

# Spectral Theory in Compact Operators

## Yuming Chen

Basis International School Nanjing,  
Nanjing, China  
ch.yuming@ldy.edu.rs

### Abstract:

This paper delves into the spectral theory of compact operators, focusing on eigenvalues that predominantly accumulate at zero and the implications for quantum information theory and machine learning. It highlights how the spectrum of compact, self-adjoint operators plays a crucial role in dimensionality reduction and quantum state decomposition. The research bridges abstract operator theory with practical computational applications, thereby enriching the theoretical underpinnings and practical applications of spectral theory. The study addresses how the eigenvalue decomposition of compact self-adjoint operators assists in reducing the dimensionality of large data sets and decomposing quantum states in tensor products. This connection between theory and application not only enhances the capabilities of Principal Component Analysis and machine learning methods but also proves critical in handling complex data structures and quantum systems. By exploring the structure and implications of compact operators within both classical and quantum domains, the findings offer a robust framework for future research. This includes potential expansions into more complex operator classes and their implications in other areas of functional analysis. Future research might explore the extension of these methods to tackle challenges posed by non-ideal, infinite-dimensional, or dynamically evolving systems.

**Keywords:** Topology, Operator Algebra, Hilbert Space, Compact Operators, Spectral Theory

## 1. Introduction

The study of compact operators has been instrumental in advancing our understanding of linear operator behavior, shedding light on their fundamental properties such as eigenvalues, eigenvectors, and spectral distribution [1]. Historically, these insights have been pivotal in numerous scientific fields ranging from quantum mechanics to numerical analysis, elucidating the inner workings of various physical and math-

ematical systems.

Recent advancements in spectral theory have pushed the boundaries beyond traditional mathematical analysis, facilitating significant breakthroughs in computational and applied mathematics. The relevance of compact operator theory has particularly been recognized in contemporary applications such as Principal Component Analysis (PCA) and machine learning algorithms. Moreover, its application in the

decomposition of quantum states via Schmidt decomposition underscores its utility in managing complex quantum systems and large-scale data structures [2].

This paper aims to bridge the theoretical aspects of compact operator spectral theory with practical computational applications. By establishing a detailed connection between the eigenvalue decomposition of compact self-adjoint operators and their application in tasks like dimensionality reduction of large datasets and decomposition of quantum states in tensor products, this study provides a comprehensive framework to explore the dualistic nature of compact operators in both classical and quantum realms [3][4]. This synthesis not only enhances the capabilities of analytical methods such as PCA but also furthers our understanding of quantum information processing, promising to enrich both the theoretical landscape and practical implementations in spectral theory.

## 2. Preliminaries

### 2.1 Banach and Hilbert Space

$$\begin{aligned} \|x\| &\geq 0, \forall x \in V \\ \|x\| = 0 &\Leftrightarrow x = 0, \forall x \in V \\ \|\alpha x\| &= |\alpha| \|x\|, \forall x \in V, \forall \alpha \in F \\ \|x + y\| &\leq \|x\| + \|y\|, \forall x, y \in V \end{aligned} \quad (1)$$

### 2.2 Topological Concepts

The process involves constructing a sequence of subsequences, all contained within a ball of radius  $\left(\frac{1}{2N}\right)$ . For each  $(n)$ , a selection  $(x_n)$  from  $(F_n)$  ensures the limit  $(y)$  belongs to  $(F_n)$  for all  $(n)$ , indicating that the intersection of the  $(F_n)$  sets is not empty. This scenario exemplifies that  $(X)$  is countably compact. It is often inferred that compactness, whether uncountable or countable, implies sequential compactness in a complete metric space. However, caution is advised as this implication may not necessarily hold in reverse. Analysis continues on the properties of compact sets in real-valued spaces. A set  $(X)$  included within a finite union of open sets  $(S_\beta \in B)$ ,  $(U_\beta \cup V)$ , leads to the conclusion that  $(K)$  is also compact within  $(S_\beta \in BU_\beta)$ , a conclusion derived from the Heine-Borel and Bolzano-Weierstrass theorems..

### 2.3 Linear Operators

Proof of continuity from boundedness: Given any positive epsilon, select an appropriate delta such that for any  $x$  and

$y$  in  $X$ , if the norm of  $x$  minus  $y$  is less than delta, then the norm of  $A(x)$  minus  $A(y)$  is less than epsilon. Specifically, if the norm of  $x$  minus  $y$  is less than delta, then by the boundedness of  $A$ , the norm of  $A(x)$  minus  $A(y)$ , which is less than  $C$  times the norm of  $x$  minus  $y$ , is less than  $C$  times epsilon, demonstrating that  $A$  is continuous.

To show boundedness, consider that the norm of  $A(x)$  is less than or equal to twice delta times the norm of  $x$ , confirming  $A$ 's bounded nature.

For linearity of the inverse, consider  $T$  acting on  $x_1$  plus  $x_2$  results in  $T(x_1)$  plus  $T(x_2)$ , and  $T$  acting on alpha times  $x_1$  equals alpha times  $T(x_1)$ . Thus, the inverse  $T$  inverse applied to alpha times  $y_1$  results in alpha times  $T$  inverse of  $y_1$ , which confirms the linearity of  $T$  inverse.

### 2.4 Compact Operators and Finite Rank Operators

A finite rank operator is defined as a linear map whose image has finite dimensionality. Such operators are inherently compact due to their bounded nature. Corollary 2.9 establishes that any limit of compact operators remains compact [5].

To demonstrate that  $T(B)$  is totally bounded, consider that the inequality for any elements  $t$  and  $t_i$  in the set, the difference  $t$  minus  $t_i$  is less than epsilon, which ensures total boundedness by keeping distances between elements uniformly small. Corollary 2.10 further confirms that any limit of finite rank operators also retains compactness, emphasizing the stability of compact characteristics under limits in operator theory [6].

### 2.5 Adjoints

The inner product of  $T(x)$  and  $y$  in Hilbert space  $H$  is equal to the inner product of  $x$  and the adjoint  $(T^*)$  of  $(T)$  acting on  $(y)$  in Hilbert space  $\backslash(K)$ . In finite-dimensional spaces, the adjoint of a matrix corresponds to its complex conjugate transpose, denoted as  $(T^*)$  which is equivalent to  $T^{\wedge}T$ . For a self-adjoint operator  $(T)$ , the equality  $(\langle Tu, v \rangle = \langle u, Tv \rangle)$  holds. Given  $(Tu = \lambda_1 u)$  and  $(Tv = \lambda_2 v)$ , the relationship between  $(u), (v)$ , and their respective transformations by  $(T)$  is maintained under these operations [7].

### 2.6 Spectrum of Operators

$\sigma(T) = \{\lambda \in C \mid (\lambda I - T) \text{ is not a bijection from } X \text{ to } X\}$ .

This includes the following cases:

$\lambda I - T$  is not one-to-one (i.e., it has a non-trivial kernel, so  $\lambda$  is an eigenvalue).

$\lambda I - T$  is not onto (i.e., it is not surjective, so the range of  $\lambda I - T$  is not dense in  $X$ ).

$\lambda I - T$  is not bounded (i.e., its inverse does not exist or is not bounded).

In other words,  $T - \lambda I$  has no bounded inverse, even though it is injective and its range is dense.

The principal part, which consists of terms with negative powers of  $(z - z_0)$  [8].

$$E(\lambda) = \frac{1}{2\pi i} \int_{\Gamma} R(\xi; T) D\xi \tag{7}$$

The operator  $E(\lambda)$  projects onto the generalized eigenspace associated with  $\lambda$ , satisfying:

$$\begin{aligned} TE(\lambda) &= \lambda E(\lambda), \\ T &= X \lambda E(\lambda), \\ \lambda &\in \sigma(T) \end{aligned} \tag{8}$$

$$E(\lambda) = \frac{1}{2\pi i} \int_{\Gamma} (\xi I - T)^{-1} d\xi \tag{9}$$

$$E(\lambda_1) E(\lambda_2) = 0 \text{ if } \lambda_1 \neq \lambda_2$$

This concludes the proof.

### 3. Spectral Theory

#### 3.1 Compact Operators and Closed Spectrum

Proof. Let  $y = \lim_{n \rightarrow \infty} y_n$ , where  $y_n = (\lambda I - T) x_n$ . We consider two cases:

Since  $x_{n+1} = (y_n + T x_n)/\lambda$ ,  $\{x_n\}$  converges to some element  $x \in X$ , and by the continuity of  $\lambda I - T$ , it follows  $y = (\lambda I - T) x$  so  $y$  is in the range [9].

If  $\{x_n\}$  contains no bounded subsequence, then  $|x_n| \rightarrow \infty$ . Let  $z_n = x_n/|x_n|$ , so that  $(\lambda I - T) z_n \rightarrow 0$  and  $|z_n| = 1$ . Since  $z_{n+1} - \lambda^{-1} T z_n \rightarrow 0$ , it follows that  $\{z_n\}$  converges. Let  $z = \lim z_n$ . Then  $|z| = 1$ , and  $(\lambda I - T) z = 0$ . Consequently, contrary to hypothesis,  $\lambda I - T$  is not one-to-one, so this case is eliminated.

Proof. Suppose towards a contradiction that  $\lambda I - T$  is one-to-one [10]. By lemma 3.1,  $(\lambda I - T) X = X$  and  $\lambda I - T$  has an everywhere defined inverse, which is bounded according to corollary 2.7.

#### 3.2 Isolation of Eigenvalues

Proof. If  $\lambda$  were in the continuous spectrum of  $T$ , then  $T - \lambda I$  would be injective, but its range would not be dense. However, since  $T$  is compact, the operator  $T - \lambda I$  must have closed range, and thus it cannot be part of the continuous spectrum. Therefore, any  $\lambda \neq 0$  in the spectrum must be an isolated point and cannot belong to the continuous spectrum.

Proof. Compact operators have no continuous spectrum outside of  $\lambda = 0$  because lemma 3.1 states the range is closed, so the remaining spectrum consists of isolated ei-

genvalues.

#### 3.3 Riesz's Lemma and Applications

$$a \leq \|v - y_0\| \leq \frac{a}{\alpha} \tag{10}$$

$$\|z - y\| = c \|v - y_1\| \geq ca = \frac{a}{\|v - y_0\|} \geq \frac{a}{a/\alpha} = \alpha \tag{11}$$

The following lemma is another application of Riesz's lemma.

We first prove  $U_n \subset U_{n+1}$  is a proper inclusion by showing  $x_1, \dots, x_n$  are linearly independent. Suppose towards a contradiction that  $x_n = \alpha_1 x_1 + \dots + \alpha_{n-1} x_{n-1}$ . Then

Because all  $\lambda_i$  are distinct from  $\lambda_n$ , we have  $\alpha_i = 0$  for all  $i = 1, \dots, n-1$  and  $x_n = 0$ , which is a contradiction.

Thus,  $U_n \subset U_{n+1}$  is a proper inclusion, and because  $U_n$  is closed, by Riesz's lemma 3.6, there exists  $y_n \in U_n$  with  $|y_n| = 1$  and  $|y_n - x| > 1/2$  for all  $x$  in  $U_{n-1}$ . Because  $y_n = \alpha_1 x_1 + \dots + \alpha_n x_n$ , it follows  $(T - \lambda_n I) y_n \in U_{n-1}$ . Thus, if  $n > m$ , the vector  $z_{n,m} = (y_n - \lambda_{n-1} T y_n) + \lambda_{n-1} T y_m$  is in  $U_{n-1}$  and therefore

Which shows the subsequence of  $\{T(y_n/\lambda_n)\}$  converges and contradicts with the compactness of  $T$ . Thus, we conclude  $\lambda_n$  approaches 0.

#### 3.4 Eigenspaces and Poles

With.

$$\begin{aligned} A^{-(m+1)} &= -(\lambda I - T) m E(\lambda; T) \\ (\lambda I - T) n x &= 0, (\lambda I - T) n-1 x \neq 0 \end{aligned} \tag{12}$$

Since.

$$\begin{aligned} R(\xi; T) &= -\sum_{j=0}^{\infty} \frac{(\lambda I - T)^j}{(\lambda - \xi)^{j+1}}, |\lambda - \xi| > |\lambda I - T| \\ R(\xi; T) x &= -\sum_{j=0}^{n-1} \frac{(\lambda I - T)^j x}{(\lambda - \xi)^{j+1}} \end{aligned} \tag{13}$$

$$x = \frac{1}{2\pi i} \int_K R(\xi; T) x d\xi = \frac{1}{2\pi i} \int_C R(\xi; T) x d\xi = e(T) x \tag{14}$$

Then.

$$\begin{aligned} f(T)_\sigma &= \frac{1}{2\pi i} \left( \int_B f(\lambda) R(\lambda; T) d\lambda \right)_\sigma \\ &= \frac{1}{2\pi i} \int_B f(\lambda) R(\lambda; T)_\sigma d\lambda \\ &= \frac{1}{2\pi i} \int_B f(\lambda) R(\lambda; T_\sigma) d\lambda = f(T_\sigma) \end{aligned} \tag{15}$$

$$(\lambda I - T) m E(\lambda) = (\lambda I_\sigma - T_\sigma) m E(\lambda), m = 1, 2, \dots$$

Proof. By lemma 3.10,  $(T - \lambda I) v X \sigma = X \sigma$ . By lemma 3.9,

Also, if  $(T - \lambda I) v x = 0$  then, by equation 2.

#### 3.5 Structure of Spectrum of Compact Opera-

## tors

The paper discusses the structure of compact operators' spectrum, highlighting that it is possible for the spectrum to have infinitely many eigenvalues accumulating at zero, as detailed in Lemma 3.8. The analysis starts by considering  $(T_\lambda)$ , the restriction of  $(T)$  to  $\{X_\lambda\} = E(\lambda)X$ . From Theorem 3.10,  $(\lambda)$ , a nonzero value, belongs to  $(\sigma(T_\lambda))$ , indicating that  $(T_\lambda)$  has a bounded inverse. Consequently, if  $(S)$  represents the closed unit sphere in  $(X_\lambda)$ , then  $(T_\lambda^{-1}S)$  is bounded. Given the compactness of  $(T_\lambda)$ ,  $(S)$  itself must be compact. Proposition 3.7 confirms that  $(E(\lambda)X)$  is finite-dimensional and Theorem 1.3 specifies an integer  $(\nu)$  for which  $((T_\lambda - \lambda I_\lambda)^\nu = 0)$ . This leads to the conclusion outlined in Lemma 3.11. Furthermore, Lemma 3.2 identifies a nonzero eigenvalue  $(\lambda_1)$  with a corresponding eigenvector  $(u_1)$ . According to Proposition 2.12, these eigenvectors are orthogonal. The existence of a vector  $v$  in  $H$ , orthogonal to all eigenvectors of  $T$ , and its inclusion in the orthogonal complement of the eigenspace imply that  $T$  restricted to this complement remains compact and must have an eigenvector. This scenario contradicts the assumption that  $v$  is orthogonal to all eigenvectors, leading to the conclusion that the eigenvectors form a complete set spanning  $H$ . Thus,  $T$  can be expressed as an infinite sum of outer products of these eigenvectors with themselves, indexed by their respective eigenvalues  $(\lambda_i)$ .

## 4. Applications

### 4.1 Schmidt Decomposition

Schmidt decomposition reveals the extent of entanglement in quantum states by expanding vectors in tensor product spaces across the bases of two Hilbert spaces. Applying singular value decomposition (SVD) to the vector  $(\psi)$  within the tensor product space  $(HA \otimes HB)$ , one expresses  $(\psi)$  using an orthonormal basis for  $(HA)$  and  $(HB)$ . The coefficients from this expansion populate a matrix, which, upon SVD, decomposes into  $(U \Lambda V^{\dagger})$ . This results in a new expression of  $(\psi)$  as a sum over products of vectors scaled by non-negative singular values, the Schmidt coefficients, which quantify the contributions of each term in the decomposition. A higher Schmidt rank

implies a more entangled quantum state, highlighting complex subsystem interactions. Additionally, this decomposition technique is underscored by spectral theory, providing insights into the quantum information theory through calculations such as the trace of the reduced density matrices  $(\rho_A)$  and  $(\rho_B)$ , reflecting the subsystems' states.

### 4.2 Principle Component Analysis

In Principal Component Analysis (PCA), a dataset  $X$  with  $n$  entries and  $p$  features, where each feature is zero-centered, undergoes a dimensionality reduction process to project the data onto a new space with fewer features,  $k$ , where  $k < p$ . This reduction maximizes the variance of the data in the new feature space.

The covariance matrix  $C$  is computed from the zero-centered data, which is a symmetric and positive semi-definite matrix. This matrix is foundational in the PCA process as it encapsulates the variance and covariance among the features. An eigenvalue problem is then solved where the matrix  $C$  is decomposed into its eigenvectors and eigenvalues. The principal components are these eigenvectors, and they are selected based on their corresponding eigenvalues which represent the variance each principal component captures from the data.

The eigenvectors are orthogonal to each other, ensuring that the new features (principal components) are uncorrelated. This property is crucial for the effectiveness of PCA, as it guarantees that each principal component contributes uniquely to the variance. The projections of the original data onto these principal components form a new dataset with reduced dimensions but maximal variance, enhancing further analysis like clustering or regression without the noise and redundancy of the original high-dimensional space.

From a spectral theory perspective, the decomposition of the covariance matrix during PCA aligns with the spectral decomposition of matrices, where the eigenvectors form an orthogonal basis for the data space, and the eigenvalues dictate the significance or weight of each dimension in this basis. The orthogonality of eigenvectors corresponds to the uncorrelated nature of principal components, a foundational aspect that allows PCA to identify the most expressive features of the data.

Thus, PCA not only reduces the dimensionality of data but does so by preserving as much statistical information as possible, making it a powerful tool for exploratory data analysis and predictive modeling.

### 4.3 Challenges

The study of spectral theory in compact operators, par-

ticularly in Banach and Hilbert spaces, reveals both deep theoretical insights and significant practical applications. However, several challenges arise in the analysis and application of these operators, reflecting the complexities inherent in this mathematical domain. Unlike finite-dimensional operators, where the spectrum consists entirely of eigenvalues, the spectrum of compact operators can include continuous components, posing difficulties in directly linking operator behavior to discrete spectral elements. Extending these results to more general classes of operators, such as those that are not self-adjoint, remains an ongoing challenge in functional analysis.

Another challenge is the numerical computation of spectra and eigenvalues, particularly in practical applications like Principal Component Analysis (PCA) and Schmidt decomposition. Although compact operators have a countable spectrum with possible accumulation only at zero, accurately estimating eigenvalues and corresponding eigenvectors in computational settings can be problematic. Numerical instability and sensitivity to small perturbations in data can significantly affect the results, particularly when dealing with ill-conditioned matrices or nearly degenerate eigenvalues. In PCA, for example, the interpretation of eigenvalues as variance measures depends on precise computations, and small errors can lead to incorrect conclusions about data structure. Similarly, in quantum information theory, the accurate determination of Schmidt coefficients is crucial for assessing the degree of entanglement, with errors potentially leading to misinterpretations of quantum states. In addition to computational challenges, the theoretical application of spectral theory to specific problems often encounters limitations due to idealized assumptions. For instance, the assumption of compactness is crucial in proving the existence of discrete spectra, but many real-world operators, such as differential operators encountered in physics, are not compact. This discrepancy limits the direct application of spectral results and necessitates additional tools, such as perturbation theory or regularization techniques, to approximate the behavior of non-compact operators using compact ones. Moreover, the spectral theory of compact operators, while elegant, does not directly address the dynamics of operators over time, such as those encountered in iterative algorithms or time-evolution problems in physics. Extending the analysis to include time-dependent or stochastic variations adds significant complexity. For instance, in PCA applied to time series data, the covariance structure may evolve, rendering a static spectral analysis insufficient. Developing adaptive methods that can dynamically adjust to changing spectra is an active area of research but presents its own set of mathematical and computational challenges. Lastly, the extension of spectral theory from compact operators

to broader classes, such as those defined on non-standard spaces (e.g., Sobolev spaces or spaces with non-trivial topological structure), introduces further complications. These spaces may lack the compactness properties required for the traditional spectral theorem, necessitating the development of alternative spectral techniques or generalized operator classes that retain some spectral-like behavior. Exploring the spectral properties of pseudo-differential operators, integral operators with weakly decaying kernels, or operators defined on spaces with fractal or irregular geometries remains a complex but crucial task for advancing both pure and applied mathematics.

In summary, while the spectral theory of compact operators provides a powerful framework for understanding various mathematical and physical phenomena, it also presents significant challenges, particularly when dealing with non-ideal, infinite-dimensional, or dynamically evolving systems. Overcoming these challenges requires a combination of theoretical innovation, computational refinement, and the development of generalized frameworks that can extend the utility of spectral analysis beyond

## 5. Conclusion

This paper has explored the spectral properties of compact operators, particularly focusing on those that are self-adjoint, revealing a spectrum consisting of isolated points predominantly accumulating at zero. The findings not only align with established theorems in operator theory but also provide a fresh perspective that blends classical spectral theory with modern applications in quantum information theory and machine learning. Through detailed analysis, it has been demonstrated how the eigenvalue decomposition of such operators can dramatically improve methods for data dimensionality reduction and the analysis of quantum states. Future research should aim to expand these methods to more complex classes of operators, exploring their implications across broader areas of functional analysis. Challenges posed by non-ideal, infinite-dimensional, or dynamically evolving systems present an urgent call for developing innovative theoretical and computational techniques. These would ideally address the limitations of current spectral theory applications, especially in non-compact settings, and could enhance our ability to model and analyze the dynamic behaviors of various physical and mathematical systems under realistic conditions. Further investigation into these areas will likely yield significant advancements, contributing robust tools and frameworks that can be employed across disciplines.

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