SYNOPSIS

1. INTRODUCTION

Mandelbrot observed that many natural objects like trees, clouds, mountains, forest horizons etc. do not resemble the traditional shapes found in Euclidean geometry. Modelling of such objects is a difficult task in comparison to man made objects due to their irregular, non-smooth, highly complex geometries. He used fractals to represent such type of objects [1]. Some of the well known mathematical fractals have many features in common with the shapes found in nature. Self-similarity is found in sets or shapes that have repetitive patterns on smaller scales. After observing the repetitive pattern, Felix Hausdorff [2] discovered an irregularity measure for the fractal in terms of fractal dimension. It measures the space occupation and complexity of the object. In general, researchers use box counting method to calculate fractal dimension for classification based on irregularity in different areas like leaves classification, cancer stage classification, human motion classification [3-4]. The main drawback of this method is that the box counting dimension may be same for two different objects as we implement the box counting algorithm any box is counted or not counted at all. Moreover, a single number may not be sufficient to describe the complexity of an object. To overcome this drawback other dimension methods are also proposed in literature [4-7].

Fractal like natural objects can be generated by the iteration of one or more affine transformations. According to the choice of the coefficients of affine transformation, we can have different forms of fractals. To acquire a desired shape of the fractal, the collage of some fractals may be used. This method is referred to as an iterated function system (IFS). Hutchinson [8] introduced the formal definition of IFS in 1981. However, this theory is practically developed by Barnsley and Demko [9] on the basis of the self-similarity property. It is observed that many objects can be closely approximated by self-similar objects that might be generated by some IFS. The method of IFS provides a useful tool to build fractals and other similar sets. Thus, IFS theory has been extended, generalized and enriched in numerous directions in different settings by a number of authors with a variety of applications in image compression, encryption, simulation etc. [10-17].

Sahu et al. [18] introduced $K$-iterated function system using Kannan mapping to obtain fixed point theorem in complete metric space. Mate [19] discussed the case of weaker contraction
whereas, Leśniak [20] investigated IFS for multivalued contractions. The Meir–Keeler contractions are used by Dumitru [21] to generalize IFS theory. Boriceanu et al. [22] explored multivalued fractals through IFS on $b$-metric spaces. Uthayakumar and Easwarsooryy [13, 23] studied iterated function systems for fuzzy and intuitionistic fuzzy metric space with Banach contraction. Miculescu and Mihail [24] introduced the concept of Reich-type IFS and obtained the existence and uniqueness of the attractor of such a system. Further, Lock et al. [25] used fractals geometry for the combined encryption compression algorithm, whereas Razzaque and Thakur [26] proposed an algorithm based on transformed Mandelbrot set for the encryption of the images. Sun et al. [27-28] used Julia sets with Hilbert curves and fractal dictionary for image compression and encryption. There are many more algorithms proposed in literature utilizing fractals and their properties [29]. Chaotic maps along with the fractals are also used for image encryption due to the high sensitivity of such maps towards the initial condition and parameters [30-33]. Thus, fractal theory has been enriched manifold in diverse directions.

2. OBJECTIVES

1. To extend Hutchinson Barnsley theory in a general setting.
2. To explore fractal theory in fuzzy metric space and intuitionistic fuzzy metric spaces for Suzuki type contractions.
3. To propose some novel schemes for encryption and compression of images using fractals.
4. To investigate the applications of fractal dimension in classification of images.

3. MAIN CONTRIBUTION

The work reported in this thesis is organized into seven chapters. The chapter wise overview is given as follows:
Chapter 1

This chapter is introductory in nature and provides the necessary background to the rest of the chapters of the thesis. Besides basic definitions and results, it gives an overview of the development of fractal theory and analysis.

Chapter 2

In 1992, Dhage [34] proposed the notion of $D$-metric space as a generalization of the metric spaces. Thereafter, a number of results appeared in the literature in this line. Unfortunately, in 2004, Mustafa et al. [35] found out that the number of claims regarding the fundamental topological structure of $D$-metric space were incorrect. To modify it, they introduced the notion of $G$-metric space. We intend to define iterated function system in $G$-metric space and $G_b$-metric space establish some existence and uniqueness results in it. As an application, a collage theorem is also derived for the same.

The main results obtained in this chapter are as follows:

**Lemma 1.** Let $(X, G)$ be a complete $G$-metric space and $T : X \to X$ a $G$-contraction with contractivity factor $0 \leq k < 1/3$. Then $T : H_g(X) \to H_g(X)$ defined by $T(B) = \{Tx : x \in B\}$ for every $B \in H_g(X)$ will also be a $G$-contraction map with same contractivity factor.

**Lemma 2.** Let $X$ be a $G$-metric space and $\{T_n\}$ a sequence of $G$-contraction maps with the contractivity factors $0 \leq k_n < 1/3$ for each $T_n$; $n = 0, 1, 2, ..., N$, then $T : H(X) \to H(X)$ defined by

$$T(B) = T_1(B) \cup T_2(B) \cup ... \cup T_N(B) = \bigcup_{n=1}^{N} T_n(B) \quad \forall B \in H(X)$$

is also a $G$-contraction with the contractivity factor $k = \max_{n} \{k_n\}$.

**Lemma 3.** Let $X$ be a complete $G$-metric space and $T : X \to X$ a contraction on $X$ with contractivity factor $0 \leq k < 1$. Then for any natural number $n$ we have

$$G(T^n x, T^{n+1} x, T^{n+1} x) \leq k^n G(x, Tx, Tx).$$

**Lemma 4.** Let $X$ be a complete $G$-metric space and $T$ a contraction on $X$ with contractivity factor $0 \leq k < 1/3$. Let fixed point of $T$ be denoted by $f$, then

$$G(x, f, f) \leq (1/1-k) G(x, Tx, Tx).$$
**Definition 5.** A G-IFS consists of a complete G-metric space $(X, G)$ together with a finite set of $G$-contraction maps $T_n : X \to X$ with contractivity factors $0 \leq k_n < 1/3$ for $n = 1, 2, \ldots, N$. It is represented by $\{X, T_n, n = 1, 2, \ldots, N\}$.

**Theorem 6.** Let $\{X, T_1, \ldots, T_N\}$ be a G-IFS with a contractivity factor $k_n$ for each $T_n$, where $n \in N$. Then

(i) the mapping $T : H(X) \to H(X)$, where $T = \bigcup_{n=1}^{N} T_n$ is a $G$-contraction on a complete Hausdorff $G$-metric space $(H(X), h_g)$.

(ii) $T$ has a unique fixed point, $A \in H(X)$, which is also called an attractor or fractal, i.e., we have $A = TA = \bigcup_{n=1}^{N} T_n(A)$ and also $A = \lim_{n \to \infty} T^n(B)$ for any $B \in H(X)$.

The following collage theorem in $G$-metric space is obvious.

**Theorem 7.** Let $X$ be a complete $G$-metric space and $T$ a contraction on $X$, where $T = \bigcup_{n=1}^{N} T_n$. Let $L \in H(X)$ and $\varepsilon > 0$ be given. Choose a G-IFS $\{X, (T_0), T_1, \ldots, T_N\}$, where $T_0$ is the condensation mapping with contractivity factor $0 \leq k < 1/3$ so that $H_g(L, \bigcup_{n=1}^{N} T_n(L), \bigcup_{n=1}^{N} T_n(L)) \leq \varepsilon$, then $H_g(L, A, A) \leq \varepsilon / (1-k)$, where $A$ is the attractor of the G-IFS. Equivalently,

$$H_g(L, A, A) \leq \frac{1}{1-k} H_g(L, \bigcup_{n=1}^{N} T_n(L), \bigcup_{n=1}^{N} T_n(L)).$$

**Chapter 3**

The Banach contraction principle is one of the most phenomenal results in metric fixed point theory. It has enormous applications in various kinds of existence problems in different branches of science and engineering. It states that a contraction map $T$ defined on a complete metric space $(X, d)$ has a unique fixed point in $X$. Connell [36] has shown with the help of an example that the converse of the Banach theorem is not always true. In 1969, Kannan [37] established an important fixed point theorem for a map satisfying a contractive condition which is independent of Banach contraction. This result of Kannan is of great significance because it characterizes metric completeness [38], i.e., a metric space is complete if and only if each Kannan type contraction ($K$-contraction) on it has a fixed point. In 2008, Suzuki [39] obtained interesting results for maps satisfying a general type of condition. This generalization is very influential because Suzuki demonstrated that such type of map...
characterizes the condition of metric completeness, i.e., a metric space $X$ is complete if and only if every Suzuki type map on $X$ has a fixed point in $X$. In this chapter, we define a Suzuki type contraction ($S$-contraction) in fuzzy metric spaces (FMS) and obtain some existence and uniqueness results. The independence of $K$-contraction and $S$-contraction in FMS is also established with simple examples. Further, iterated function systems for FMS are defined and some existence and uniqueness results are established for them.

Main outcomes of this chapter are as follows:

**Theorem 8.** Let $(X, M, *)$ be a complete fuzzy metric space and $T : X \to X$. Define a non-increasing function $\theta$ from $(0, 1)$ onto $[0.5, 1)$ by

$$
\theta(r) = \begin{cases} 
1 - r & \text{if } 0 < r < 0.5, \\
r & \text{if } 0.5 \leq r < 1.
\end{cases}
$$

Assume that there exists $r \in [0, 1)$ such that

$$
M(x, y, \theta(r)t) \leq M(x, Tx, t) \implies M(Tx, Ty, rt) \geq M(x, y, t) \forall x, y \in X. \tag{1}
$$

Then $T$ has a unique fixed point $z$ in $X$. Moreover,

$$
\lim_{n \to \infty} T^n(x) = z \forall x \in X.
$$

If we relax the condition on $\theta(r)$ in inequality (1), we obtain the following result of Mihet [40].

**Corollary 1 [40].** Let $(X, M, *)$ be a complete fuzzy metric space and $T : X \to X$ be a $B$-contraction such that $M(Tx, Ty, kt) \geq M(x, y, t)$ for all $x, y$ in $X$, $0 < k < 1$. Then $T$ has a unique fixed point.

**Lemma 9.** Suppose $T_i : K(X) \to K(X)$ are $S$-contractions on $(K(X), H_M, *)$ for $i = 1, 2, \ldots, N$. Then $\bigcup_{i=1}^{N} T_i$ is also an $S$-contraction on $(K(X), H_M, *)$.

**Theorem 10.** Let $(X, M, *)$ be a complete FMS and $(K(X), H_M, *)$ be the corresponding Hausdorff-fuzzy metric space. Suppose $(K(X), T_1, T_2, \ldots, T_N)$ be a Fuzzy IFS, where $T_1, T_2, \ldots, T_N$ are $S$-contractions in $K(X)$. Then, there exists a unique fixed point or an attractor $A \in K(X)$ of the IFS.

**Theorem 11.** Let $(X, M, *)$ be a complete FMS and $(K(X), H_M, *)$ be the corresponding Hausdorff FMS. Suppose $(K(X), T_1, T_2, \ldots, T_N)$ be a fuzzy IFS, where $T_1, T_2, \ldots, T_N$ are $S$-contractions in $K(X)$ and $A$ be the attractor of the IFS. Then
Again, if we relax the condition on $\theta (r)$ in inequality (1), we obtain the following result of Easwaramoorthy and Uthayakumar [13].

**Corollary 2** [13]. Let $\{X, M, T_1, T_2, \ldots, T_n\}$ be a fuzzy IFS induced by the IFS $\{X, T_1, T_2, \ldots, T_n\}$. Then, there exists a unique attractor $A \in K(X)$ of $T$.

**Chapter 4**

In this chapter, we define a Suzuki type contraction ($S$-contraction) in intuitionistic fuzzy metric spaces (IFMS) and obtain some existence and uniqueness results. Further, an iterated function system in IFMS is defined and some existence and uniqueness results are also derived.

The main outcomes of this chapter are as follows:

**Lemma 12.** Let $(X, M, N, *, \diamond)$ be an IFMS such that $M(x, y, t) \to 1$ and $N(x, y, t) \to 0$ as $t \to \infty$ for all $x, y \in X$. Let $*$ be Hadzic type $t$-norm and $\diamond$ Hadzic type $t$-conorm. If the sequence $\{x_n\}$ in $X$ is such that for all $n \in N$,

\[
M(x_n, x_{n+1}, t) \geq M(x_{n-1}, x_n, t/k) \quad \text{and} \quad N(x_n, x_{n+1}, t) \leq N(x_{n-1}, x_n, t/k)
\]

where $0 < k < 1$, $t > 0$, then the sequence $\{x_n\}$ is a Cauchy sequence.

**Theorem 13.** Let $(X, M, N, *, \diamond)$ be a complete IFMS and $T: X \to X$ satisfy

\[
M(Tx, Ty, kt) \geq M(x, Ty, t) \land M(y, Tx, t) \quad \text{and} \quad N(Tx, Ty, kt) \leq N(x, Tx, t) \lor N(y, Ty, t)
\]

for all $x, y$ in $X$, $0 < k < 1$. Then $T$ has a unique fixed point.

**Definition 14.** Let $(X, M, N, *, \diamond)$ be a complete IFMS, $T: X \to X$ and $\theta$ a non-increasing function as defined in Theorem 8. Assume that there exists $r \in [0, 1)$ such that

\[
M(x, y, \theta (r)t) \leq M(x, Tx, t) \Rightarrow M(Tx, Ty, rt) \geq M(x, y, t) \quad \forall x, y \in X
\]

\[
N(x, y, \theta (r)t) \geq N(x, Tx, t) \Rightarrow N(Tx, Ty, rt) \leq N(x, y, t) \quad \forall x, y \in X.
\]

Then $T$ is said to be an $S$-contraction on $X$.

**Theorem 15.** Let $(X, M, N, *, \diamond)$ be a complete IFMS and $T: X \to X$, an $S$-contraction on $X$. Then, there exists a unique fixed point $z$ of $T$. Moreover,
\[ \lim_{n \to \infty} T^n(x) = z \quad \forall x \in X. \]

**Definition 16.** Let \((X, M, N, *, \diamond)\) be an IFMS and \(T_i : X \to X, i = 1, 2, 3, \ldots, N\) be \(S\)-contractions with the corresponding contractivity ratios \(k_n, n = 1, 2, 3, \ldots, N\). Then the system \(\{X; T_n, i = 1, 2, 3, \ldots, N\}\) is called an \(S\)-type IFS in IFMS.

**Lemma 17.** Suppose \(T_i : K(X) \to K(X)\) are \(S\)-contractions on IFMS \((K(X), H_M, H_N, *, \diamond)\) for \(i = 1, 2, \ldots, N\). Then \(\bigcup_{i=1}^{N} T_i\) is also an \(S\)-contraction on \((K(X), H_M, H_N, *, \diamond)\).

**Theorem 18.** Let \((X, M, N, *, \diamond)\) be a complete IFMS and \((K(X), H_M, H_N, *, \diamond)\) the corresponding Hausdorff -IFMS. Suppose \((K(X), T_1, T_2, \ldots, T_N)\) be an \(S\)-type IFS, where \(T_1, T_2, \ldots, T_N\) are \(S\)-contractions in \(K(X)\). Then, there exists a unique fixed point or an attractor \(A \in K(X)\).

**Theorem 19.** Let \((X, M, N, *, \diamond)\) be an IFMS and \((K(X), H_M, H_N, *, \diamond)\) be the corresponding H-IFMS. Suppose \((K(X), T_1, T_2, \ldots, T_N)\) be an \(S\)-type IFS, where \(T_1, T_2, \ldots, T_N\) are \(S\)-contractions in \(K(X)\). Then

\[
M(L, A, t) \geq M\left(L, TL, \frac{rt}{2r-1}\right) \quad \text{and} \quad N(L, A, t) \leq N\left(L, TL, \frac{rt}{2r-1}\right) \quad \forall L \in K(X).
\]

Now, If we relax the condition on \(\theta (r)\) in inequality (4) and (5), we obtain the result of Alaca et. al. [41] as a corollary.

**Corollary 3 [41].** Let \((X, M, N, *, \diamond)\) be a complete IFMS and \(T : X \to X\), a \(B\)-contraction on \(X\). Then there exists a unique fixed point of \(T\).

If we relax the condition on \(\theta (r)\) in inequality (1), we obtain the following result of Uthayakumar and Easwaramoorthy [23].

**Corollary 4 [23].** Let \(\{X, M, N, T_1, T_2, \ldots, T_n\}\) be a intuitionistic fuzzy IFS induced by the IFS \(\{X, T_1, T_2, \ldots, T_n\}\). Then, there exists a unique attractor \(A \in K(X)\) of \(T\).
Chapter 5

The intent of the chapter is to propose some novel fractal based encryption compression schemes. In our study of images, we obtain significant lossless compression and secure encryption of the image data. Steps of the proposed techniques are given in brief as follows.

5.1. Combined Encryption Compression Scheme using Chaotic Maps (CECSCM)

The encryption algorithm includes the following steps.

**Step 1.** Choose initial values \( x_0 \) and \( y_0 \) and the system parameters \( a \) and \( b \) for creating the chaotic sequences. Chaotic sequences \( \{x_n\} \) and \( \{y_n\} \) are constructed using logistic map equations

\[
x_{n+1} = a x_n (1-x_n), \quad a \in [3.5699456, 4), \quad x_n \in (0, 1), \quad n = 1, 2, \ldots
\]

and

\[
y_{n+1} = b y_n (1-y_n), \quad b \in [3.5699456, 4), \quad y_n \in (0, 1), \quad n = 1, 2, \ldots
\]

**Step 2.** Create position matrix \( P \) by sorting the chaotic sequence \( x \) in ascending order. All the values of \( P \) denote the index values of the original matrix, which are not being sorted.

**Step 3.** Turn the original image matrix \( E \) into scrambling image matrix \( I \) according to position matrix \( P \).

**Step 4.** Turn the chaotic sequence \( y \) into chaotic matrix \( C \).

**Step 5.** Obtain ciphered image \( N \) by using XOR operation between image matrix \( I \) and chaotic matrix \( C \).

\[
N = I \oplus C
\]

**Step 6.** Choose appropriate \( m \) and a prime number \( n \). Divide the ciphered image \( N \) obtained in the last step into units of length \( m \) and turn each unit into a single value.

**Step 7.** Combine all the values obtained in step 6 to get the ciphered image in the compressed form.

The decryption process is the inverse process of encryption. Original image can be obtained with correct key combinations.
5.2. Combined Encryption Compression Scheme using Julia Set (CECSJS)

**Step 1.** Creating Confusion Image Matrix: The logistic sequence is used to construct \( m \times n \) matrix \( M \). Then a position matrix \( P \) is created by sorting the values of the matrix \( M \) in ascending orders. All the values of \( P \) denote the index values of the original matrix \( E \), which are not being sorted. Finally, the matrix \( E \) is turned into confusion image matrix \( I \) according to position matrix \( P \).

**Step 2.** Matrix with chaotic properties: In order to keep the property of chaotic sequences, we perform XOR operation between image matrix \( I \) and the Julia matrix \( J \). This creates another matrix \( N \), i.e., \( N = I \oplus J \), where \( J \) is the image matrix of filled in Julia set.

**Step 3.** Compression of the data: Let \( n \) be the array of relatively prime numbers \( n[i] \), \( i = 1, 2, \ldots, s \) and \( L[i] = M / n[i] \), where \( M = \prod n[i] \). First divide the matrix with chaotic properties \( N \) into blocks of size \( 1 \times s \) and then divide each pixel \( N[i] \) by 16 in the block. Let \( p[i] = N[i] / 16 \) and \( q[i] = N[i] \mod 16 \), \( i = 1 \) to \( s \).

Now, generate the following system of linear congruencies
\[
N[i] \times x[i] = 1 \pmod{n[i]}, \ i = 1, 2, \ldots, s.
\]

The values to be transmitted are determined as
\[
U = \sum L[i] \times x[i] \times p[i] \pmod{M} \quad \text{and} \quad V = \sum L[i] \times x[i] \times q[i] \pmod{M}.
\]

**Step 4.** For each \( s \) half pixel values, single \( U \) and single \( V \) are calculated. Then count distinct \( U \)'s and sort them in descending order. A new set of numbers are assigned to each distinct \( U \) to generate a table of an equivalent code, which is also provided to the receiver. Using this code each \( U \) is encoded. Same procedure is repeated for \( V \).

At the receiving end, the obtained encoding table is used to reconstruct \( U \) and \( V \). Then \( s \) half pixel values are generated from \( U \) and \( V \) with right key \( n \), as \( p[i] = U \pmod{n[i]} \) and \( q[i] = V \pmod{n[i]} \). The pixels are then reconstructed from the half pixels for each \( i \) as \( N[i] = p[i] \times 16 + q[i] \).

Remaining decryption process is the inverse process of encryption. Original image can be obtained using only correct key combinations of \( x_0, a \) and \( n \).
5.3. Image Encryption using Iterated Function Systems (IEIFS)

5.3.1. Encoding

**Step 1.** Divide the image of size $M \times N$ into blocks of size $1 \times k$. Take first block and divide each pixel $p[i]$ by 16 to produce two half pixels $a[1, 2, \ldots, k]$ and $a'[1, 2, \ldots, k]$. Choose key as a set of relatively prime numbers $m[i]$, all greater than $a[i]$ and $a'[i]$ for $i = 1$ to $k$.

**Step 2.** For each $m[i]$ coefficients of Chinese remainder theorem are given by $\prod_{i}^{\sum_{i}^{m[i]}} m[i] = 1 \mod (m[i])$ and $C[i] = \prod_{i}^{m[i]*x[i]}$. Generate the linear congruencies as $\prod_{i}^{m[i]*x[i]} = 1 \mod (m[i])$ and $C[i] = \prod_{i}^{m[i]*x[i]}$.

**Step 3.** We calculate $S_1$ and $S_2$ as $S_1 = \sum C[i]*a[i] \mod (\prod_{i}^{m[i]})$, $S_2 = \sum C[i]*a'[i] \mod (\prod_{i}^{m[i]})$ and $S = S_1 + xS_2$, where $x$ is a prime number greater than $S_1$ and $S_2$.

**Step 4.** Construct the IFS transformations $T_i$’s from all $S$ using the possibilities of the arrangements that agreed between sender and the receiver. Here, contractivity factor for the transformation is $\frac{1}{\max S[i]}$. Use $T_i$’s to generate the attractor $A$ using the random iteration algorithm.

5.3.2. Decoding

**Step 1.** Upon the receipt of the attractor (picture) $A$, retrieve the IFS $T$ (say) using collage theorem.

**Step 2.** Modify the entries of the retrieved IFS $T$, to get $T_i$’s as they agree on the order of formation of maps in IFS.

**Step 3.** Find the value of $S$ for each block from $T_i$’s by multiplication of $\max S[i]$ and calculate $S_1$ and $S_2$ from each $S$ as follows:

$S_2 = \text{int} (S/x)$;

$R = S \mod (x)$;

$S_1 = R \mod (x)$.

**Step 4.** Find Half pixel values for each block $a[i]$ and $a'[i]$ as:

$a[i] = S_1 \mod (m[i]); a'[i] = S_2 \mod (m[i])$. 

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Step 5. Reconstruct each pixel $p[i]$ in the following manner:

$$p[i] = a[i] \times 16 + a'[i].$$

The proposed techniques are expected to be useful for the transmission of various confidential image data relating to medical imaging, military and other multimedia applications. All the three algorithms have sufficient key space to combat all kinds of brute force attacks, which ensures a very high security to the transmitted image data. We have also done compression analysis for all proposed techniques and found a lossless compression ratios comparable with JPEG 2000.

Chapter 6

In the present chapter, we propose an improved version of multi-scale generalized fractal dimension (GFD) method for classification of medical images. The efficiency of the technique with the classical GFD for the classification of EEG signals obtained from seizure and seizure free patients and classification of retina of healthy and diabetic people. The results verify that the improved GFD provides better classification at all scales. To statistically verify it, we apply Kruskal Walli's test on the GFD and improved GFD. Box plots and Anova tables indicate the efficiency of the improved GFD over GFD. This method may be of important use for the analysis of various other biomedical signals also and thus, it can also be used for the classification in different areas such as speech recognition, human motion analysis, handwriting analysis etc.

Chapter 7

This chapter summarizes the conclusions of the present work along with the future scope.

LIST OF PUBLICATIONS

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[1] Mishra K., Prasad B., "A Novel Encryption Compression Scheme Using Julia Sets" Accepted for Publication in International Journal of Advanced Intelligence Paradigm (IJAIP), In Press. [Print ISSN: 1755-0386, Online ISSN: 1755-0394, Peer reviewed: Yes, Impact Factor: 0.61, H Index: 5, Indexing: SCOPUS (Elsevier), Academic OneFile (Gale), ACM Digital Library, DBLP Computer Science
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