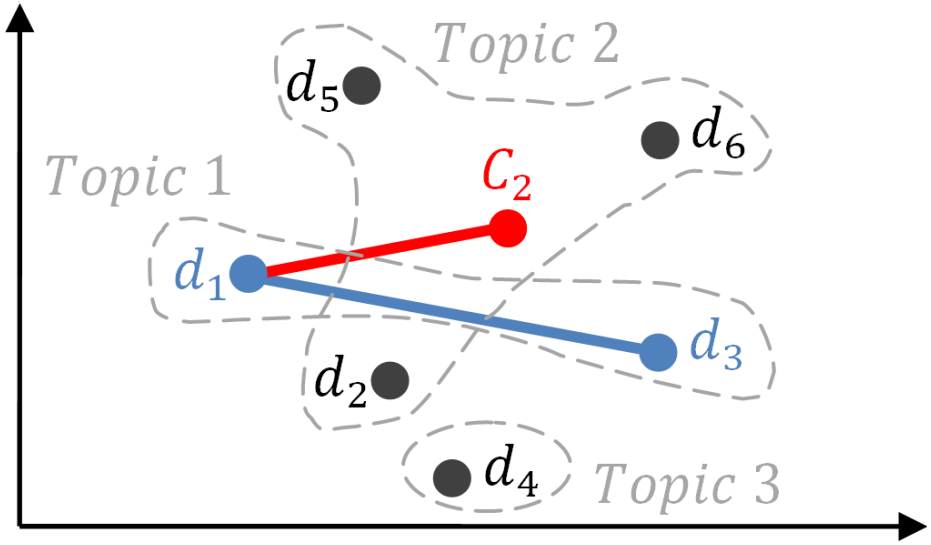
LDA Model 2

#Iterations$_2$; #topics$_2$; α_2; β_2



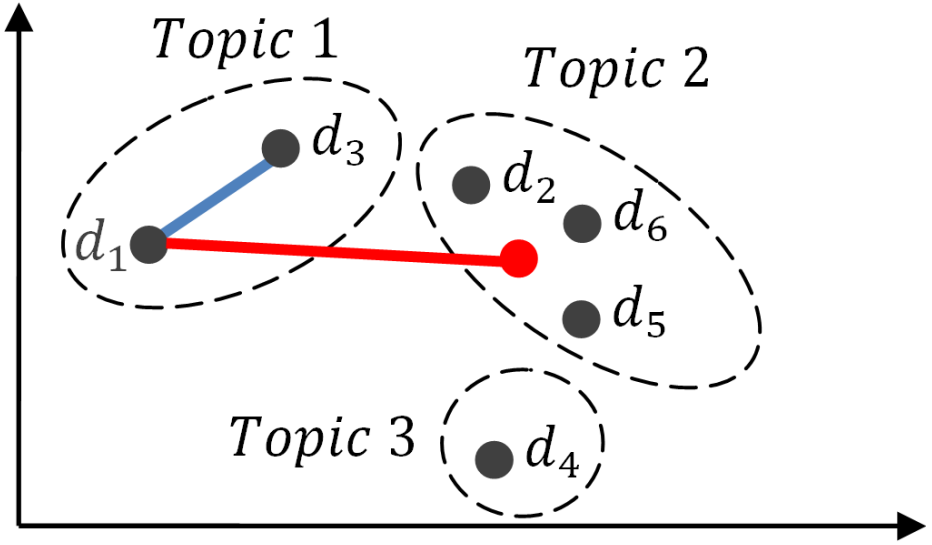
LDA Model 1

#Iterations$_1$; #topics$_1$; α$_1$; β$_1$



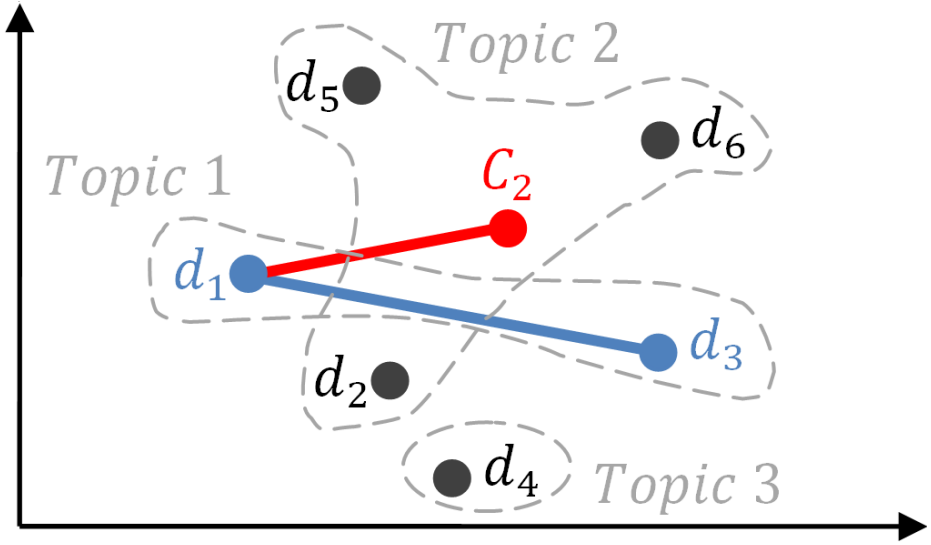
LDA Model 2

#Iterations$_2$; #topics$_2$; α$_2$; β$_2$



LDA Model 1

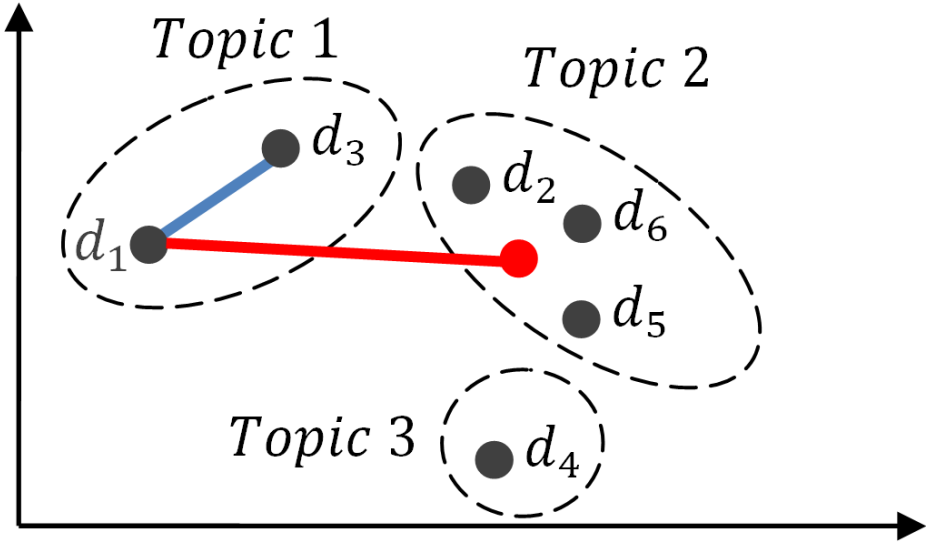
#Iterations$_1$; #topics$_1$; α$_1$; β$_1$



silhouette = 0.3

LDA Model 2

#Iterations$_2$; #topics$_2$; α$_2$; β$_2$



silhouette = 0.9

Clusters more cohesive
Clusters well separated

How to **evaluate** how "good" an LDA configuration is?

How to **identify** the "good" LDA parameter configurations?

How to identify the "good" LDA parameter configurations?

```
for numIter in [500, …]
    for numTopics in [5, …]
        for α in [0.01, …]
            for β in [0.01, …]
                LDA[numIter , numTopics , α, β]
```

Exhaustive approach:
- Discretize search space & iterate?

How to identify the "good" LDA parameter configurations?

```
for numIter in [500, …]
    for numTopics in [5, …]
        for α in [0.01, …]
            for β in [0.01, …]
                LDA[numIter, numTopics , α, β]
```

Exhaustive approach:
- Discretize search space & iterate?

Too many possibilities

Use a Genetic Algorithm

What is a **G**enetic **A**lgorithm (GA)?

- Stochastic search technique based on the process of natural evolution to identify *near-optimal solutions* to search problems

Choose a random population of LDA parameters

Choose a random population of LDA parameters

	iteration	topics	α	β
LDA Cfg. 1	510	74	0.34	2.5
LDA Cfg. 2	725	128	1.28	0.4
LDA Cfg. 3	814	97	0.43	0.9
…	…	…	…	…
LDA Cfg. n	618	250	1.14	0.74

First generation: Population of random chromosomes

Choose a random population of LDA parameters

	iteration	topics	α	β
LDA Cfg. 1	510	74	0.34	2.5
LDA Cfg. 2	725	128	1.28	0.4
LDA Cfg. 3	814	97	0.43	0.9
...				
LDA Cfg. n	618	250	1.14	0.74

First generation:
Population of random chromosomes

Individual (chromosome):
Represents one possible LDA parameter configuration

Choose a random population of LDA parameters

	iteration	topics	α	β
LDA Cfg. 1	510	74	0.34	2.5
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LDA Cfg. 3	814	97	0.43	0.9
...				
LDA Cfg. n	618	250	1.14	0.74

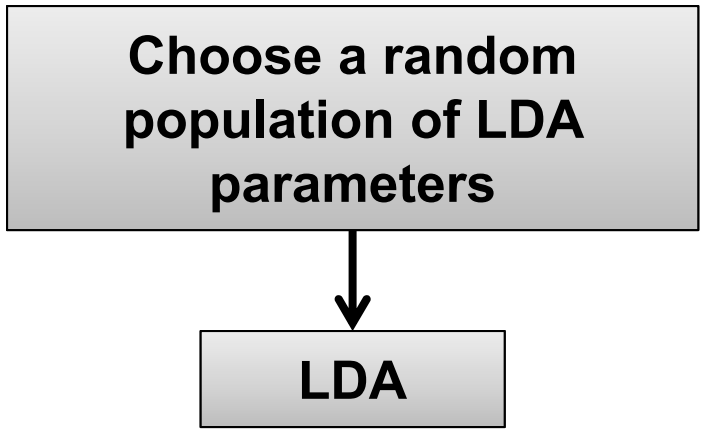
First generation:
Population of random chromosomes

Individual (chromosome):
Represents one possible LDA parameter configuration

Gene:
LDA parameter

Choose a random population of LDA parameters

	iteration	topics	α	β
LDA Cfg. 1	510	74	0.34	2.5
LDA Cfg. 2	725	128	1.28	0.4
LDA Cfg. 3	814	97	0.43	0.9
…	…	…	…	…
LDA Cfg. n	618	250	1.14	0.74



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…	…	…	…	…
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Choose a random population of LDA parameters

↓

LDA

↓

Determine **fitness** of each *chromosome* (individual)

	iteration	topics	α	β
LDA Cfg. 1	510	74	0.34	2.5
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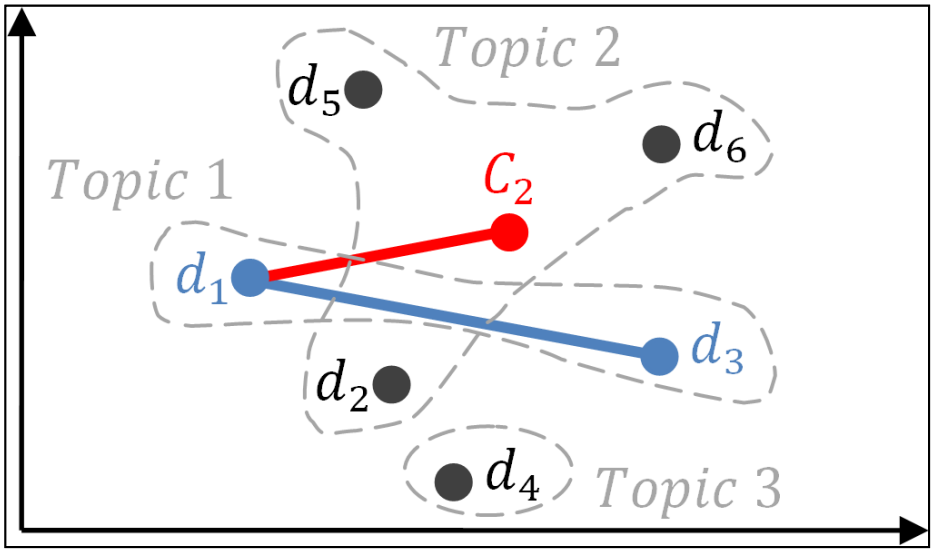
...	...	...	...	...
LDA Cfg. n	618	250	1.14	0.74

Fitness = silhouette coefficient



Choose a random population of LDA parameters

↓

LDA

↓

Determine **fitness** of each *chromosome* (individual)

	iteration	topics	α	β	Fitness
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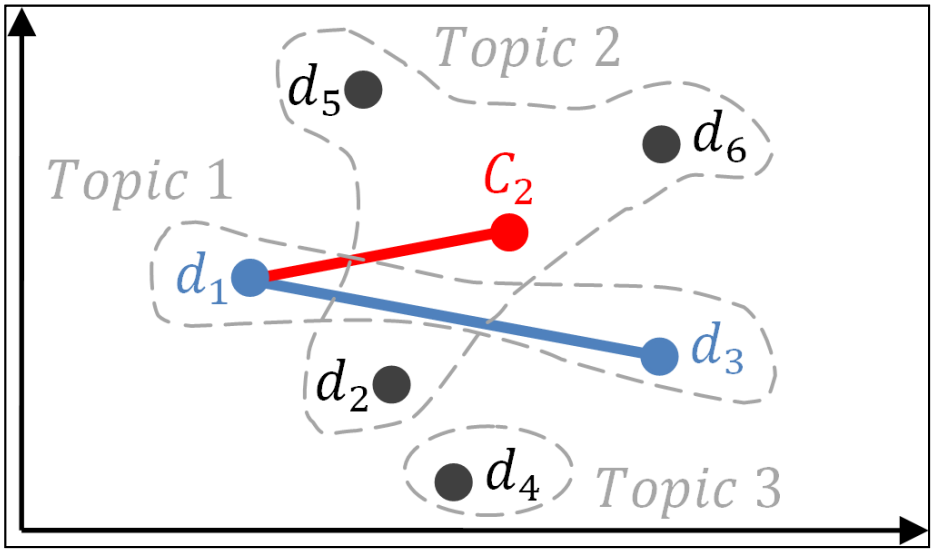
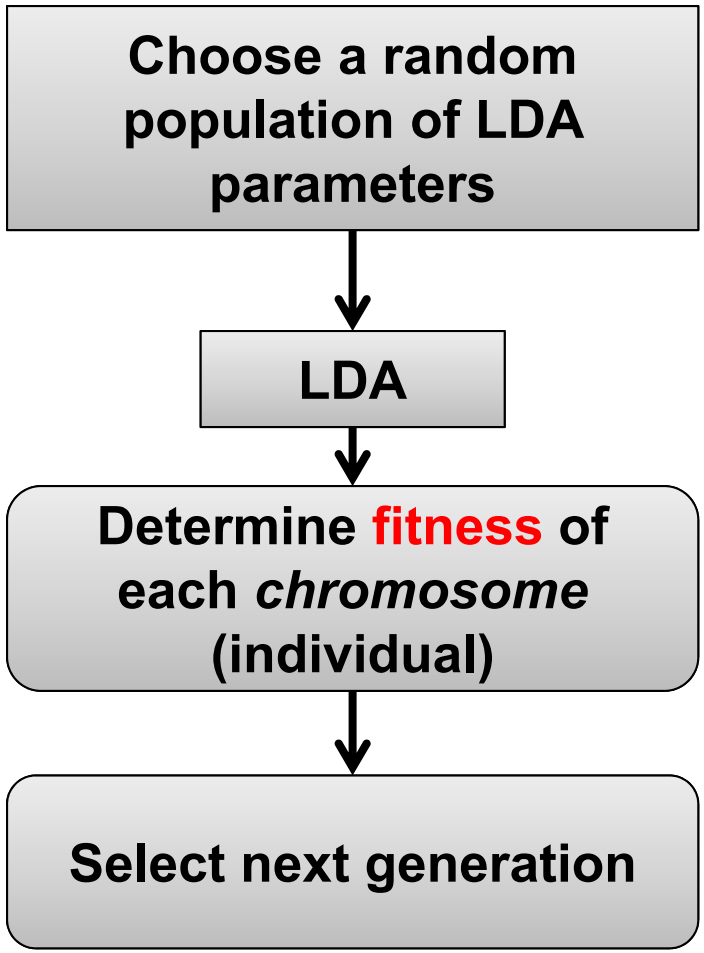
…	…	…	…	…	…
LDA Cfg. n	618	250	1.14	0.74	0.1

Fitness = silhouette coefficient





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...	...	...	...	...	...
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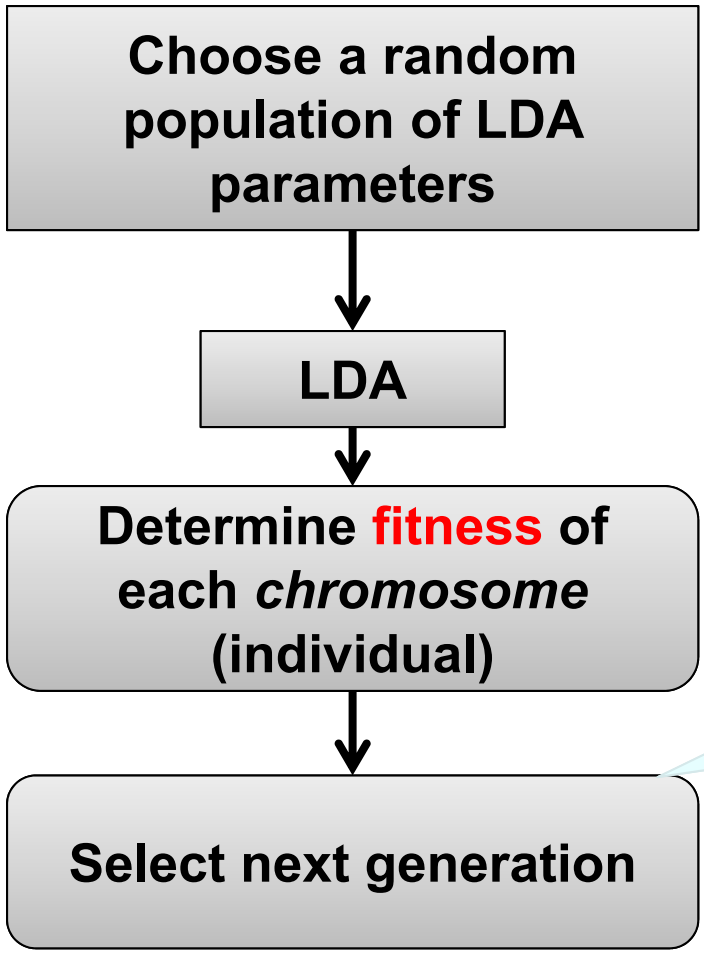

	iteration	topics	α	β	Fitness
LDA Cfg. 1	510	74	0.34	2.5	0.2
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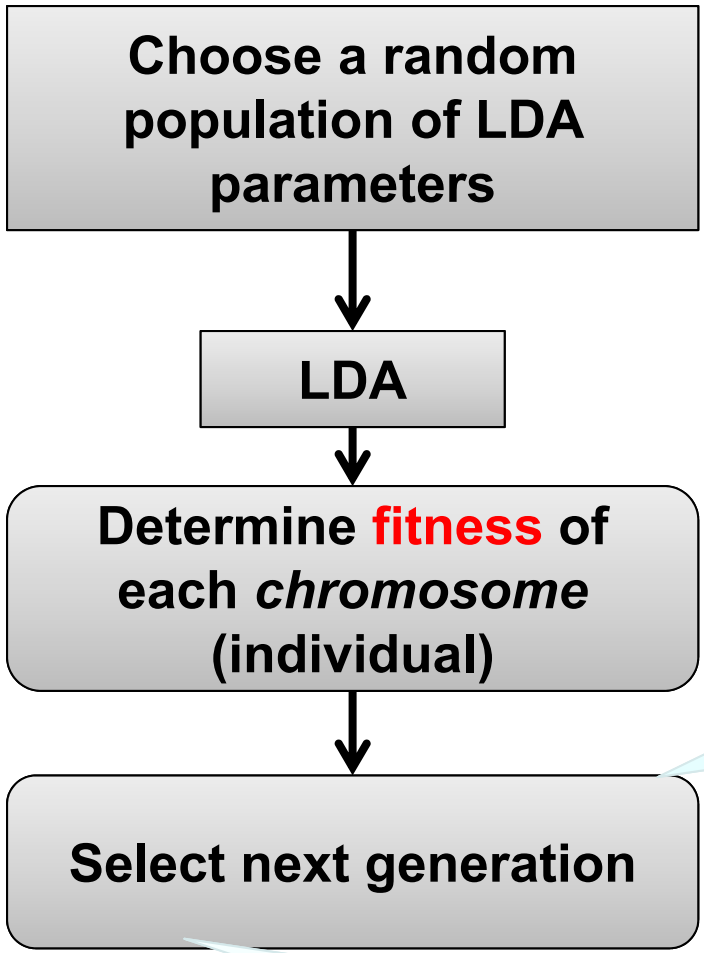
LDA Cfg. 3	814	97	0.43	0.9	0.35
...	...	...	...	...	...
LDA Cfg. n	618	250	1.14	0	0.1

Elitism:
best (n=2) configurations will survive for next generation



	iteration	topics	α	β	Fitness
LDA Cfg. 1	510	74	0.34	2.5	0.2
LDA Cfg. 2	725	128	1.28	0.4	0.4
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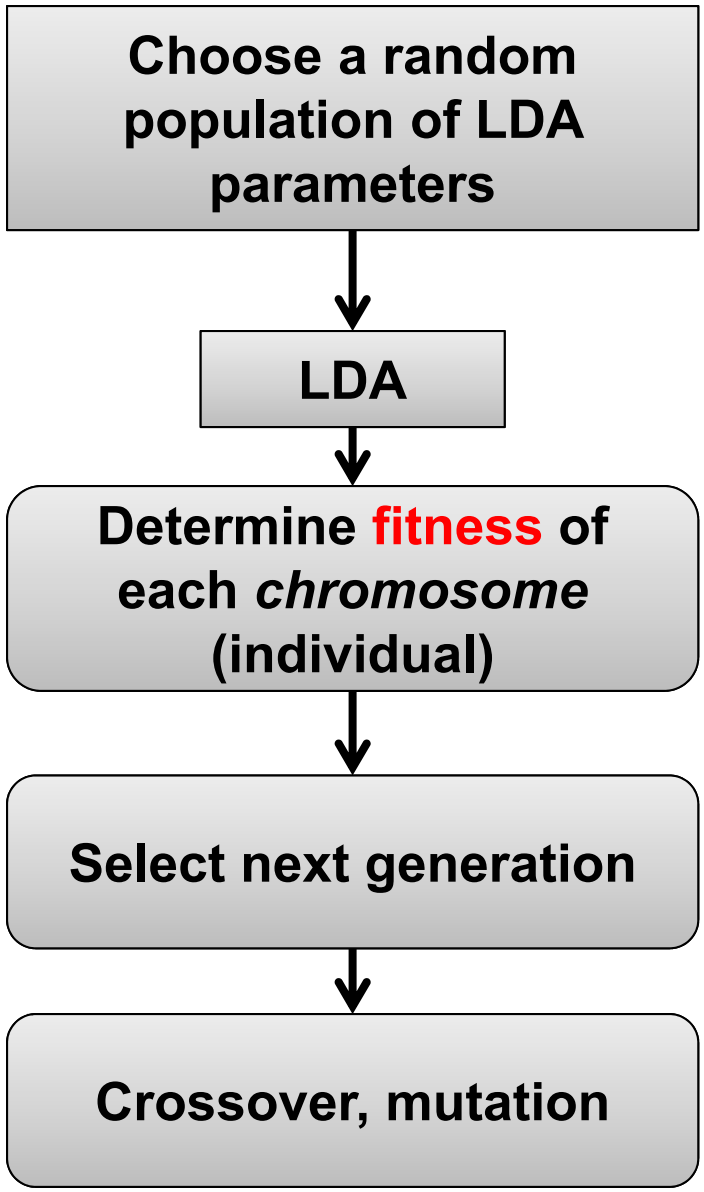
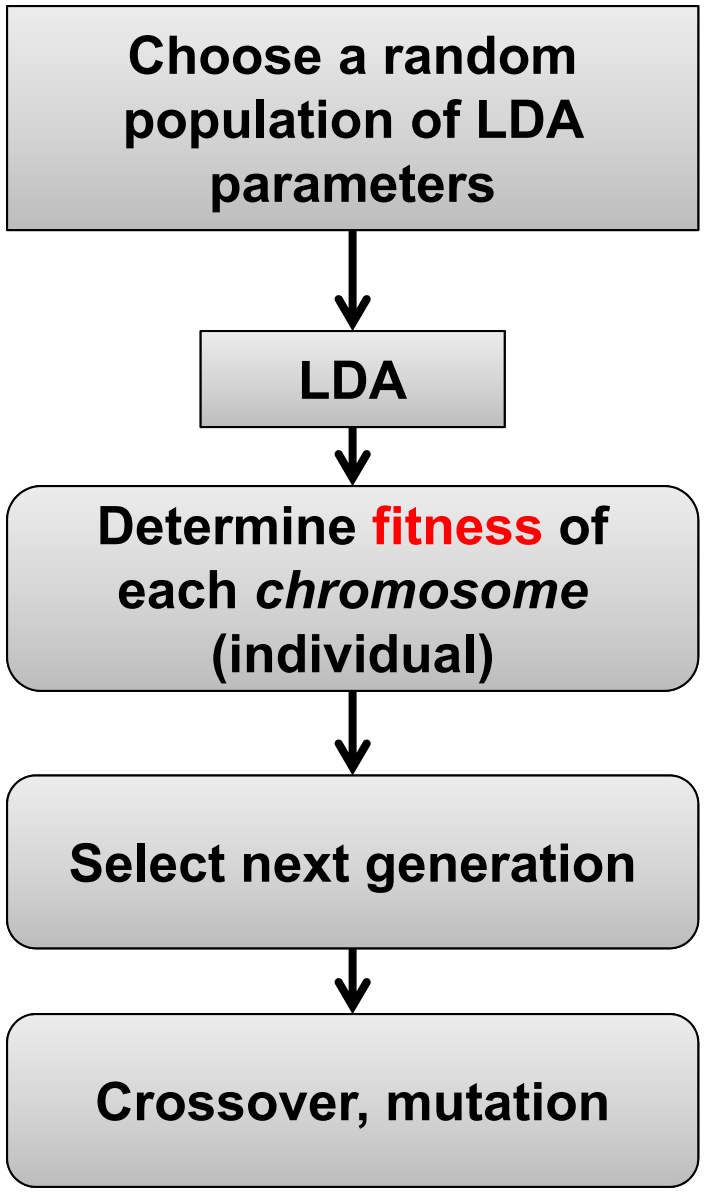
…	…	…	…	…	…
LDA Cfg. n	618	250	1.14	0	0.1

Elitism:
best (n=2) configurations will survive for next generation

Roulette selection:
Chance of chromosomes to contribute to next generation is proportional to their fitness

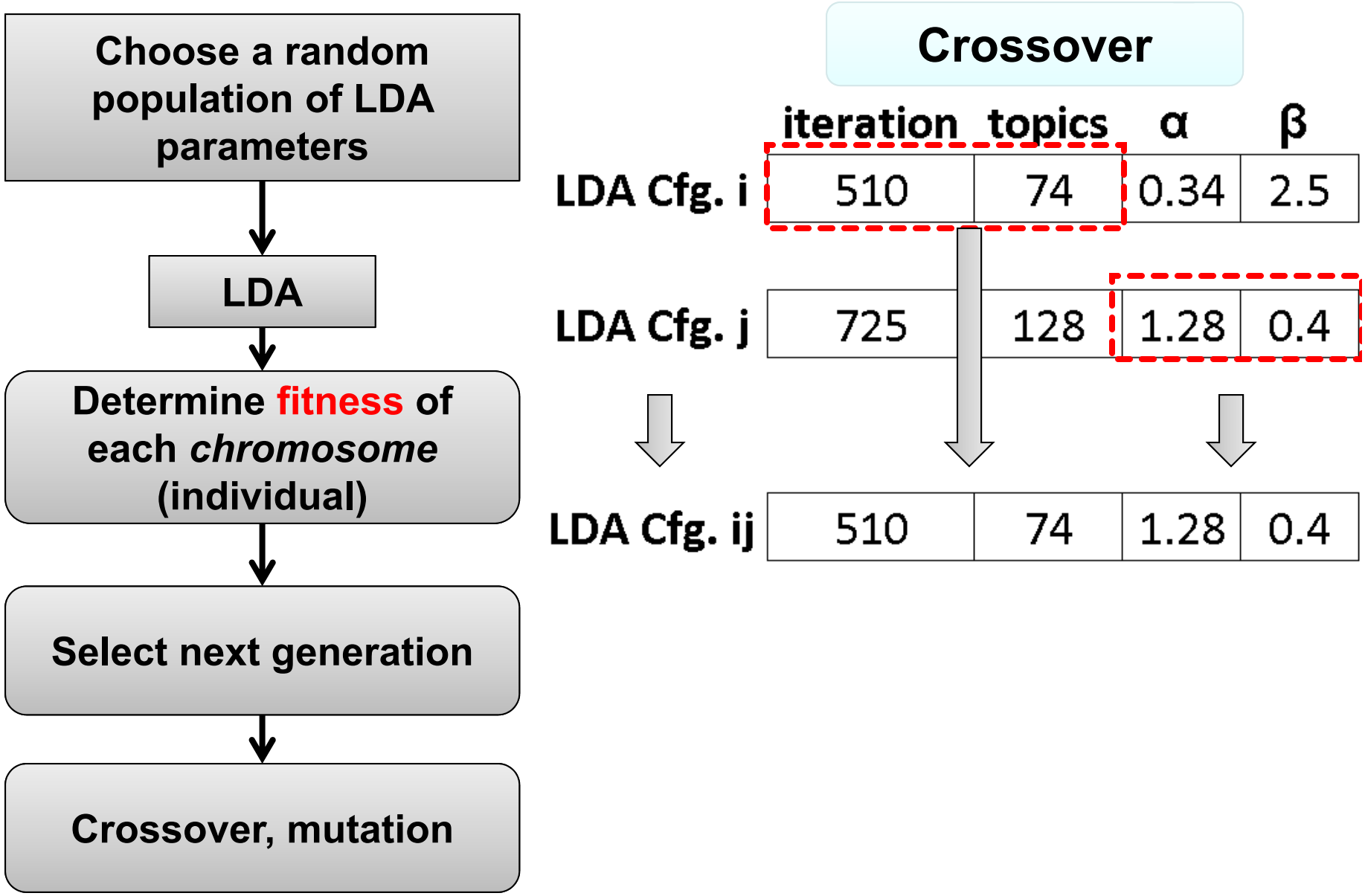

Choose a random population of LDA parameters
LDA
Determine fitness of each *chromosome* (individual)
Select next generation
Crossover, mutation

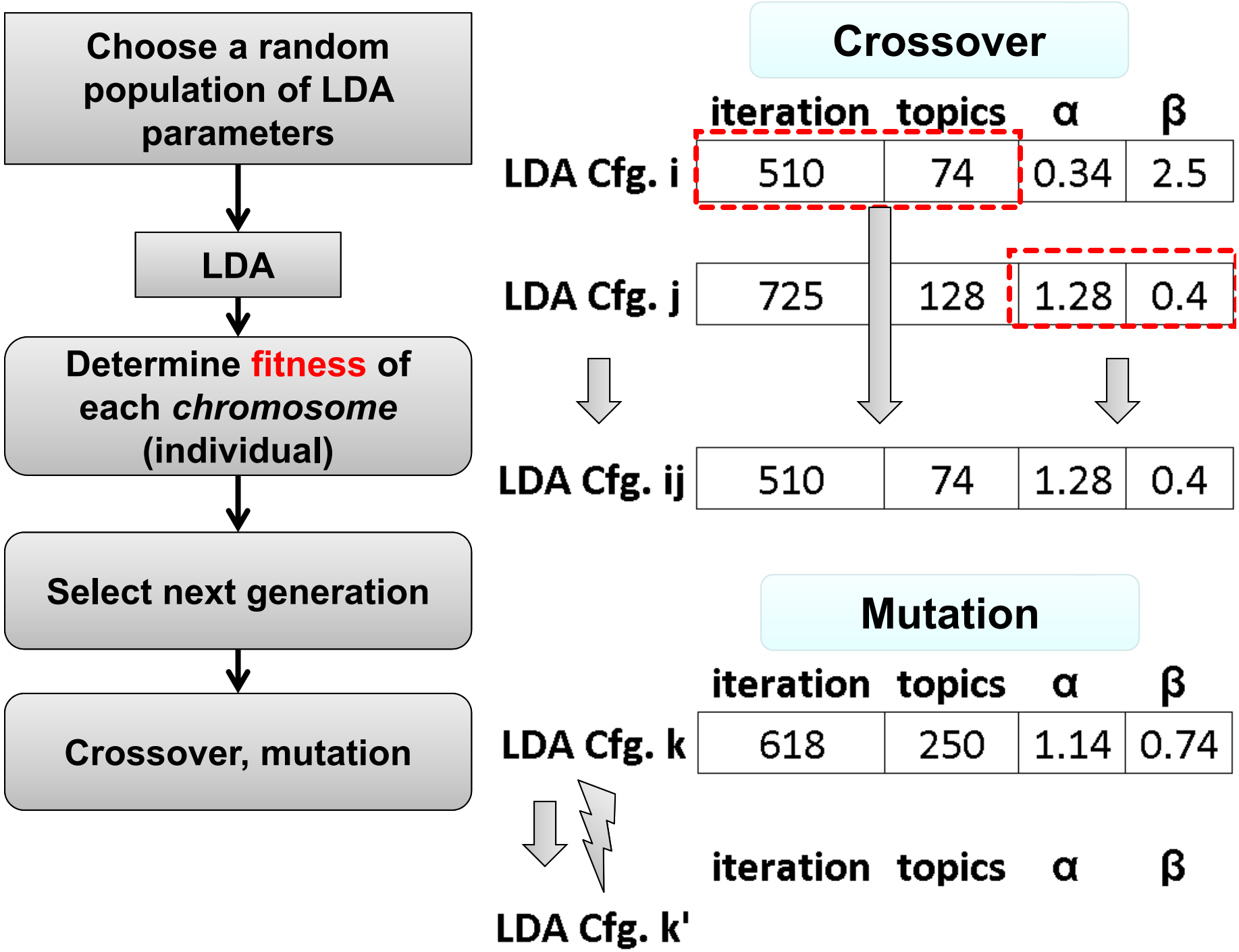


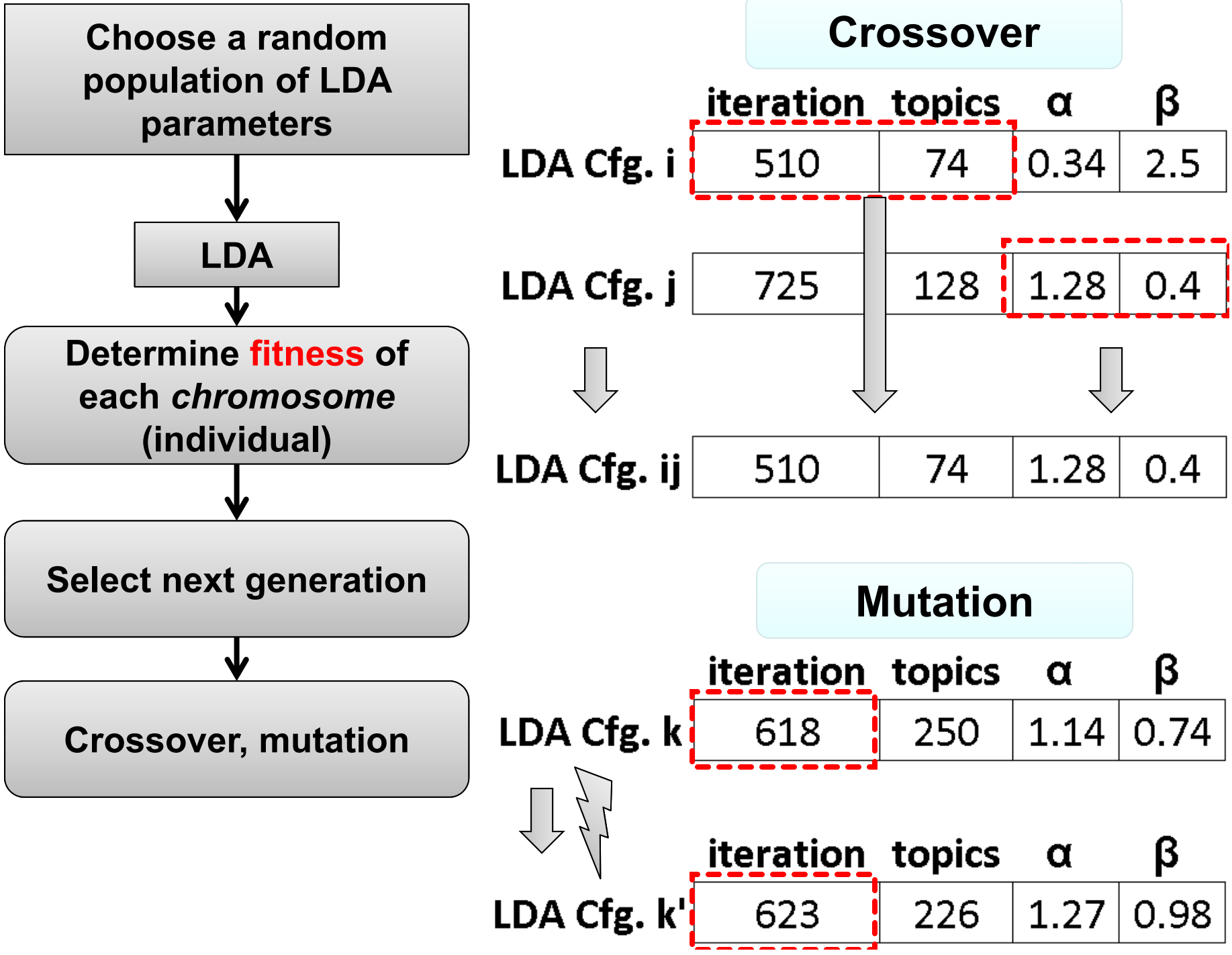
Crossover

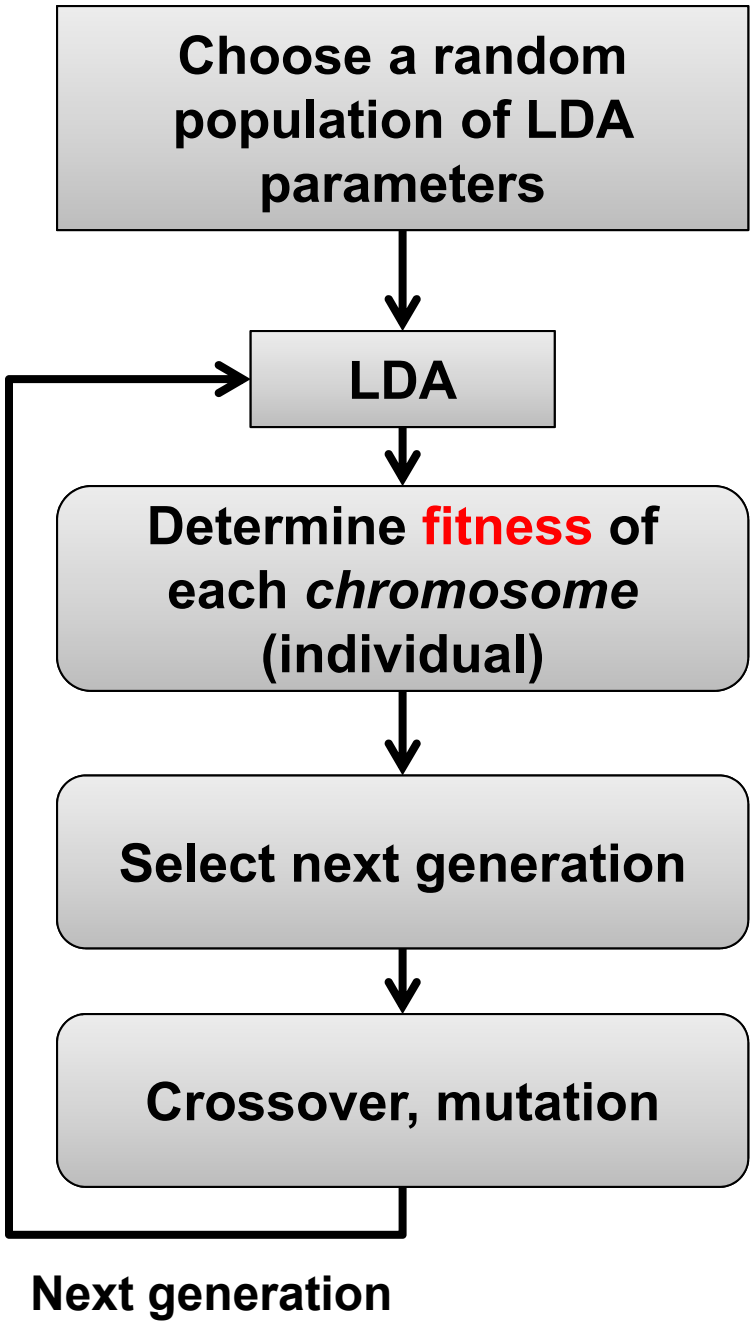
	iteration	topics	α	β
LDA Cfg. i	510	74	0.34	2.5
LDA Cfg. j	725	128	1.28	0.4

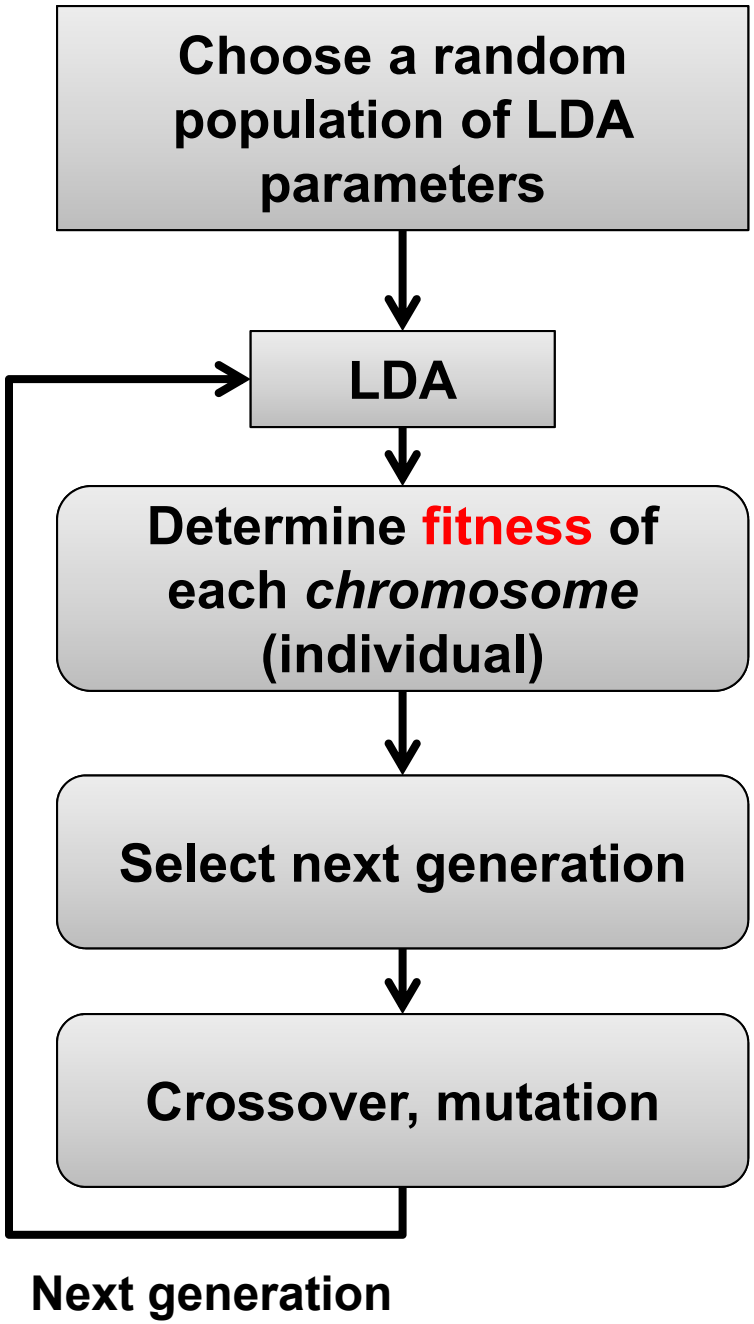
LDA Cfg. ij


Choose a random population of LDA parameters
LDA
Determine fitness of each chromosome (individual)
Select next generation
Crossover, mutation
Crossover
iteration
topics
α
β
LDA Cfg. i
510
74
0.34
2.5
LDA Cfg. j
725
128
1.28
0.4
LDA Cfg. ij
510
74
1.28
0.4

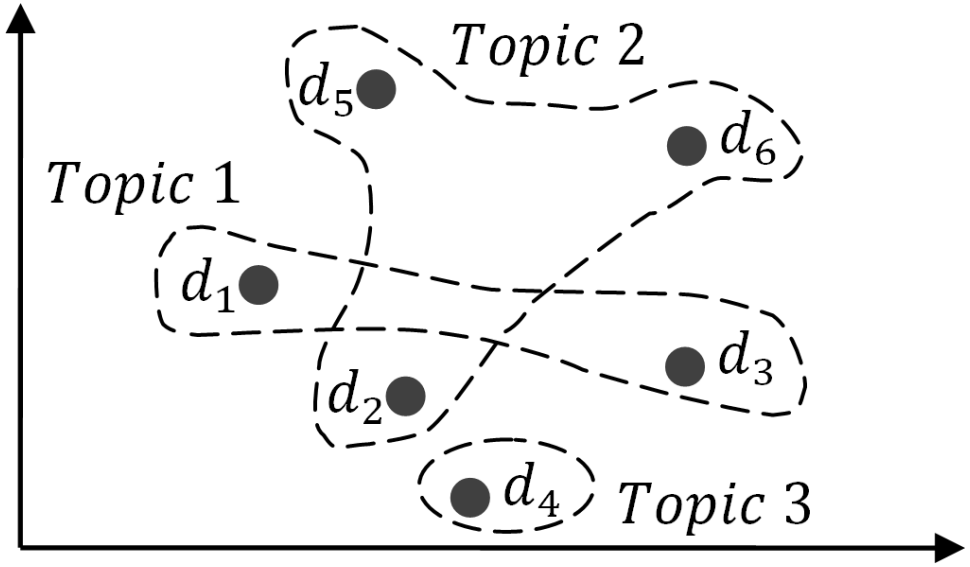

Choose a random population of LDA parameters
LDA
Determine fitness of each chromosome (individual)
Select next generation
Crossover, mutation
Crossover
iteration
topics
α
β
LDA Cfg. i
510
74
0.34
2.5
LDA Cfg. j
725
128
1.28
0.4
LDA Cfg. ij
510
74
1.28
0.4
Mutation
iteration
topics
α
β
LDA Cfg. k
618
250
1.14
0.74
iteration
topics
α
β
LDA Cfg. k'

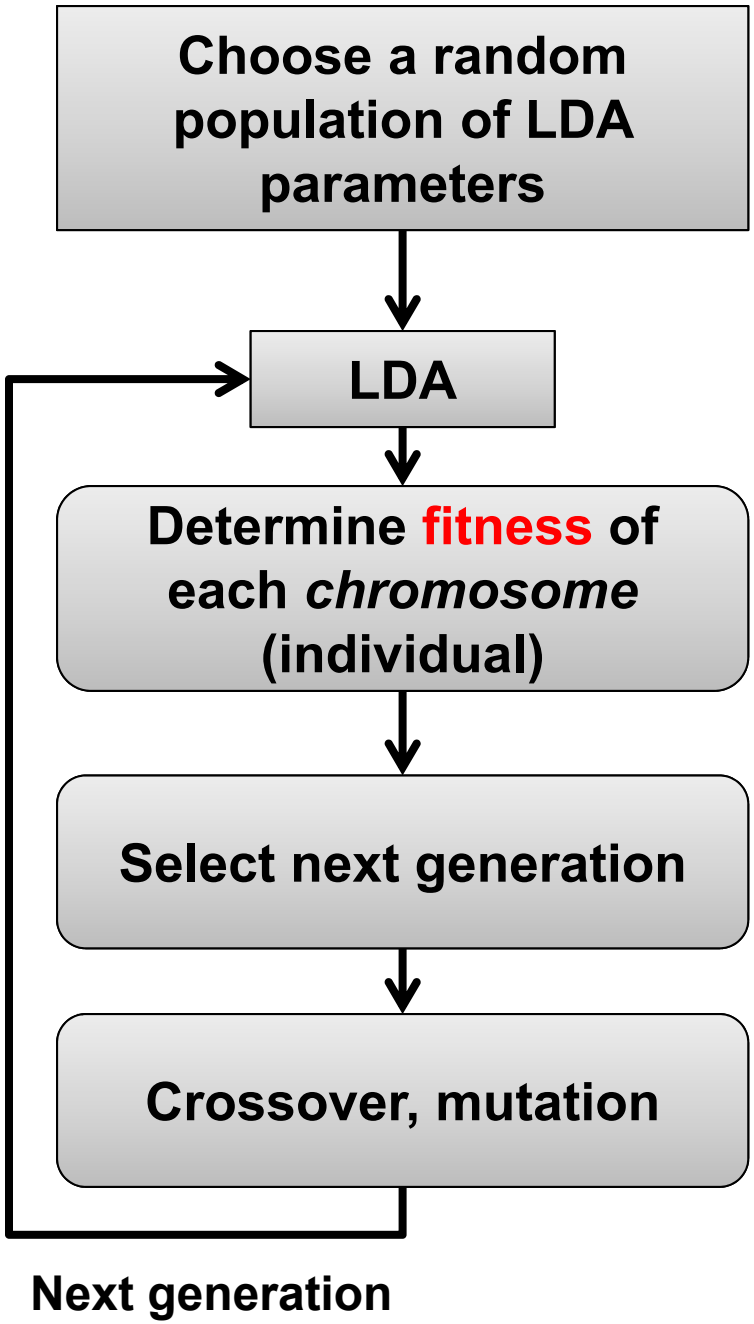

Choose a random population of LDA parameters
LDA
Determine fitness of each chromosome (individual)
Select next generation
Crossover, mutation
Crossover
iteration
topics
α
β
LDA Cfg. i
510
74
0.34
2.5
LDA Cfg. j
725
128
1.28
0.4
LDA Cfg. ij
510
74
1.28
0.4
Mutation
iteration
topics
α
β
LDA Cfg. k
618
250
1.14
0.74
iteration
topics
α
β
LDA Cfg. k'
623
226
1.27
0.98

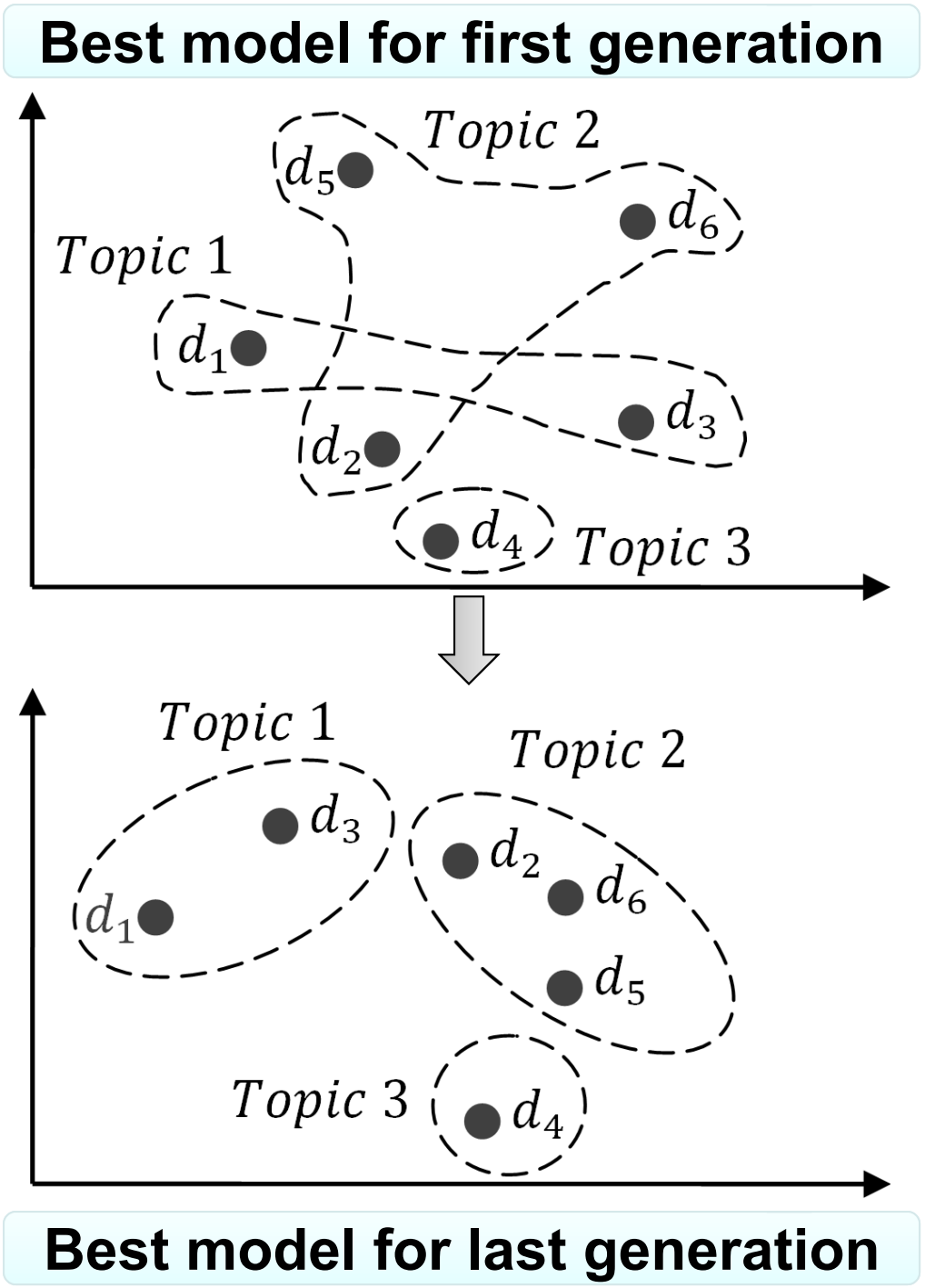

Choose a random population of LDA parameters
LDA
Determine fitness of each *chromosome* (individual)
Select next generation
Crossover, mutation
Next generation

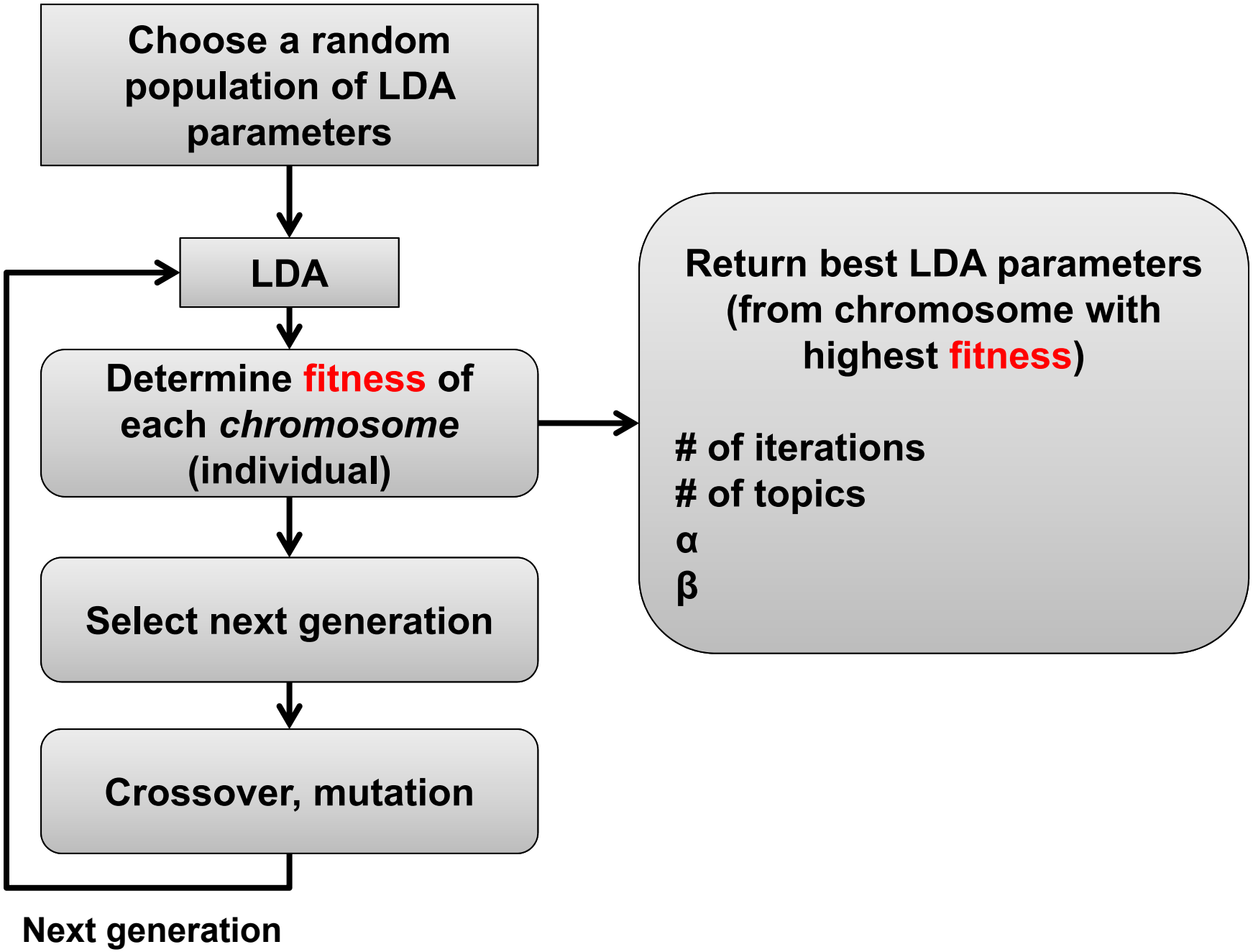


Best model for first generation

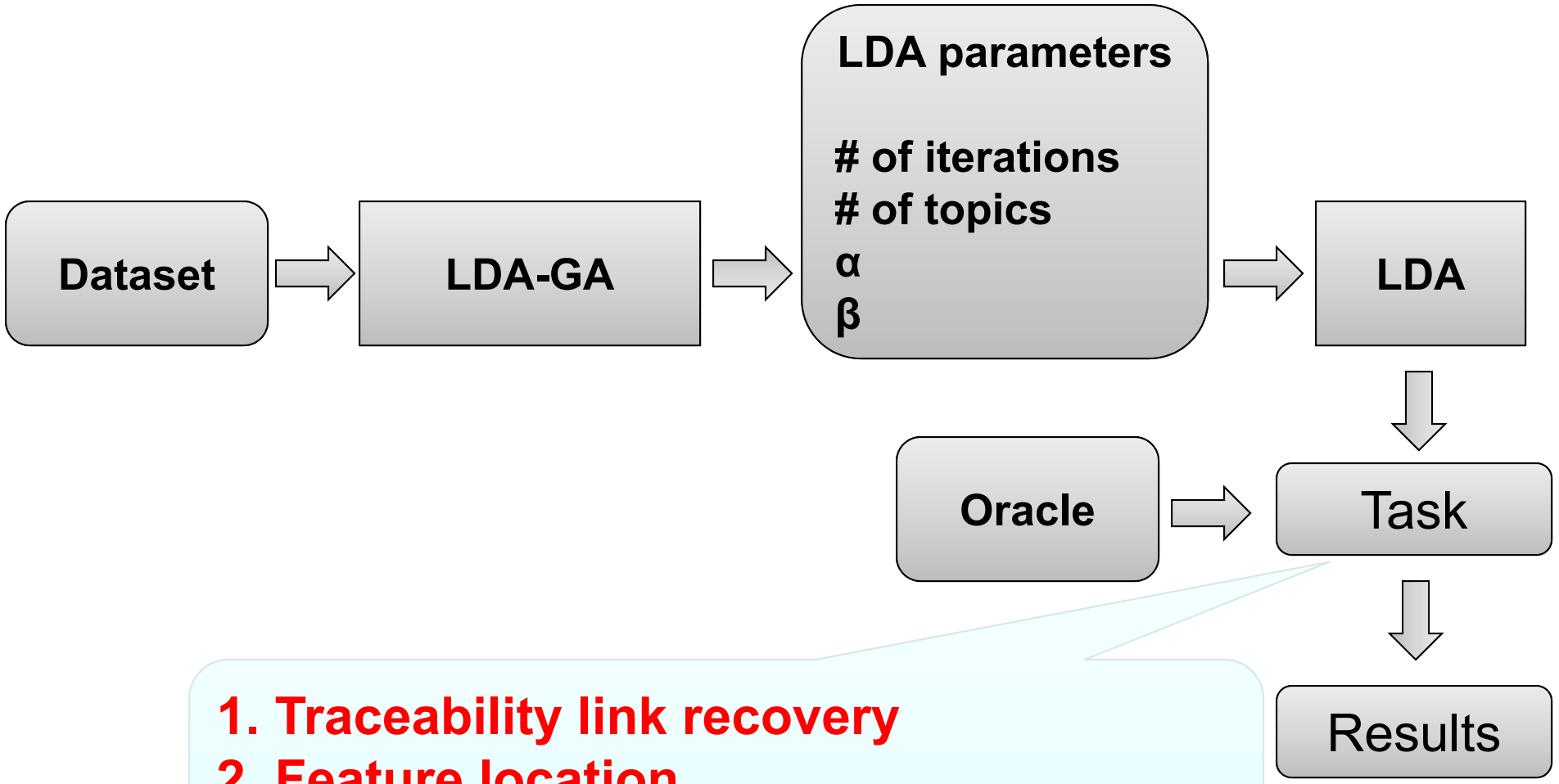



Choose a random population of LDA parameters
LDA
Determine fitness of each chromosome (individual)
Select next generation
Crossover, mutation
Next generation


Best model for first generation
Topic 2
Topic 1
Topic 3
d_1
d_2
d_3
d_4
d_5
d_6
Topic 1
Topic 2
Topic 3
Best model for last generation


Choose a random population of LDA parameters
LDA
Determine fitness of each chromosome (individual)
Select next generation
Crossover, mutation
Next generation
Return best LDA parameters (from chromosome with highest fitness)
# of iterations
# of topics
α
β

Evaluation…



1. **Traceability link recovery**
2. **Feature location**
3. **Software artifact labeling (see paper)**

Evaluation: Traceability Link Recovery

- Recover links between ***use cases*** and ***code classes***

System	Size	# use cases	# code classes	# correct links
EasyClinic	20KLOC	30	47	93
eTour	45KLOC	58	174	366

Combinatorial:

for numIter in [500, …]
  for numTopics in [5, …]
    for α in [0.01, …]
      for β in [0.01, …]
        LDA[numIter , numTopics , α, β]

Choose LDA parameters with best average precision using an *oracle*

Combinatorial:

for numIter in [500, …]
  for numTopics in [5, …]
    for α in [0.01, …]
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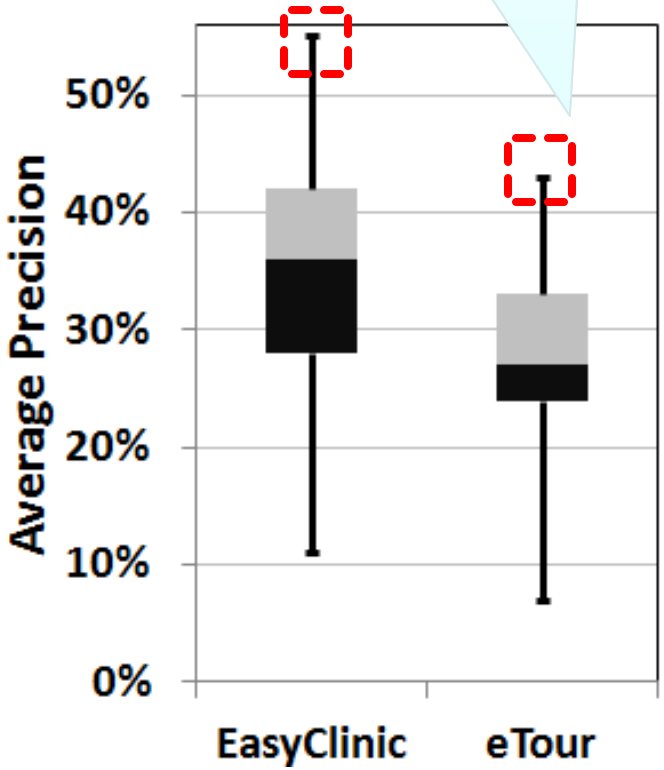
        LDA[numIter , numTopics , α, β]

Choose LDA parameters with best average precision using an *oracle*



Combinatorial:

for numIter in [500, …]
  for numTopics in [5, …]
    for α in [0.01, …]
      for β in [0.01, …]
        LDA[numIter , numTopics , α, β]

Choose LDA parameters with best average precision using an *oracle*

LDA-GA:

run LDA-GA 30 times (to account for randomness)

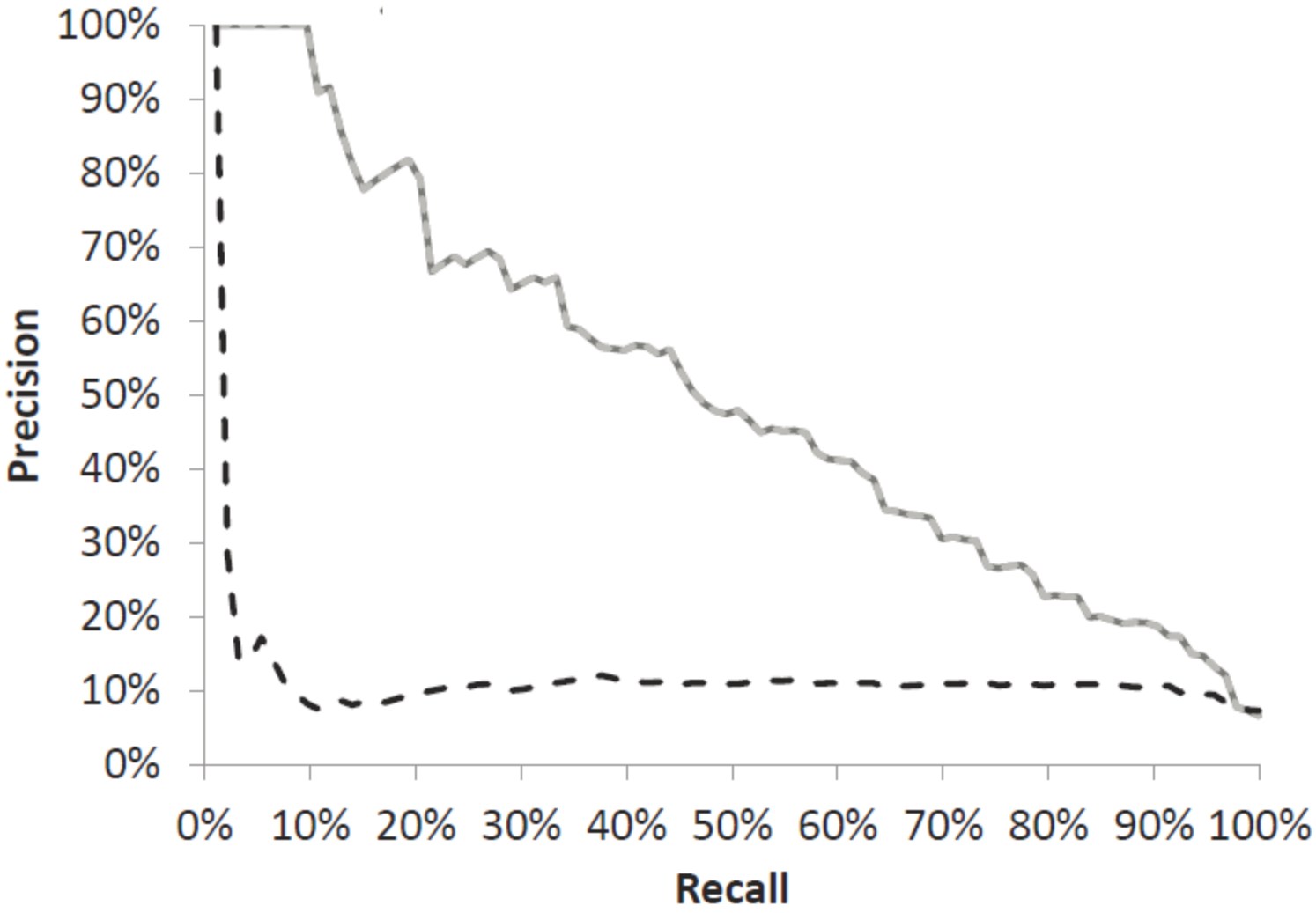
Choose LDA parameters corresponding to median fitness over 30 runs

Baseline:

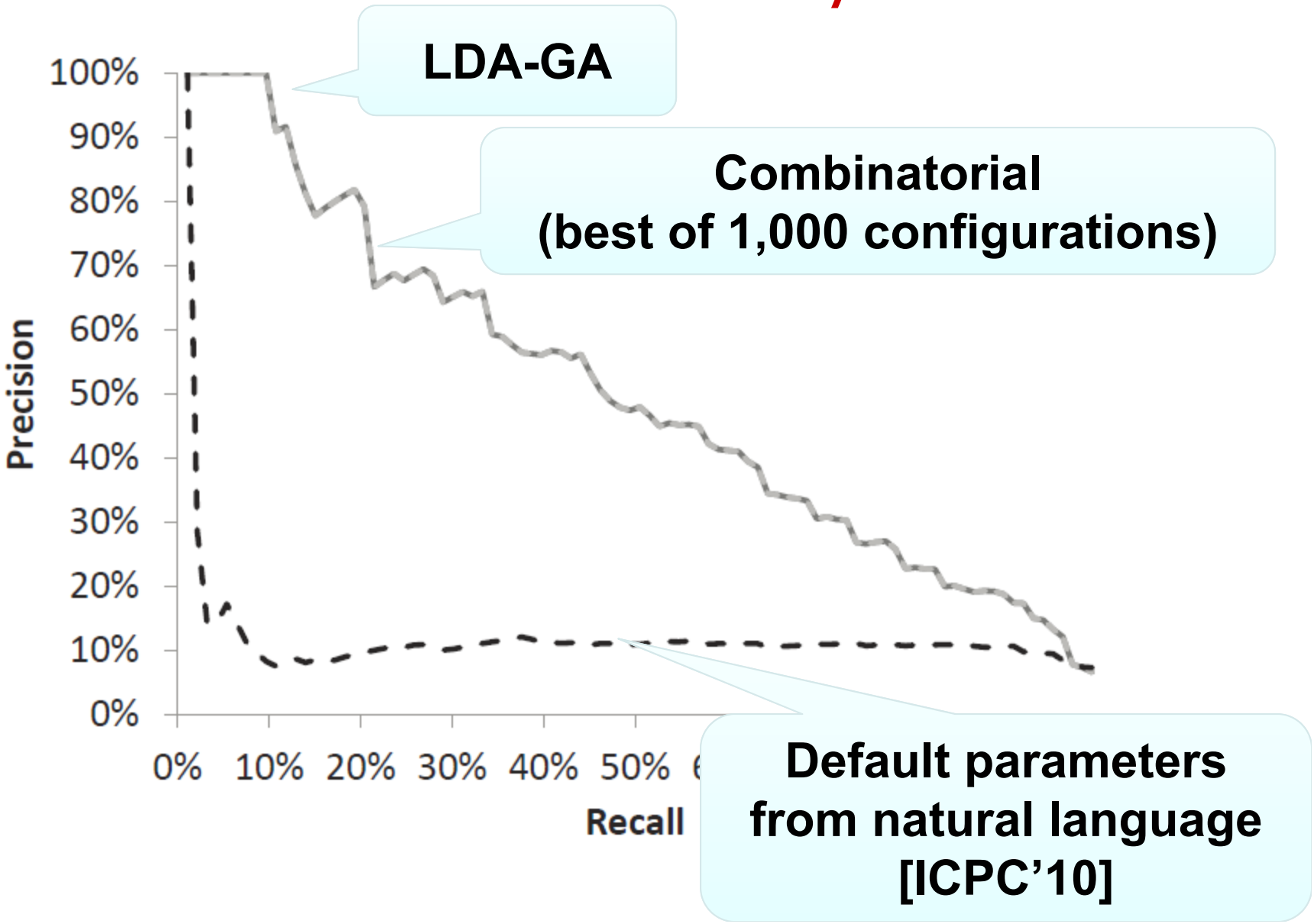
[ICPC'10]

Use default LDA parameters from natural language

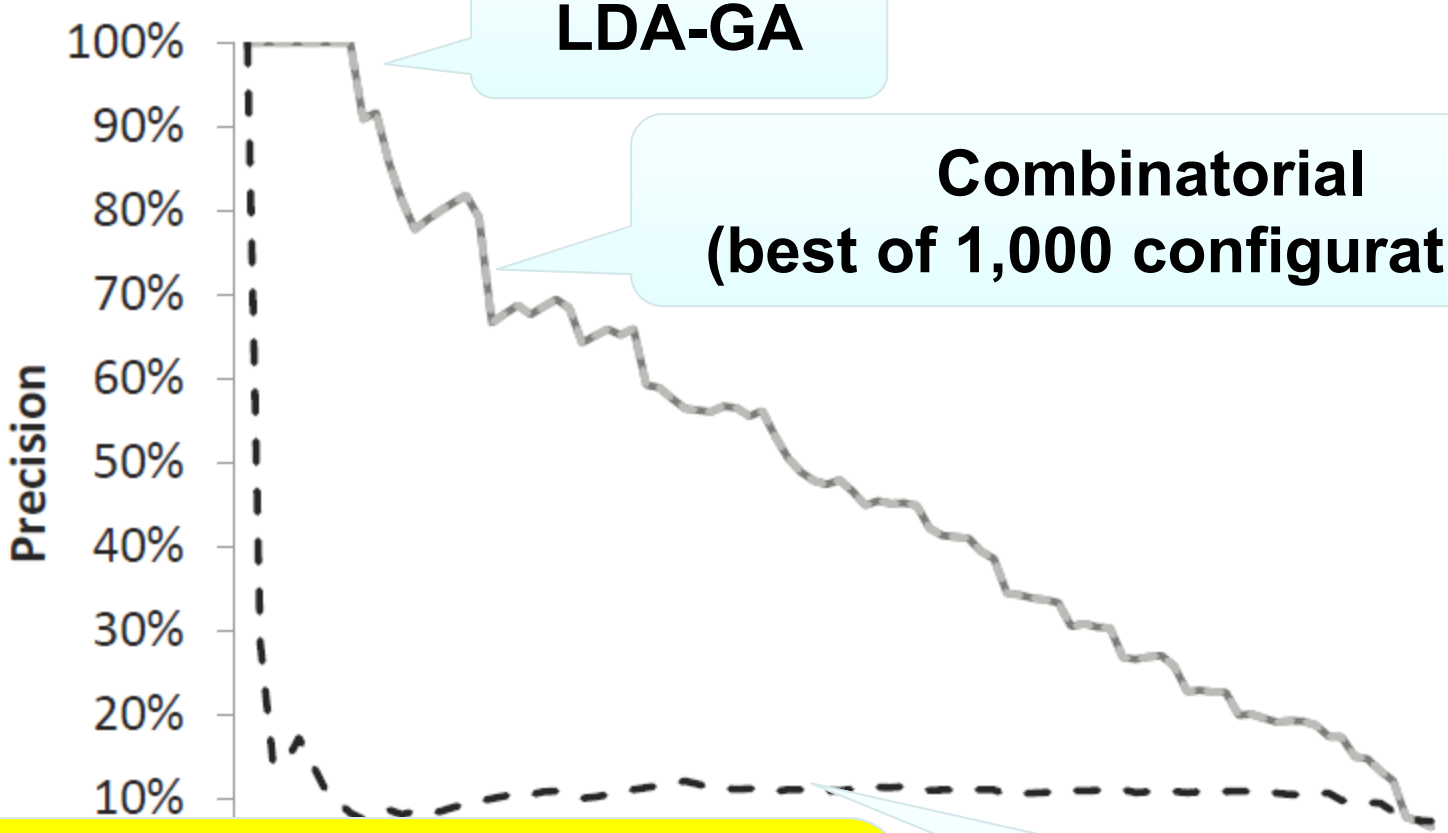
Precision/Recall EasyClinic



Precision/Recall EasyClinic



Precision/Recall EasyClinic

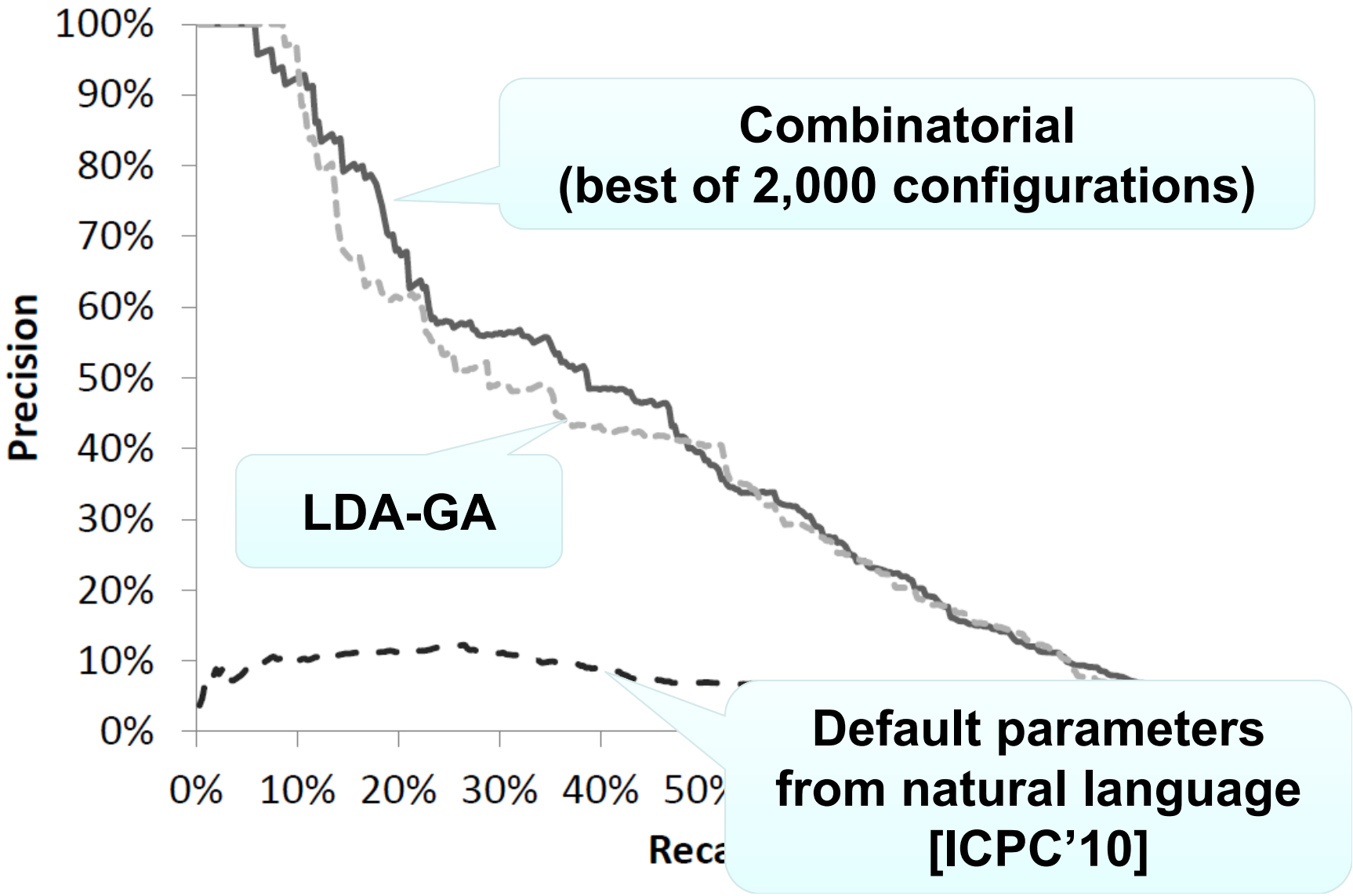


LDA-GA = Combinatorial

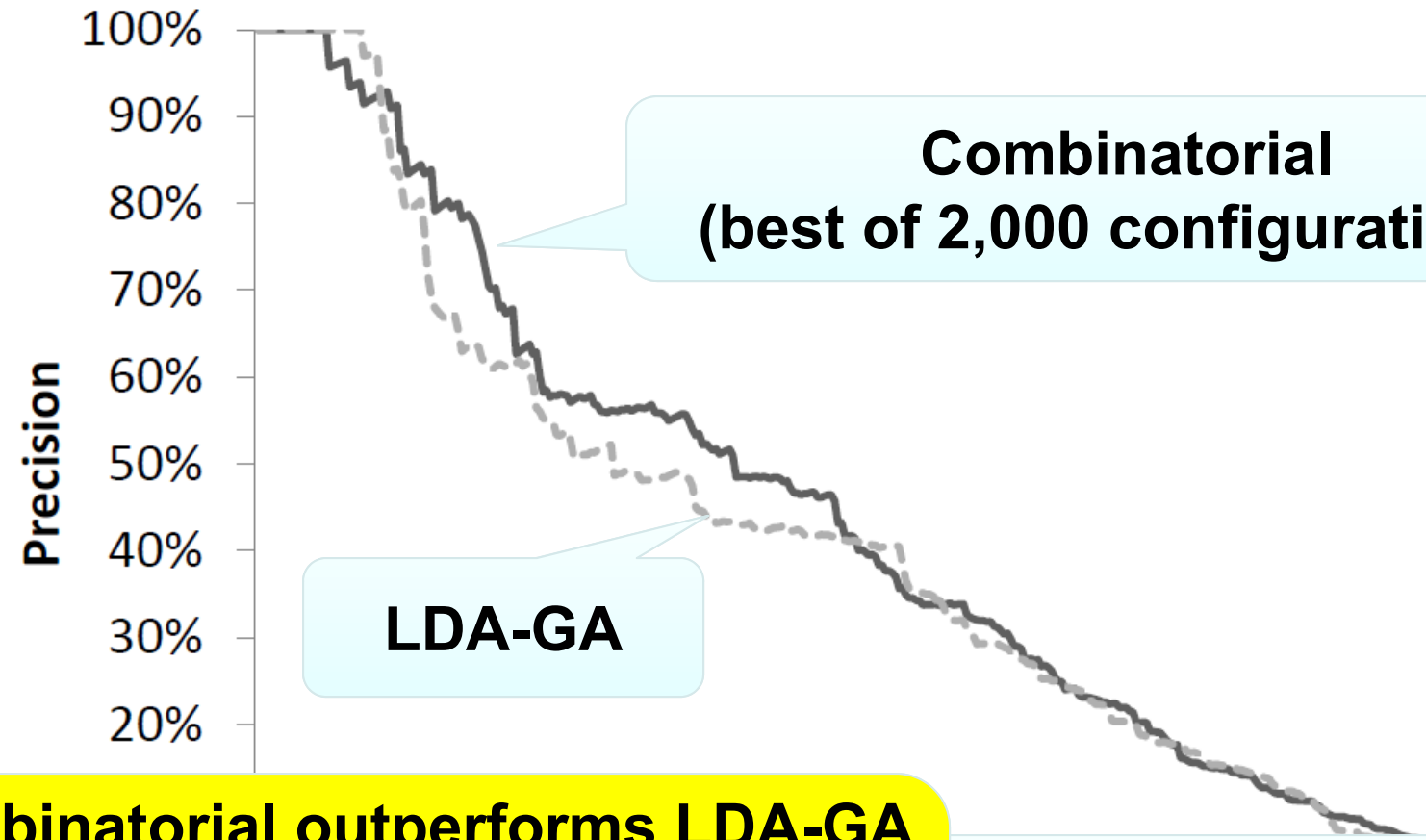
LDA-GA outperforms baseline
[p-value < 0.05]

Default parameters from natural language [ICPC'10]

Precision/Recall eTour



Precision/Recall eTour



Combinatorial outperforms LDA-GA
[p-value < 0.05]

LDA-GA outperforms baseline

Default parameters from natural language [ICPC'10]

Evaluation: Feature location

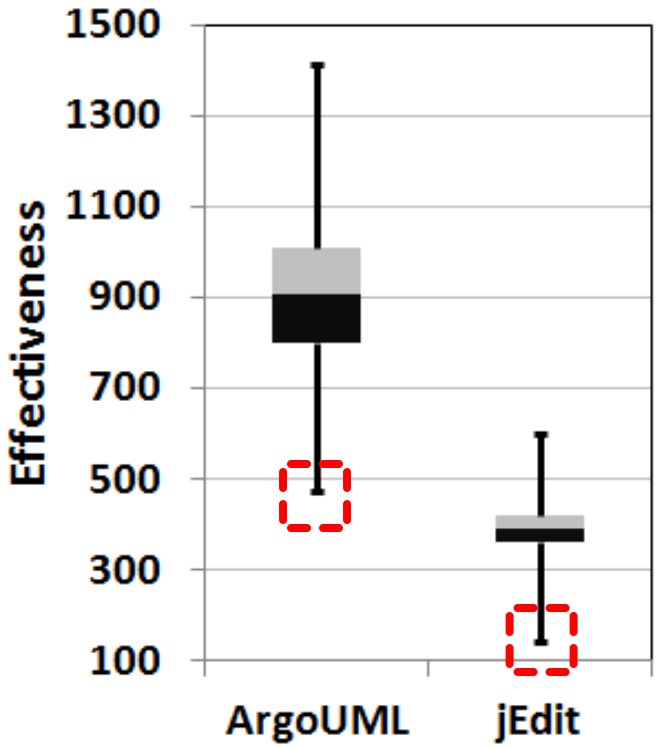
- Identify methods related to a maintenance task (e.g., bug, feature)

System	Size	# features	# methods
jEdit	104KLOC	150	6,413
ArgoUML	149KLOC	91	11,000

Combinatorial:

```
for numIter in [500, …]
    for numTopics in [5, …]
        for α in [0.01, …]
            for β in [0.01, …]
                LDA[numIter , numTopics , α, β]
```

Choose LDA parameters with best average effectiveness using an *oracle*



Combinatorial:

```
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        for α in [0.01, …]
            for β in [0.01, …]
                LDA[numIter , numTopics , α, β]
```

Choose LDA parameters with best average effectiveness using an *oracle*

LDA-GA:

run LDA-GA 30 times (to account for randomness)

Choose LDA parameters corresponding to median fitness over 30 runs

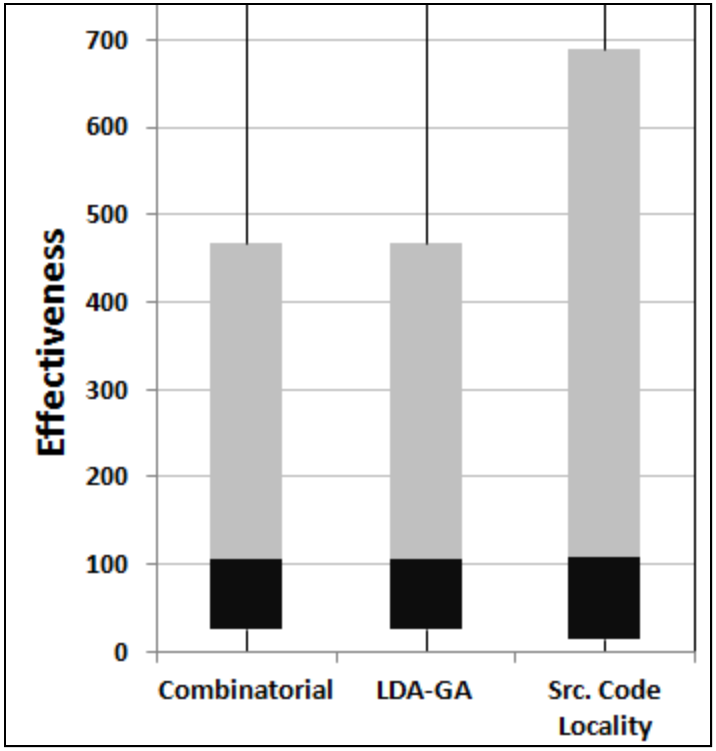
Baseline:

[SCAM'10]

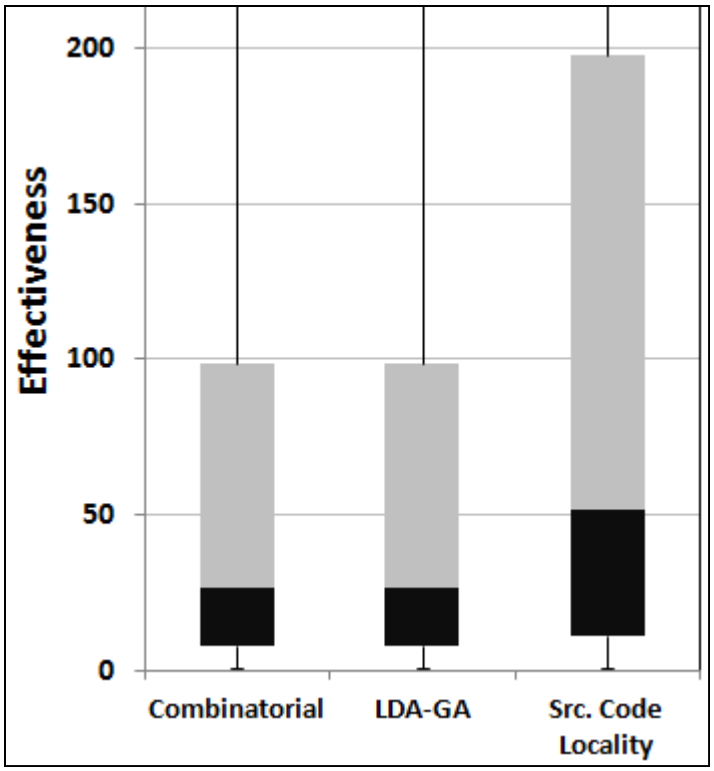
Use LDA parameters from *source locality heuristic*

Effectiveness measure

ArgoUML

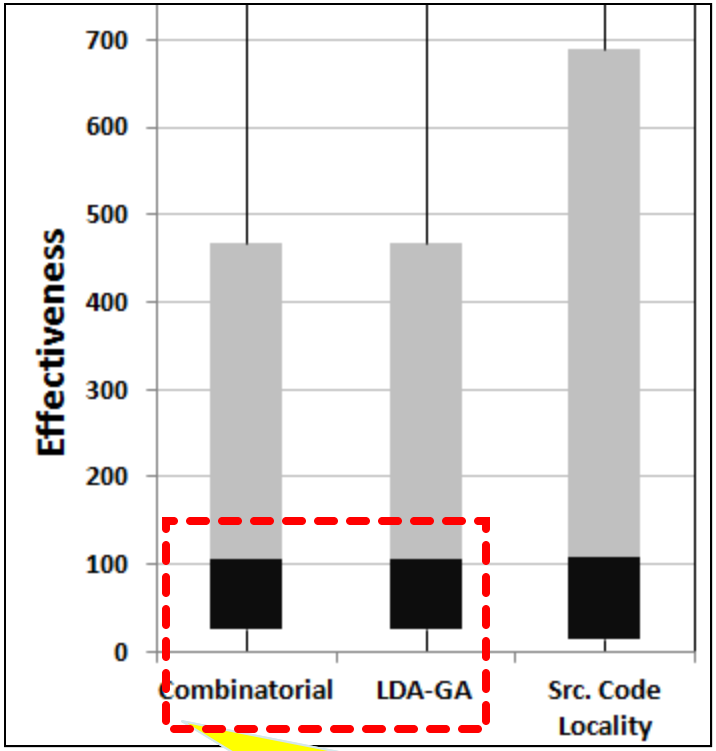


jEdit



Effectiveness measure

ArgoUML



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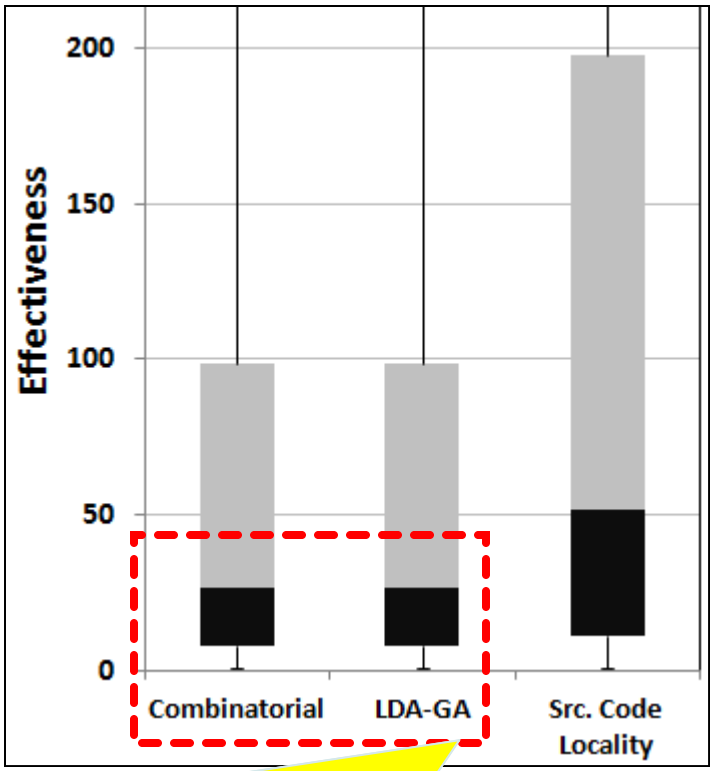
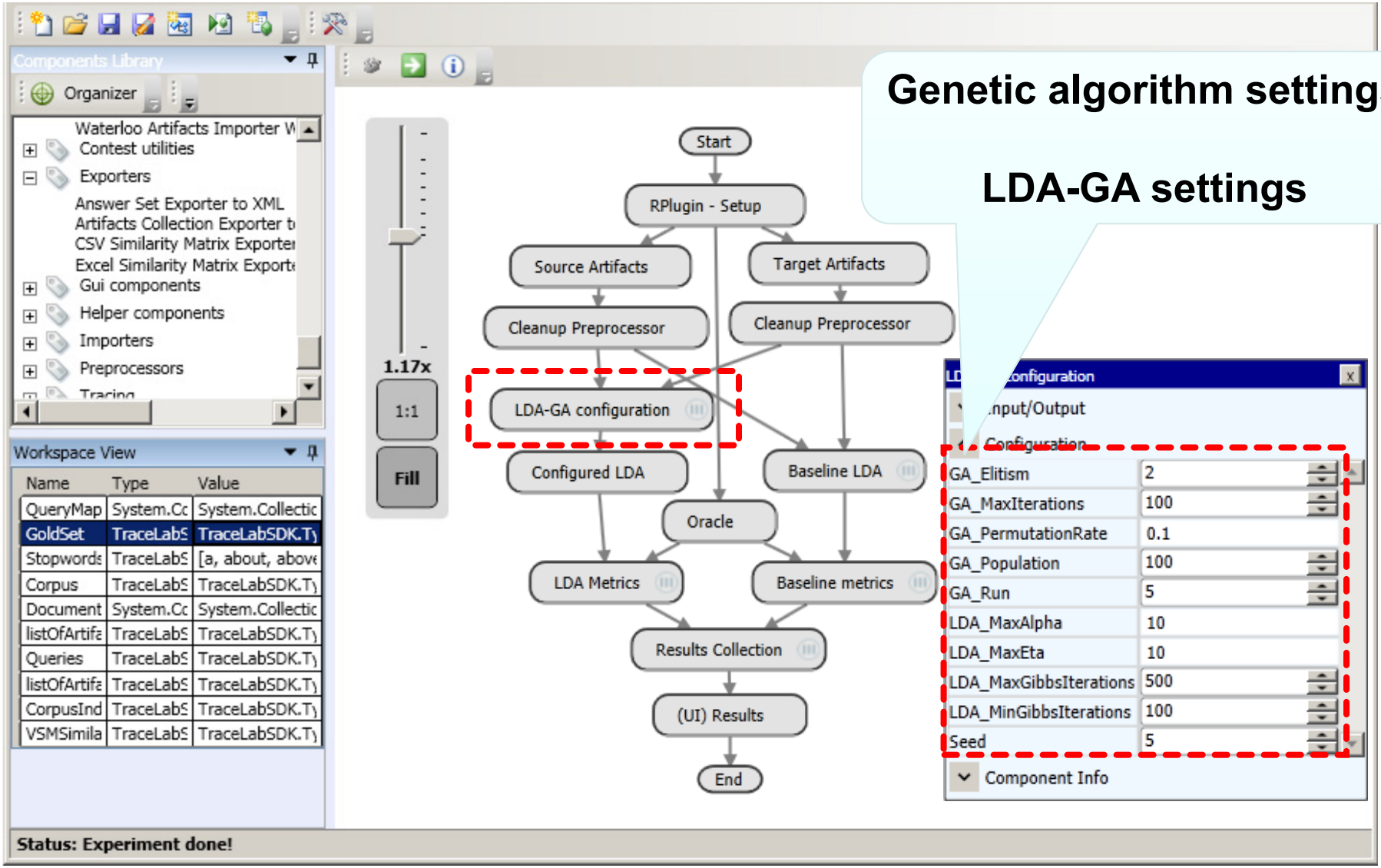


LDA-GA = Combinatorial
LDA-GA outperforms baseline *[p-value < 0.05]*

Conclusions

- Showed the impact of setting the LDA parameters on the results
- We proposed LDA-GA, a genetic based approach to automatically configure and find the near-optimal solution for LDA parameters
  - Dataset dependent
  - Oracle & task independent
- The approach was evaluated on three maintenance tasks

LDA-GA in TraceLab



Thank you! Questions?

http://www.distat.unimol.it/reports/LDA-GA/

http://www.cs.wm.edu/semeru/data/tefse13/

References

- [Hindle et al., ICSE'12] A. Hindle, E. T. Barr, Z. Su, M. Gabel, and P. T. Devanbu, "On the naturalness of software," in Proc. of the 34th IEEE/ACM International Conference on Software Engineering (ICSE'12), Zurich, Switzerland, June 2-9, 2012, pp. 837–847.
- [ICPC'10] R. Oliveto, M. Gethers, D. Poshyvanyk, and A. De Lucia, "On the equivalence of information retrieval methods for automated traceability link recovery," in Proc of the 18th IEEE International Conference on Program Comprehension (ICPC'10), Braga, Portugal, 2010, pp. 68–71.
- [SCAM'10] S. Grant and J. R. Cordy, "Estimating the optimal number of latent concepts in source code analysis," in Proc. of the 10th International Working Conference on Source Code Analysis and Manipulation (SCAM'10), 2010, pp. 65–74.

Threats to Validity

- We used datasets that have been used in other studies
- We ran GA 30 times to account for randomness
- Non-parametric statistical test
- Generalizability of results to other SE tasks

GA Settings

- Implementation: GA library in R
- Population size: 100
- Elitism of 2 individuals
- Roulette wheel selection operator
- Crossover probability: 0.6
- Mutation probability: 0.01
- Stop criteria:
  - No improvement in 10 generations
  - When reaching 100 generations

Software Artifact Labeling

TABLE IV
AVERAGE OVERLAP BETWEEN AUTOMATIC AND MANUAL LABELING.

exVantage					
	LDA		De Lucia et al. [13]		
	LDA-GA	Combinatorial	n = M	n = M/2	n = 2
Max	**100%**	**100%**	100%	100%	100%
3rd Quartile	**95%**	**95%**	71%	70%	69%
Median	67%	**70%**	59%	60%	54%
2nd Quartile	60%	**67%**	34%	50%	41%
Min	**50%**	**50%**	0%	0%	40%
Mean	74%	77%	52%	56%	60%
St. Deviation	19%	17%	31%	34%	23%

JHotDraw					
	LDA		De Lucia et al. [13]		
	LDA-GA	Combinatorial	n = M	n = M/2	n = 2
Max	**100%**	**100%**	100%	100%	100%
3 Quartile	81%	**82%**	73%	70%	66%
Median	71%	**75%**	65%	61%	56%
2 Quartile	47%	**50%**	46%	45%	41%
Min	14%	14%	0%	38%	**29%**
Mean	65%	66%	59%	60%	59%
St. Deviation	28%	26%	28%	20%	24%