Group Theory in Quantum Mechanics Lecture 4 (1.24.13)

Matrix Eigensolutions and Spectral Decompositions

(Quantum Theory for Computer Age - Ch. 3 of Unit 1) (Principles of Symmetry, Dynamics, and Spectroscopy - Sec. 1-3 of Ch. 1)

Unitary operators and matrices that change state vectors ...and eigenstates ("ownstates) that are mostly immune

Geometric visualization of real symmetric matrices and eigenvectors Circle-to-ellipse mapping (and I'm Ba-aaack!) Ellipse-to-ellipse mapping (Normal space vs. tangent space) Eigensolutions as stationary extreme-values (Lagrange λ -multipliers)

Matrix-algebraic eigensolutions with example $M = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}$ Secular equation Hamilton-Cayley equation and projectors Idempotent projectors (how eigenvalues \Rightarrow eigenvectors) Operator orthonormality and completeness

Spectral Decompositions

Functional spectral decomposition Orthonormality vs. Completeness vis-a`-vis Operator vs. State Lagrange functional interpolation formula Proof that completeness relation is "Truer-than-true"

Diagonalizing Transformations (D-Ttran) from projectors Eigensolutions for active analyzers Unitary operators and matrices that change state vectors ...and eigenstates ("ownstates) that are mostly immune

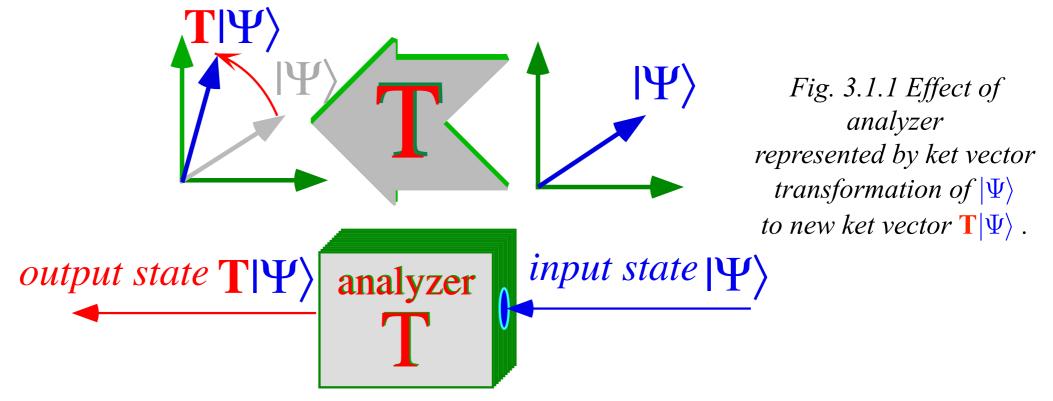
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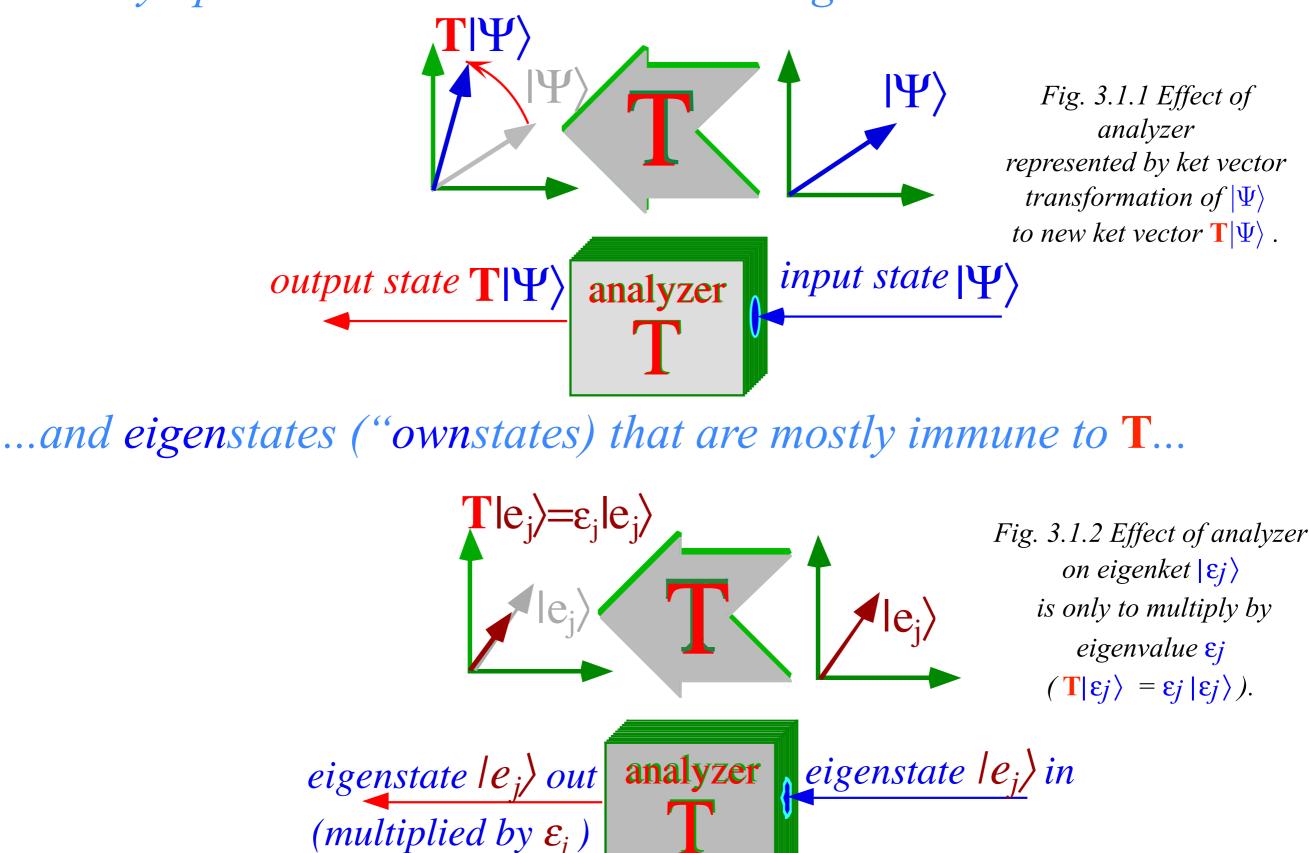
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Spectral Decompositions with degeneracy Functional spectral decomposition Unitary operators and matrices that change state vectors



Unitary operators and matrices that change state vectors...



For Unitary operators $\mathbf{T}=\mathbf{U}$, the eigenvalues must be phase factors $\varepsilon_k=e^{i\alpha_k}$

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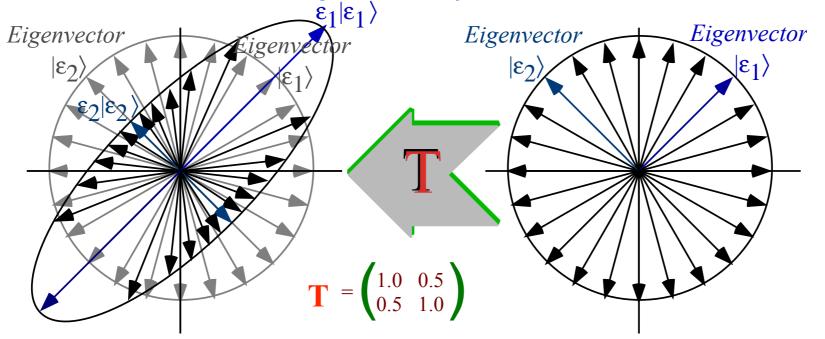
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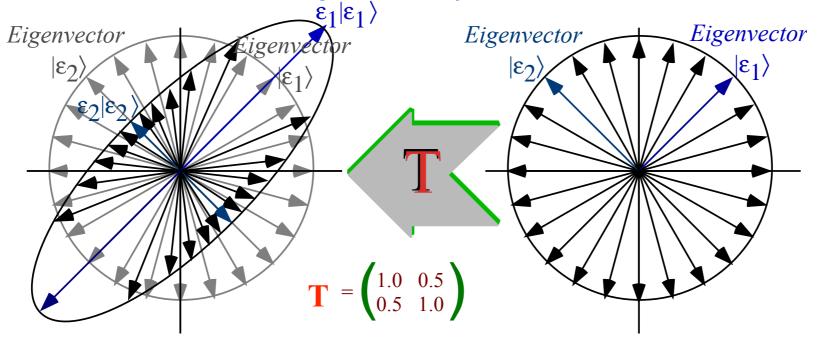
Geometric visualization of real symmetric matrices and eigenvectors



Study a real symmetric matrix **T** by applying it to a circular array of unit vectors **c**.

A matrix $\mathbf{T} = \begin{pmatrix} 1 & 1/2 \\ 1/2 & 1 \end{pmatrix}$ maps the circular array into an elliptical one.

Geometric visualization of real symmetric matrices and eigenvectors



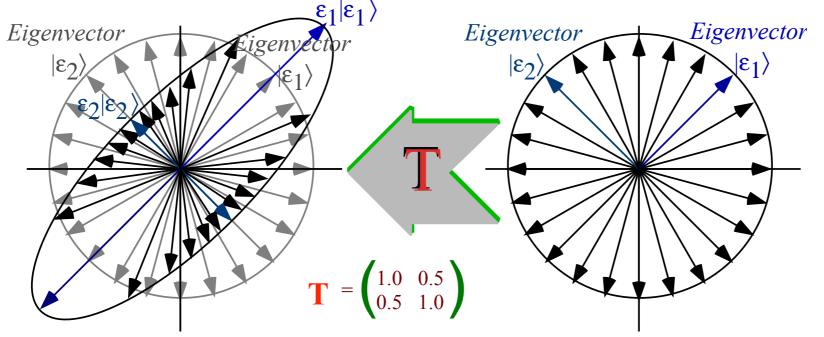
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Two vectors in the upper half plane survive **T** without changing direction. These lucky vectors are the *eigenvectors of matrix* **T**.

$$\left| \boldsymbol{\varepsilon}_{1} \right\rangle = \begin{pmatrix} 1 \\ 1 \end{pmatrix} / \sqrt{2} , \qquad \left| \boldsymbol{\varepsilon}_{2} \right\rangle = \begin{pmatrix} -1 \\ 1 \end{pmatrix} / \sqrt{2}$$

Geometric visualization of real symmetric matrices and eigenvectors



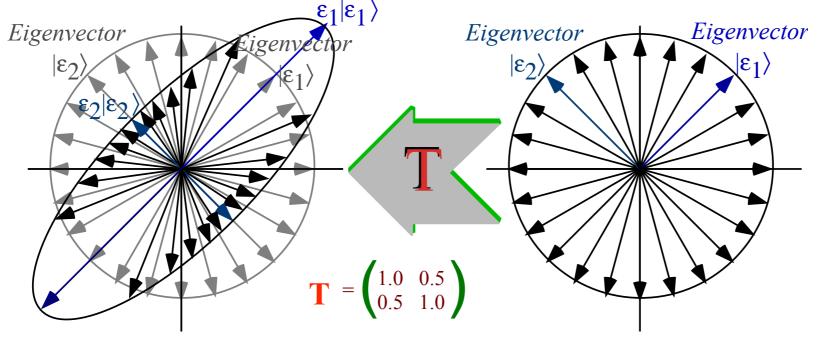
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They transform as follows: $\mathbf{T}|\boldsymbol{\varepsilon}_1\rangle = \boldsymbol{\varepsilon}_1|\boldsymbol{\varepsilon}_1\rangle = 1.5|\boldsymbol{\varepsilon}_1\rangle$, and $\mathbf{T}|\boldsymbol{\varepsilon}_2\rangle = \boldsymbol{\varepsilon}_2|\boldsymbol{\varepsilon}_2\rangle = 0.5|\boldsymbol{\varepsilon}_2\rangle$ to only suffer length change given by *eigenvalues* $\boldsymbol{\varepsilon}_1 = 1.5$ and $\boldsymbol{\varepsilon}_2 = 0.5$

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Normalization ($\langle \mathbf{c} | \mathbf{c} \rangle = 1$) is a condition separate from eigen-relations $\mathbf{T} | \varepsilon_k \rangle = \varepsilon_k | \varepsilon_k \rangle$

Unitary operators and matrices that change state vectors ...and eigenstates ("ownstates) that are mostly immune

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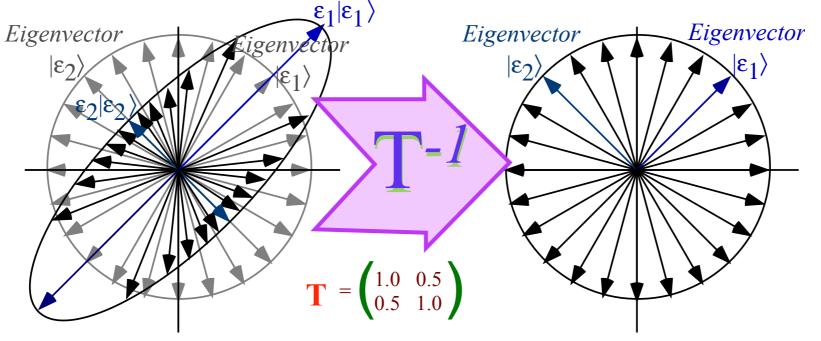
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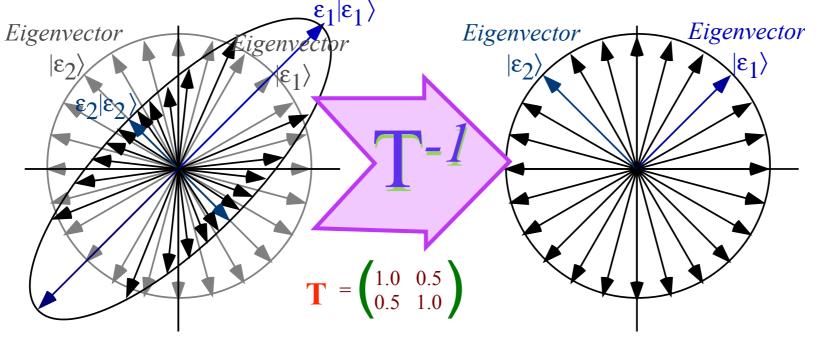


Circle-to-ellipse mapping (and I'm Ba-aaack!)

Each vector $|\mathbf{r}\rangle$ on left ellipse maps back to vector $|\mathbf{c}\rangle = \mathbf{T}^{-1} |\mathbf{r}\rangle$ on right unit circle. Each $|\mathbf{c}\rangle$ has unit length: $\langle \mathbf{c} | \mathbf{c} \rangle = 1 = \langle \mathbf{r} | \mathbf{T}^{-1} \mathbf{T}^{-1} | \mathbf{r} \rangle = \langle \mathbf{r} | \mathbf{T}^{-2} | \mathbf{r} \rangle$. (**T** is real-symmetric: $\mathbf{T}^{\dagger} = \mathbf{T} = \mathbf{T}^{T}$.)

$$\mathbf{c} \bullet \mathbf{c} = 1 = \mathbf{r} \bullet \mathbf{T}^{-2} \bullet \mathbf{r} = \begin{pmatrix} x & y \end{pmatrix} \begin{pmatrix} T_{xx} & T_{xy} \\ T_{yx} & T_{y} \end{pmatrix}^{-2} \begin{pmatrix} x \\ y \end{pmatrix}$$

Geometric visualization of real symmetric matrices and eigenvectors



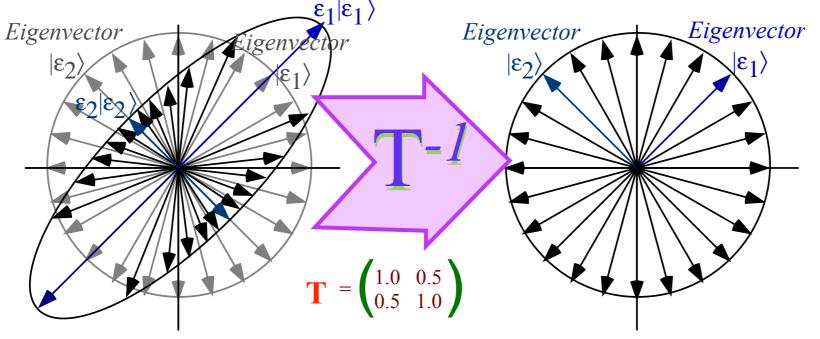
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This simplifies if rewritten in a coordinate system (x_1, x_2) of eigenvectors $|\varepsilon_1\rangle$ and $|\varepsilon_2\rangle$ where $\mathbf{T}^{-2}|\varepsilon_1\rangle = \varepsilon_1^{-2}|\varepsilon_1\rangle$ and $\mathbf{T}^{-2}|\varepsilon_2\rangle = \varepsilon_2^{-2}|\varepsilon_2\rangle$, that is, \mathbf{T} , \mathbf{T}^{-1} , and \mathbf{T}^{-2} are each diagonal. $\begin{pmatrix} \langle \varepsilon_1 | \mathbf{T} | \varepsilon_1 \rangle & \langle \varepsilon_1 | \mathbf{T} | \varepsilon_2 \rangle \\ \langle \varepsilon_2 | \mathbf{T} | \varepsilon_1 \rangle & \langle \varepsilon_2 | \mathbf{T} | \varepsilon_2 \rangle \end{pmatrix} = \begin{pmatrix} \varepsilon_1 & 0 \\ 0 & \varepsilon_2 \end{pmatrix}$, and $\begin{pmatrix} \langle \varepsilon_1 | \mathbf{T} | \varepsilon_1 \rangle & \langle \varepsilon_1 | \mathbf{T} | \varepsilon_2 \rangle \\ \langle \varepsilon_2 | \mathbf{T} | \varepsilon_1 \rangle & \langle \varepsilon_2 | \mathbf{T} | \varepsilon_2 \rangle \end{pmatrix}^{-2} = \begin{pmatrix} \varepsilon_1^{-2} & 0 \\ 0 & \varepsilon_2^{-2} \end{pmatrix}$

Geometric visualization of real symmetric matrices and eigenvectors



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$$\begin{pmatrix} \boldsymbol{\varepsilon}_1 | \mathbf{T} | \boldsymbol{\varepsilon}_1 \rangle & \langle \boldsymbol{\varepsilon}_1 | \mathbf{T} | \boldsymbol{\varepsilon}_2 \rangle \\ \langle \boldsymbol{\varepsilon}_2 | \mathbf{T} | \boldsymbol{\varepsilon}_1 \rangle & \langle \boldsymbol{\varepsilon}_2 | \mathbf{T} | \boldsymbol{\varepsilon}_2 \rangle \end{pmatrix} = \begin{pmatrix} \boldsymbol{\varepsilon}_1 & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{\varepsilon}_2 \end{pmatrix}, \text{ and } \begin{pmatrix} \langle \boldsymbol{\varepsilon}_1 | \mathbf{T} | \boldsymbol{\varepsilon}_1 \rangle & \langle \boldsymbol{\varepsilon}_1 | \mathbf{T} | \boldsymbol{\varepsilon}_2 \rangle \\ \langle \boldsymbol{\varepsilon}_2 | \mathbf{T} | \boldsymbol{\varepsilon}_1 \rangle & \langle \boldsymbol{\varepsilon}_2 | \mathbf{T} | \boldsymbol{\varepsilon}_2 \rangle \end{pmatrix}^{-2} = \begin{pmatrix} \boldsymbol{\varepsilon}_1^{-2} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{\varepsilon}_2^{-2} \end{pmatrix}$$

Matrix equation simplifies to an elementary ellipse equation of the form $(x/a)^2 + (y/b)^2 = 1$.

$$\mathbf{c} \bullet \mathbf{c} = 1 = \begin{pmatrix} x_1 & x_2 \end{pmatrix} \begin{pmatrix} \varepsilon_1^{-2} & 0 \\ 0 & \varepsilon_2^{-2} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} \frac{x_1}{\varepsilon_1} \end{pmatrix}^2 + \begin{pmatrix} \frac{x_2}{\varepsilon_2} \end{pmatrix}^2$$

Unitary operators and matrices that change state vectors ...and eigenstates ("ownstates) that are mostly immune

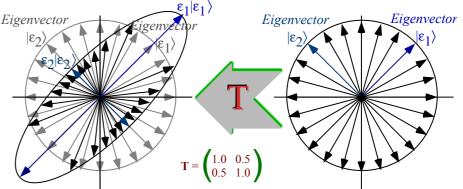
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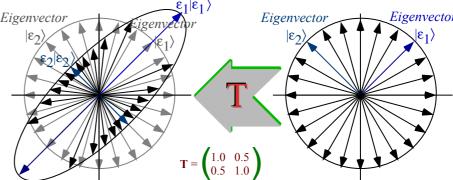
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Ellipse-to-ellipse mapping (Normal vs. tangent space)

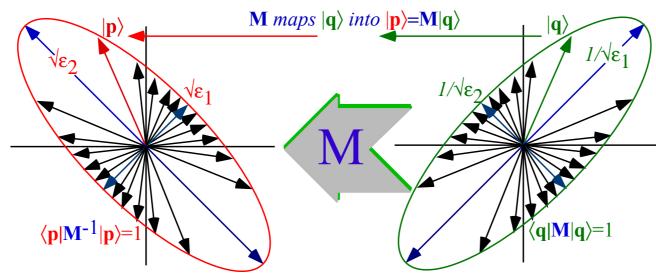
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Ellipse-to-ellipse mapping (Normal vs. tangent space)

Now **M** maps vector $|\mathbf{q}\rangle$ from a *quadratic form* $1 = \langle \mathbf{q} | \mathbf{M} | \mathbf{q} \rangle$ to vector $|\mathbf{p}\rangle = \mathbf{M} | \mathbf{q} \rangle$ on surface $1 = \langle \mathbf{p} | \mathbf{M}^{-1} | \mathbf{p} \rangle$.

$$1 = \langle \mathbf{q} | \mathbf{M} | \mathbf{q} \rangle = \langle \mathbf{q} | \mathbf{p} \rangle = \langle \mathbf{p} | \mathbf{M}^{-1} | \mathbf{p} \rangle$$



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(p|M⁻¹|n)

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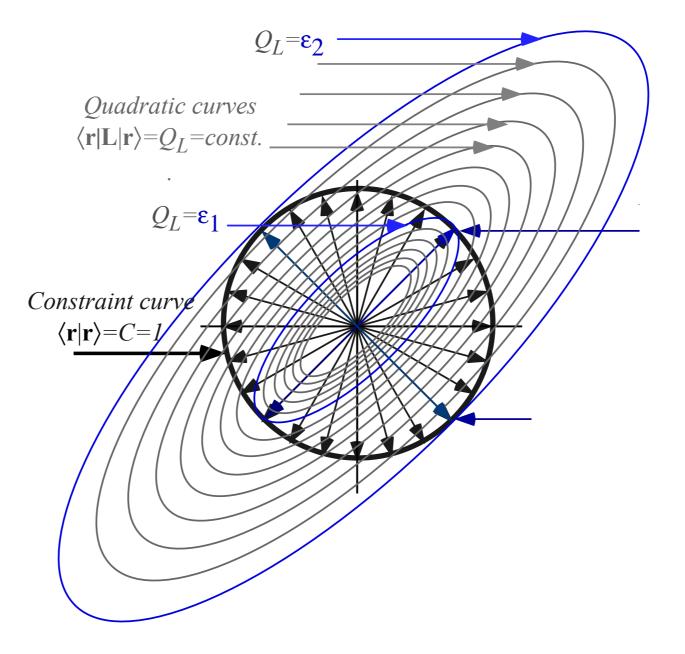
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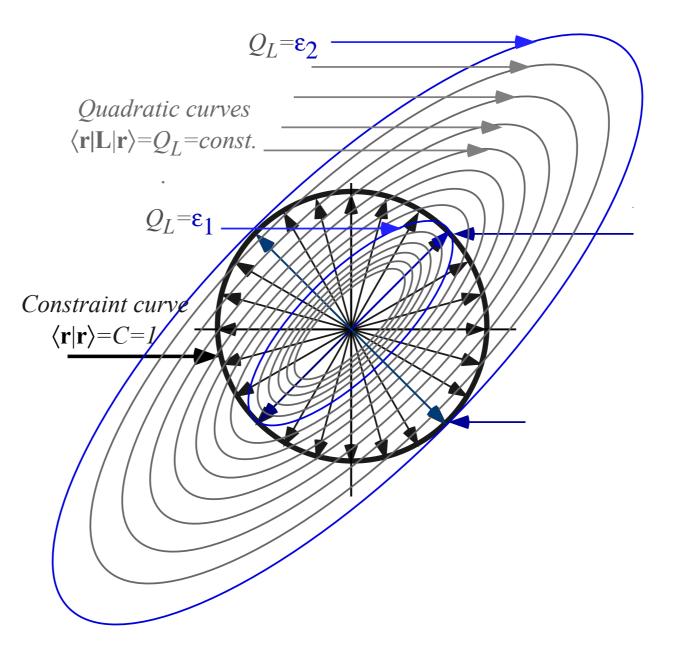
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Eigenvalues λ of a matrix **L** can be viewed as stationary-values of its *quadratic form* $Q_L = L(\mathbf{r}) = \langle \mathbf{r} | \mathbf{L} | \mathbf{r} \rangle$



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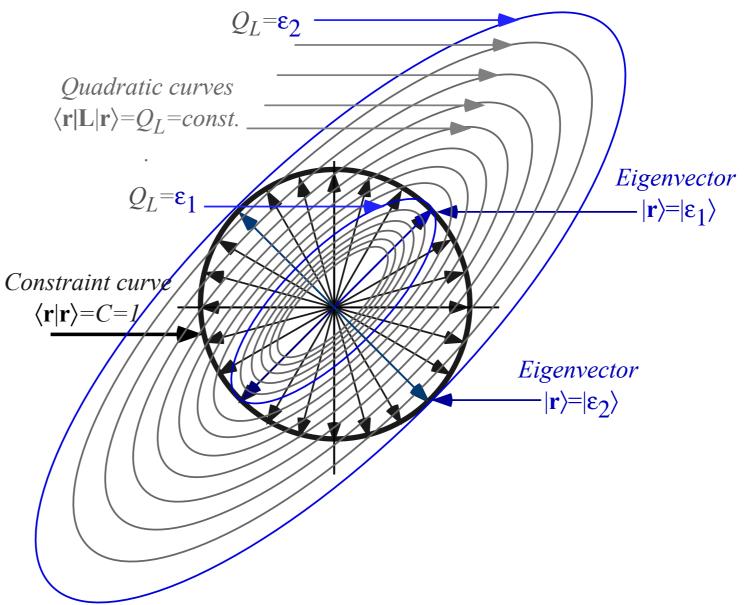
Q: What are min-max values of the function $Q(\mathbf{r})$ subject to the **constraint** of unit norm: $C(\mathbf{r}) = \langle \mathbf{r} | \mathbf{r} \rangle = 1$.



Eigenvalues λ of a matrix **L** can be viewed as stationary-values of its *quadratic form* $Q_L = L(\mathbf{r}) = \langle \mathbf{r} | \mathbf{L} | \mathbf{r} \rangle$

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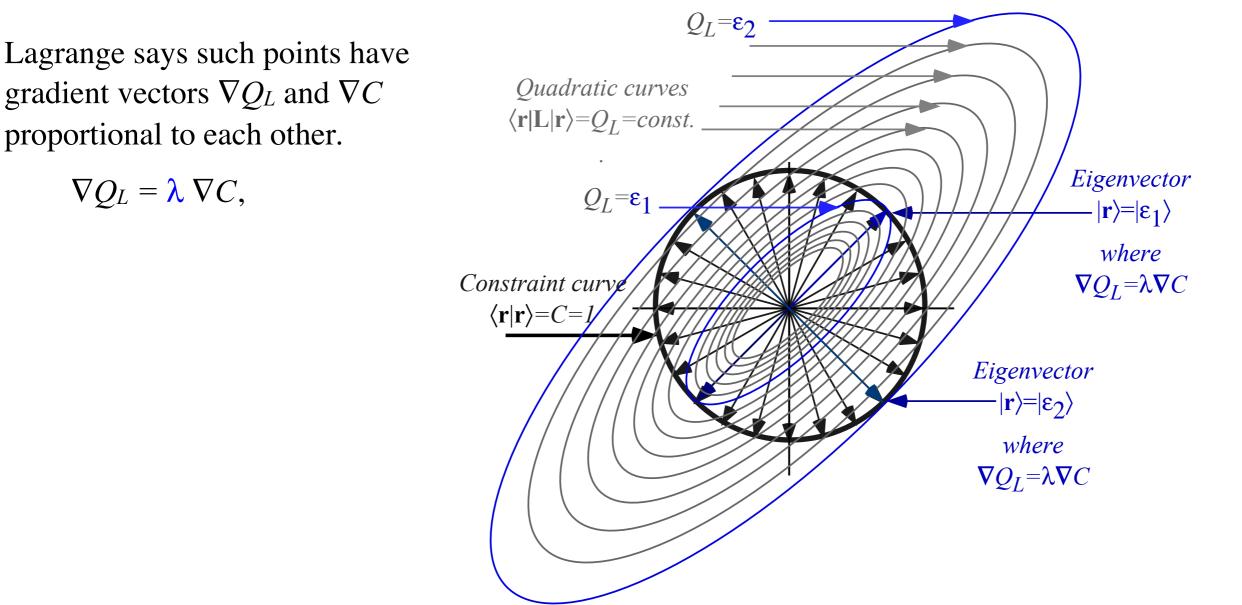
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 $Q_L = \epsilon_2$ Lagrange says such points have gradient vectors ∇Q_L and ∇C *Quadratic curves* $\langle \mathbf{r} | \mathbf{L} | \mathbf{r} \rangle = Q_L = const.$ proportional to each other. Eigenvector $\nabla Q_L = \lambda \nabla C,$ $Q_L = \epsilon_1$ $|\mathbf{r}\rangle = |\epsilon_1\rangle$ Proportionality constant λ is where called a *Lagrange Multiplier*. Constraint curve $\nabla Q_L = \lambda \nabla C$ $\langle \mathbf{r} | \mathbf{r} \rangle = C = l$ Eigenvector $|\mathbf{r}\rangle = |\varepsilon_{\gamma}\rangle$ where $\nabla Q_L = \lambda \nabla C$

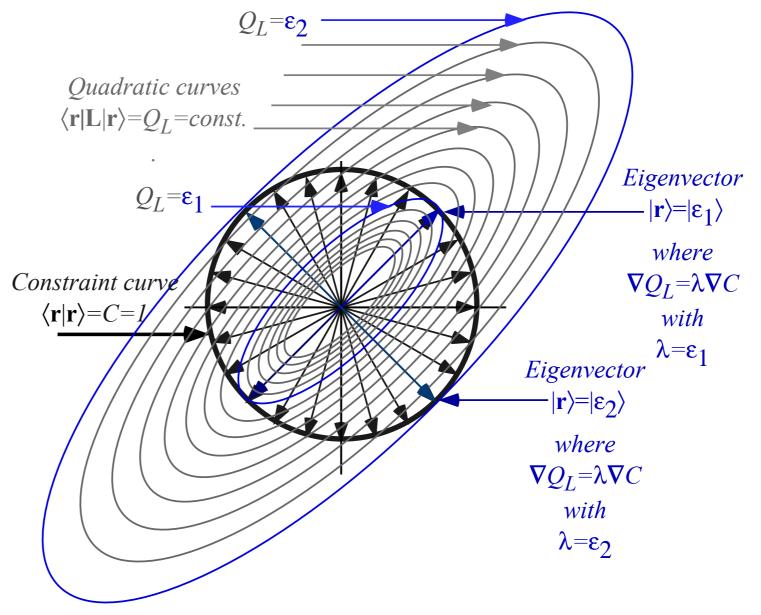
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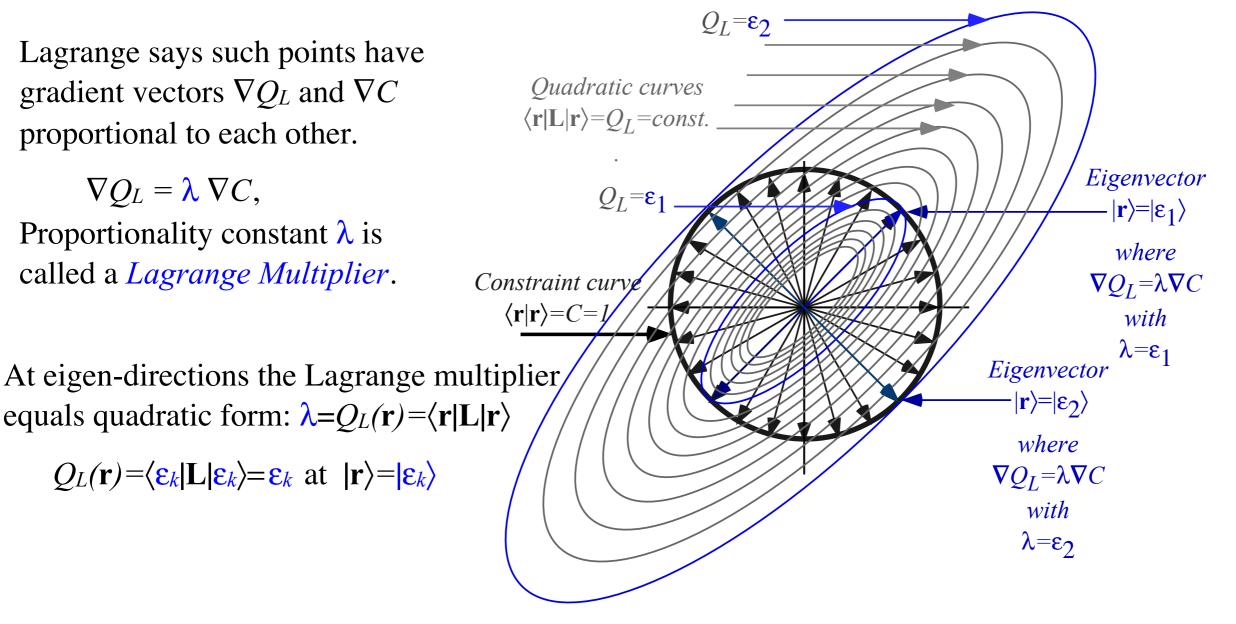
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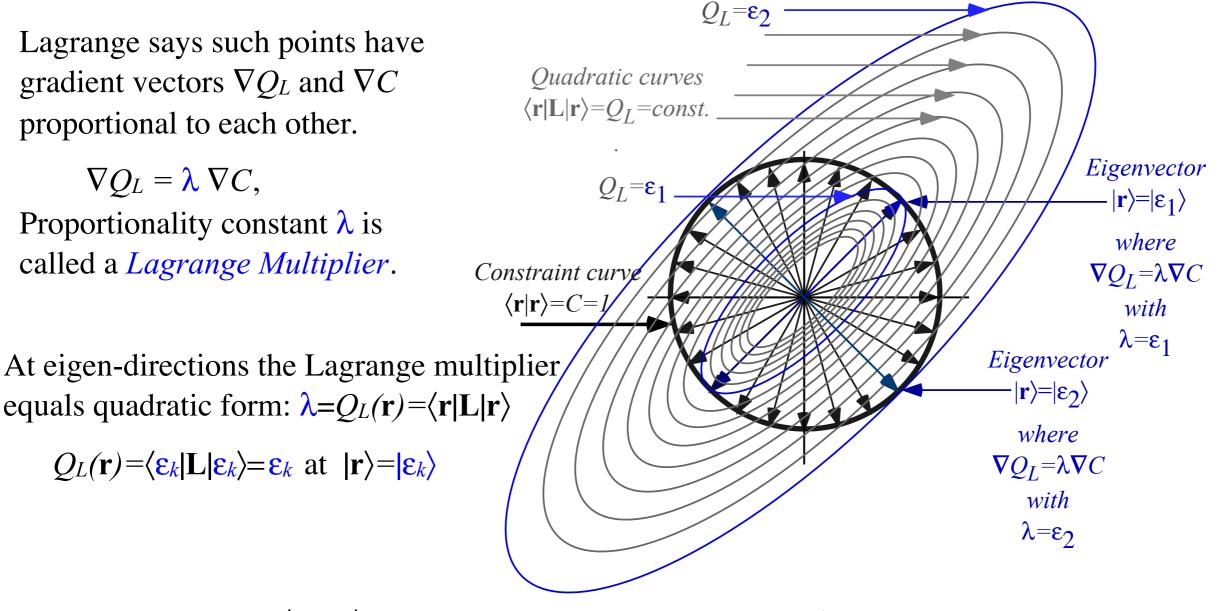
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 $\langle \mathbf{r} | \mathbf{L} | \mathbf{r} \rangle$ is called a quantum *expectation value* of operator L at r. Eigenvalues are extreme expectation values.

Unitary operators and matrices that change state vectors ...and eigenstates ("ownstates) that are mostly immune

Geometric visualization of real symmetric matrices and eigenvectors Circle-to-ellipse mapping Ellipse-to-ellipse mapping (Normal space vs. tangent space) Eigensolutions as stationary extreme-values (Lagrange λ -multipliers)

Matrix-algebraic eigensolutions with example $M = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}$ Secular equation Hamilton-Cayley equation and projectors Idempotent projectors (how eigenvalues \Rightarrow eigenvectors) Operator orthonormality and Completeness

Spectral Decompositions

Functional spectral decomposition Orthonormality vs. Completeness vis-a`-vis Operator vs. State Lagrange functional interpolation formula Proof that completeness relation is "Truer-than-true"

Spectral Decompositions with degeneracy Functional spectral decomposition

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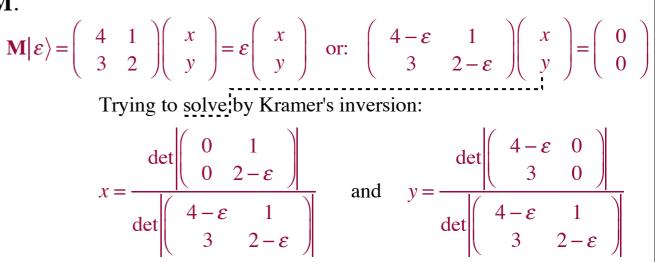
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 so let: $\varepsilon_1 = 1$ and: $\varepsilon_2 = 5$

Geometric visualization of real symmetric matrices and eigenvectors Circle-to-ellipse mapping Ellipse-to-ellipse mapping (Normal space vs. tangent space) Eigensolutions as stationary extreme-values (Lagrange λ -multipliers)

Matrix-algebraic eigensolutions with example $M = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}$ *Secular equation*

 \rightarrow

Hamilton-Cayley equation and projectors Idempotent projectors (how eigenvalues⇒eigenvectors) Operator orthonormality and Completeness

Spectral Decompositions

Functional spectral decomposition Orthonormality vs. Completeness vis-a`-vis Operator vs. State Lagrange functional interpolation formula Proof that completeness relation is "Truer-than-true"

Matrix-algebraic method for finding eigenvector and eigenvalues With example matrix $\mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}$

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$$|\mathbf{M} - \varepsilon \mathbf{1}| = 0 = (-1)^n (\varepsilon - \varepsilon_1) (\varepsilon - \varepsilon_2) \cdots (\varepsilon - \varepsilon_n)$$

Each ε replaced by **M** and each ε_k by $\varepsilon_k \mathbf{1}$ gives *Hamilton-Cayley* matrix equation.

$$\mathbf{0} = (\mathbf{M} - \varepsilon_1 \mathbf{1})(\mathbf{M} - \varepsilon_2 \mathbf{1}) \cdots (\mathbf{M} - \varepsilon_n \mathbf{1})$$

Obviously true if **M** has diagonal form. (But, that's circular logic. Faith needed!)

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 so let: $\varepsilon_1 = 1$ and: $\varepsilon_2 = 5$

$$0 = \mathbf{M}^{2} - 6\mathbf{M} + 5\mathbf{1} = (\mathbf{M} - 1 \cdot \mathbf{1})(\mathbf{M} - 5 \cdot \mathbf{1})$$
$$\begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}^{2} - 6 \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} + 5 \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

Matrix-algebraic method for finding eigenvector and eigenvalues With example matrix $\mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}$

An *eigenvector* $|\varepsilon_k\rangle$ of **M** is in a direction that is left unchanged by **M**.

$$\mathbf{M} | \boldsymbol{\varepsilon}_{k} \rangle = \boldsymbol{\varepsilon}_{k} | \boldsymbol{\varepsilon}_{k} \rangle, \text{ or: } (\mathbf{M} - \boldsymbol{\varepsilon}_{k} \mathbf{1}) | \boldsymbol{\varepsilon}_{k} \rangle = \mathbf{0}$$

 ε_k is *eigenvalue* associated with eigenvector $|\varepsilon_k\rangle$ direction. A change of basis to $\{|\varepsilon_1\rangle, |\varepsilon_2\rangle, \dots |\varepsilon_n\rangle\}$ called *diagonalization* gives

 $\begin{pmatrix} \langle \boldsymbol{\varepsilon}_{1} | \mathbf{M} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{1} | \mathbf{M} | \boldsymbol{\varepsilon}_{2} \rangle & \cdots & \langle \boldsymbol{\varepsilon}_{1} | \mathbf{M} | \boldsymbol{\varepsilon}_{n} \rangle \\ \langle \boldsymbol{\varepsilon}_{2} | \mathbf{M} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{2} | \mathbf{M} | \boldsymbol{\varepsilon}_{2} \rangle & \cdots & \langle \boldsymbol{\varepsilon}_{2} | \mathbf{M} | \boldsymbol{\varepsilon}_{n} \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle \boldsymbol{\varepsilon}_{n} | \mathbf{M} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{n} | \mathbf{M} | \boldsymbol{\varepsilon}_{2} \rangle & \cdots & \langle \boldsymbol{\varepsilon}_{n} | \mathbf{M} | \boldsymbol{\varepsilon}_{n} \rangle \end{pmatrix} = \begin{pmatrix} \boldsymbol{\varepsilon}_{1} & 0 & \cdots & 0 \\ 0 & \boldsymbol{\varepsilon}_{2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \boldsymbol{\varepsilon}_{n} \end{pmatrix}$

1st step in finding eigenvalues: Solve secular equation

$$\det |\mathbf{M} - \boldsymbol{\varepsilon} \mathbf{1}| = 0 = (-1)^n \left(\boldsymbol{\varepsilon}^n + a_1 \boldsymbol{\varepsilon}^{n-1} + a_2 \boldsymbol{\varepsilon}^{n-2} + \dots + a_{n-1} \boldsymbol{\varepsilon} + a_n \right)$$

where:

$$a_1 = -Trace \mathbf{M}, \dots, a_k = (-1)^k \sum \text{diagonal k-by-k minors of } \mathbf{M}, \dots, a_n = (-1)^n \det |\mathbf{M}|$$

Secular equation has *n*-factors, one for each eigenvalue.

$$\det |\mathbf{M} - \boldsymbol{\varepsilon} \mathbf{1}| = 0 = (-1)^n (\boldsymbol{\varepsilon} - \boldsymbol{\varepsilon}_1) (\boldsymbol{\varepsilon} - \boldsymbol{\varepsilon}_2) \cdots (\boldsymbol{\varepsilon} - \boldsymbol{\varepsilon}_n)$$

Each ε replaced by **M** and each ε_k by $\varepsilon_k \mathbf{1}$ gives *Hamilton-Cayley* matrix equation.

$$\mathbf{0} = (\mathbf{M} - \varepsilon_1 \mathbf{1}) (\mathbf{M} - \varepsilon_2 \mathbf{1}) \cdots (\mathbf{M} - \varepsilon_n \mathbf{1})$$

Obviously true if **M** has diagonal form. (But, that's circular logic. Faith needed!)

Replace j^{th} HC-factor by (1) to make *projection operators* $\mathbf{p}_{k} = \prod_{j \neq k} (\mathbf{M} - \varepsilon_{j} \mathbf{1})$. $\mathbf{p}_{1} = (\mathbf{1})(\mathbf{M} - \varepsilon_{2} \mathbf{1})\cdots(\mathbf{M} - \varepsilon_{n} \mathbf{1})$ $\mathbf{p}_{2} = (\mathbf{M} - \varepsilon_{1} \mathbf{1})(-\mathbf{1})\cdots(\mathbf{M} - \varepsilon_{n} \mathbf{1})$ (Assume distinct e-values here: Non-degeneracy clause) $\varepsilon_{j} \neq \varepsilon_{k} \neq \dots$ $\mathbf{p}_{n} = (\mathbf{M} - \varepsilon_{1} \mathbf{1})(\mathbf{M} - \varepsilon_{2} \mathbf{1})\cdots(-\mathbf{1})$

$$\mathbf{M}|\varepsilon\rangle = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \varepsilon \begin{pmatrix} x \\ y \end{pmatrix} \text{ or: } \begin{pmatrix} 4-\varepsilon & 1 \\ 3 & 2-\varepsilon \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

Trying to solve by Kramer's inversion:

$$x = \frac{\det \left| \begin{pmatrix} 0 & 1 \\ 0 & 2 - \varepsilon \end{pmatrix} \right|}{\det \left| \begin{pmatrix} 4 - \varepsilon & 1 \\ 3 & 2 - \varepsilon \end{pmatrix} \right|} \quad \text{and} \quad y = \frac{\det \left| \begin{pmatrix} 4 - \varepsilon & 0 \\ 3 & 0 \end{pmatrix} \right|}{\det \left| \begin{pmatrix} 4 - \varepsilon & 1 \\ 3 & 2 - \varepsilon \end{pmatrix} \right|}$$

Only possible non-zero $\{x, y\}$ if denominator is zero, too!

$$0 = \det \left| \mathbf{M} - \varepsilon \cdot \mathbf{I} \right| = \det \left| \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} - \varepsilon \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \right| = \det \left| \begin{pmatrix} 4 - \varepsilon & 1 \\ 3 & 2 - \varepsilon \end{pmatrix} \right|$$
$$0 = (4 - \varepsilon)(2 - \varepsilon) - 1 \cdot 3 = 8 - 6\varepsilon + \varepsilon^2 - 1 \cdot 3 = \varepsilon^2 - 6\varepsilon + 5$$
$$0 = \varepsilon^2 - Trace(\mathbf{M})\varepsilon + \det(\mathbf{M}) = \varepsilon^2 - 6\varepsilon + 5$$

$$0 = (\varepsilon - 1)(\varepsilon - 5)$$
 so let: $\varepsilon_1 = 1$ and: $\varepsilon_2 = 5$

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$$\mathbf{p}_{1} = (\mathbf{1})(\mathbf{M} - 5\cdot\mathbf{1}) = \begin{pmatrix} 4-5 & 1 \\ 3 & 2-5 \end{pmatrix} = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix}$$

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 $\begin{pmatrix} \langle \boldsymbol{\varepsilon}_{1} | \mathbf{M} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{1} | \mathbf{M} | \boldsymbol{\varepsilon}_{2} \rangle & \cdots & \langle \boldsymbol{\varepsilon}_{1} | \mathbf{M} | \boldsymbol{\varepsilon}_{n} \rangle \\ \langle \boldsymbol{\varepsilon}_{2} | \mathbf{M} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{2} | \mathbf{M} | \boldsymbol{\varepsilon}_{2} \rangle & \cdots & \langle \boldsymbol{\varepsilon}_{2} | \mathbf{M} | \boldsymbol{\varepsilon}_{n} \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle \boldsymbol{\varepsilon}_{n} | \mathbf{M} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{n} | \mathbf{M} | \boldsymbol{\varepsilon}_{2} \rangle & \cdots & \langle \boldsymbol{\varepsilon}_{n} | \mathbf{M} | \boldsymbol{\varepsilon}_{n} \rangle \end{pmatrix} = \begin{pmatrix} \boldsymbol{\varepsilon}_{1} & 0 & \cdots & 0 \\ 0 & \boldsymbol{\varepsilon}_{2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \boldsymbol{\varepsilon}_{n} \end{pmatrix}$

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Each ε replaced by **M** and each ε_k by $\varepsilon_k \mathbf{1}$ gives *Hamilton-Cayley* matrix equation.

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Each \mathbf{p}_k contains *eigen-bra-kets* since: $(\mathbf{M} - \varepsilon_k \mathbf{1})\mathbf{p}_k = 0$ or: $\mathbf{M}\mathbf{p}_k = \varepsilon_k \mathbf{p}_k = \mathbf{p}_k \mathbf{M}$.

 $\mathbf{M}|\boldsymbol{\varepsilon}\rangle = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \boldsymbol{\varepsilon} \begin{pmatrix} x \\ y \end{pmatrix} \text{ or: } \begin{pmatrix} 4-\boldsymbol{\varepsilon} & 1 \\ 3 & 2-\boldsymbol{\varepsilon} \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$

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$$\mathbf{Mp}_{1} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} \cdot \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix} = 1 \cdot \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix} = 1 \cdot \mathbf{p}_{1}$$

$$\mathbf{Mp}_{2} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} \cdot \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = 5 \cdot \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = 5 \cdot \mathbf{p}_{2}$$

Geometric visualization of real symmetric matrices and eigenvectors Circle-to-ellipse mapping Ellipse-to-ellipse mapping (Normal space vs. tangent space) Eigensolutions as stationary extreme-values (Lagrange λ -multipliers)

 Matrix-algebraic eigensolutions with example M= (4 1) 3 2) Secular equation Hamilton-Cayley equation and projectors
 Idempotent projectors (how eigenvalues⇒eigenvectors) Operator orthonormality and Completeness Idempotent r

Idempotent means: P·P=P

Spectral Decompositions

Functional spectral decomposition Orthonormality vs. Completeness vis-a`-vis Operator vs. State Lagrange functional interpolation formula Proof that completeness relation is "Truer-than-true"

$$\begin{aligned} \text{Matrix-algebraic method for finding eigenvector and eigenvalues}} & \text{With example matrix} & \mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} \\ \mathbf{p}_{j} \mathbf{p}_{k} = \mathbf{p}_{j} \prod_{m \neq k} (\mathbf{M} - \varepsilon_{m} \mathbf{1}) = \prod_{m \neq k} (\mathbf{p}_{j} \mathbf{M} - \varepsilon_{m} \mathbf{p}_{j} \mathbf{1}) & \mathbf{M} \mathbf{p}_{k} = \varepsilon_{k} \mathbf{p}_{k} = \mathbf{p}_{k} \mathbf{M} \\ \text{Multiplication properties of } \mathbf{p}_{j} : \\ \mathbf{p}_{j} \mathbf{p}_{k} = \prod_{m \neq k} (\varepsilon_{j} \mathbf{p}_{j} - \varepsilon_{m} \mathbf{p}_{j}) = \mathbf{p}_{j} \prod_{m \neq k} (\varepsilon_{j} - \varepsilon_{m}) = \begin{cases} \mathbf{0} & \text{if } : j \neq k \\ \mathbf{p}_{k} \prod_{m \neq k} (\varepsilon_{k} - \varepsilon_{m}) & \text{if } : j = k \end{cases} & \mathbf{p}_{k} \mathbf{P}_{k} = k \end{aligned}$$

$$\begin{aligned} \text{Matrix-algebraic method for finding eigenvector and eigenvalues}} & \text{With example matrix} & \mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} \\ \mathbf{p}_{j}\mathbf{p}_{k} = \mathbf{p}_{j}\prod_{m\neq k} (\mathbf{M} - \varepsilon_{m}\mathbf{1}) = \prod_{m\neq k} (\mathbf{p}_{j}\mathbf{M} - \varepsilon_{m}\mathbf{p}_{j}\mathbf{1}) & \mathbf{M}\mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} = \mathbf{p}_{k}\mathbf{M} \\ \text{Multiplication properties of } \mathbf{p}_{j}: \\ \mathbf{p}_{j}\mathbf{p}_{k} = \prod_{m\neq k} (\varepsilon_{j}\mathbf{p}_{j} - \varepsilon_{m}\mathbf{p}_{j}) = \mathbf{p}_{j}\prod_{m\neq k} (\varepsilon_{j} - \varepsilon_{m}) = \begin{cases} \mathbf{0} & \text{if } : j \neq k \\ \mathbf{p}_{k}\prod_{m\neq k} (\varepsilon_{k} - \varepsilon_{m}) & \text{if } : j = k \end{cases} \\ \mathbf{p}_{k}\prod_{m\neq k} (\varepsilon_{k} - \varepsilon_{m}) & \text{if } : j = k \end{cases} \\ \text{Last step:} \\ \text{make Idempotent Projectors: } \mathbf{P}_{k} = \frac{\mathbf{P}_{k}}{\prod_{m\neq k} (\varepsilon_{k} - \varepsilon_{m})} = \frac{\prod_{m\neq k} (\mathbf{M} - \varepsilon_{m}\mathbf{1})}{\prod_{m\neq k} (\varepsilon_{k} - \varepsilon_{m})} \quad \mathbf{P}_{1} = \frac{(\mathbf{M} - \mathbf{5} \cdot \mathbf{1})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} \\ \mathbf{P}_{2} = \frac{(\mathbf{M} - 1 \cdot \mathbf{1})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} \end{aligned}$$

$$\begin{array}{ll} \text{Matrix-algebraic method for finding eigenvector and eigenvalues} \\ \mathbf{p}_{j}\mathbf{p}_{k} = \mathbf{p}_{j}\prod_{m\neq k}(\mathbf{M}-\varepsilon_{m}\mathbf{1}) = \prod_{m\neq k}(\mathbf{p}_{j}\mathbf{M}-\varepsilon_{m}\mathbf{p}_{j}\mathbf{1}) \\ \text{Multiplication properties of } \mathbf{p}_{j}: \\ \mathbf{p}_{j}\mathbf{p}_{k} = \prod_{m\neq k}(\varepsilon_{j}\mathbf{p}_{j}-\varepsilon_{m}\mathbf{p}_{j}) = \mathbf{p}_{j}\prod_{m\neq k}(\varepsilon_{j}-\varepsilon_{m}) = \begin{cases} \mathbf{0} & \text{if } : j\neq k \\ \mathbf{p}_{k}\prod_{m\neq k}(\varepsilon_{k}-\varepsilon_{m}) & \text{if } : j=k \end{cases} \\ \mathbf{p}_{k}\prod_{m\neq k}(\varepsilon_{k}-\varepsilon_{m}) & \text{if } : j=k \end{cases} \\ \mathbf{p}_{i}\mathbf{p}_{k} = \begin{bmatrix} \mathbf{0} & \text{if } : j\neq k \\ \mathbf{p}_{k}\prod_{m\neq k}(\varepsilon_{k}-\varepsilon_{m}) & \text{if } : j=k \end{cases} \\ \mathbf{p}_{i}\mathbf{p}_{k} = \begin{cases} \mathbf{0} & \text{if } : j\neq k \\ \mathbf{p}_{k}\prod_{m\neq k}(\varepsilon_{k}-\varepsilon_{m}) & \text{if } : j=k \end{cases} \\ \mathbf{p}_{i}\mathbf{p}_{k} = \begin{bmatrix} \mathbf{0} & \text{if } : j\neq k \\ \mathbf{p}_{k} & \text{if } : j=k \end{cases} \\ \mathbf{p}_{k} = \begin{bmatrix} \mathbf{0} & \text{if } : j\neq k \\ \mathbf{p}_{k} & \text{if } : j=k \end{cases} \\ \mathbf{p}_{k} = \begin{bmatrix} \mathbf{0} & \text{if } : j\neq k \\ \mathbf{p}_{k} & \text{if } : j=k \end{cases} \\ \mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} = \mathbf{p}_{k} \\ \mathbf{p}_{k} & \text{if } : j=k \end{cases} \\ \mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} = \mathbf{p}_{k} \\ \mathbf{p}_{k} & \text{if } : j=k \end{cases} \\ \mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} = \mathbf{p}_{k} \\ \mathbf{p}_{k} & \text{if } : j=k \end{cases} \\ \mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} = \mathbf{p}_{k} \\ \mathbf{p}_{k} & \text{if } : j=k \end{cases} \\ \mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} = \mathbf{p}_{k} \\ \mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} = \mathbf{p}_{k} \\ \mathbf{p}_{k} & \text{if } : j=k \end{cases} \\ \mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} = \mathbf{p}_{k} \\ \mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} \\ \mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} \\ \mathbf{p}_{k$$

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 Matrix-algebraic eigensolutions with example M=(4 1) Secular equation Hamilton-Cayley equation and projectors
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(S) Factoring bra-kets into "Ket-Bras:

a-kets

Spectral Decompositions

Functional spectral decomposition Orthonormality vs. Completeness vis-a`-vis Operator vs. State Lagrange functional interpolation formula Proof that completeness relation is "Truer-than-true"

$$\begin{aligned} & \text{Matrix-algebraic method for finding eigenvector and eigenvalues} \\ & \mathbf{p}_{j}\mathbf{p}_{k} = \mathbf{p}_{j}\prod_{m\neq k} (\mathbf{M}-\varepsilon_{m}\mathbf{1}) = \prod_{m\neq k} (\mathbf{p}_{j}\mathbf{M}-\varepsilon_{m}\mathbf{p}_{j}\mathbf{1}) \\ & \mathbf{M}\mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} = \mathbf{p}_{k}\mathbf{M} \\ & \mathbf{M}\mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} = \mathbf{p}_{k}\mathbf{M} \\ & \mathbf{p}_{1} = (\mathbf{M}-5\mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix} \\ & \mathbf{p}_{1} = (\mathbf{M}-5\mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix} \\ & \mathbf{p}_{1}\mathbf{p}_{2} = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix} \\ & \mathbf{p}_{2} = (\mathbf{M}-1\mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix} \\ & \mathbf{p}_{2} = (\mathbf{M}-1\mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix} \\ & \mathbf{p}_{2} = (\mathbf{M}-1\mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix} \\ & \mathbf{p}_{2} = (\mathbf{M}-1\mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix} \\ & \mathbf{p}_{2} = (\mathbf{M}-1\mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix} \\ & \mathbf{p}_{2} = (\mathbf{M}-1\mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix} \\ & \mathbf{p}_{2} = (\mathbf{M}-1\mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & 1 \end{pmatrix} \\ & \mathbf{p}_{2} = (\mathbf{M}-1\mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & 1 \end{pmatrix} \\ & \mathbf{p}_{2} = (\mathbf{M}-1\mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & 1 \end{pmatrix} \\ & \mathbf{p}_{2} = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix} \\ & \mathbf{p}_{1} = \begin{pmatrix} -1 & -1 \\ -3 & 3 \end{pmatrix} = k_{1} \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \\ & \frac{1}{k_{1}} = |\varepsilon_{1}\rangle\langle\varepsilon_{1} \\ & k_{1} = |\varepsilon_{1}\rangle\langle\varepsilon_{2} \\ & k_{2} = |\varepsilon_{2}\rangle\langle\varepsilon_{2} \\ & \frac{1}{2} \end{pmatrix} \\ & \mathbf{p}_{1} = \begin{pmatrix} 0 & if : j \neq k \\ & implies : \\ & \mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} = \mathbf{p}_{k}\mathbf{M} \\ & \mathbf{p}_{k} = \varepsilon_{k}\mathbf{p}_{k} = \mathbf{p}_{k}\mathbf{M} \\ & \mathbf{p}_{2} = \frac{(\mathbf{M}-1\mathbf{1})}{(5-1)} = \frac{1}{4}\begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} \\ & = k_{2}\begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \\ & \frac{1}{k_{2}} \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\$$

$$\begin{aligned} \text{Matrix-algebraic method for finding eigenvector and eigenvalues}} & \text{With example matrix} \quad \mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} \\ \mathbf{p}_{p\mathbf{k}} = \mathbf{p}_{1} \prod_{max} (\mathbf{M} - \varepsilon_{m} \mathbf{1}) = \prod_{max} (\mathbf{p}_{1} \mathbf{M} - \varepsilon_{m} \mathbf{p}_{1} \mathbf{1}) \\ \mathbf{M} \text{Utiplication properties of } \mathbf{p}_{1} \\ \mathbf{p}_{p\mathbf{p}_{k}} = \prod_{max} (\varepsilon_{p\mathbf{p}_{1}} - \varepsilon_{m} \mathbf{p}_{1}) = \mathbf{p}_{1} \prod_{max} (\varepsilon_{1} - \varepsilon_{m}) = \begin{cases} \mathbf{0} & \text{if } \text{if }$$

Geometric visualization of real symmetric matrices and eigenvectors Circle-to-ellipse mapping Ellipse-to-ellipse mapping (Normal space vs. tangent space) Eigensolutions as stationary extreme-values (Lagrange λ -multipliers)

 Matrix-algebraic eigensolutions with example M=(4 1)

 Secular equation

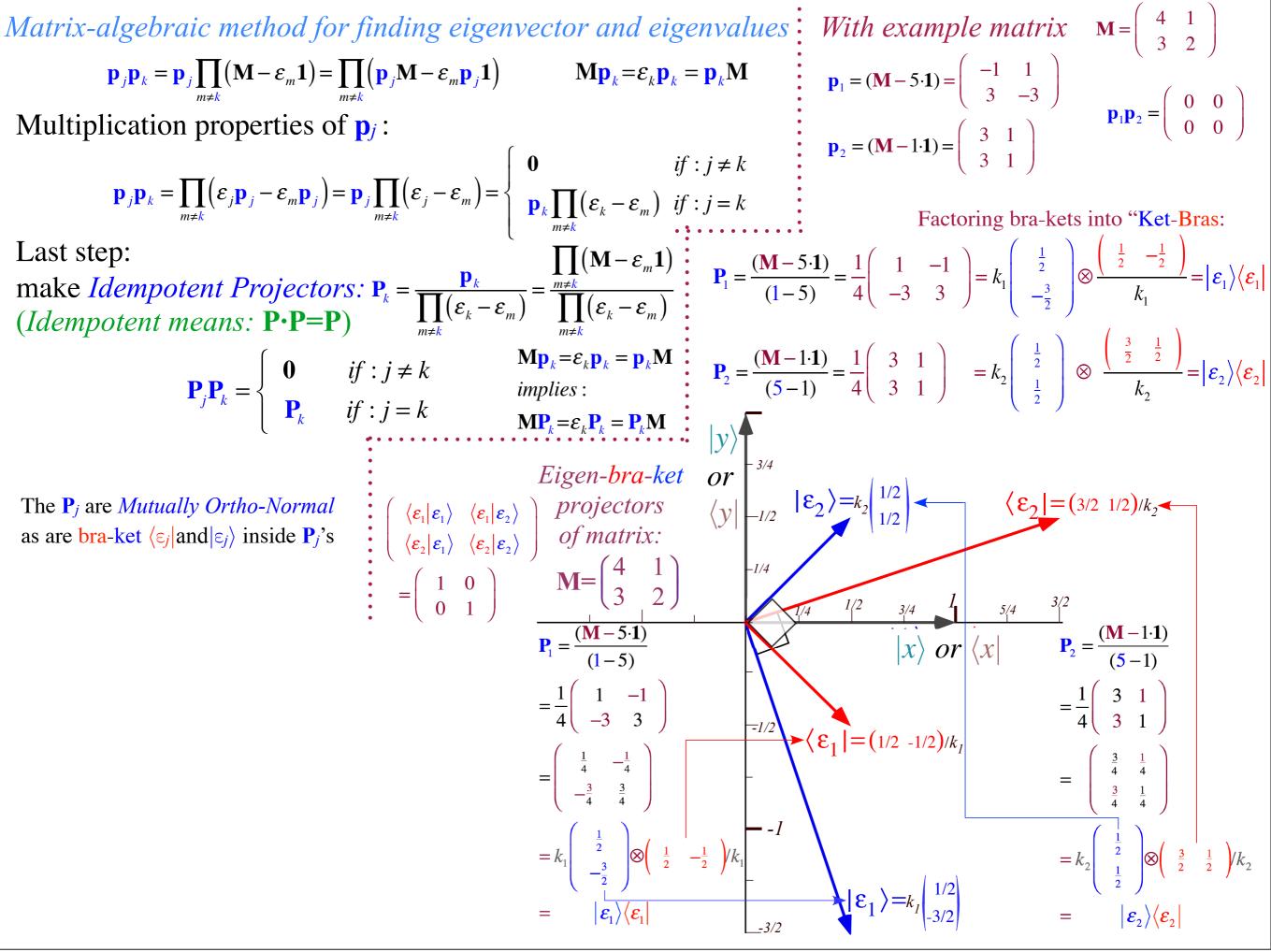
 Hamilton-Cayley equation and projectors

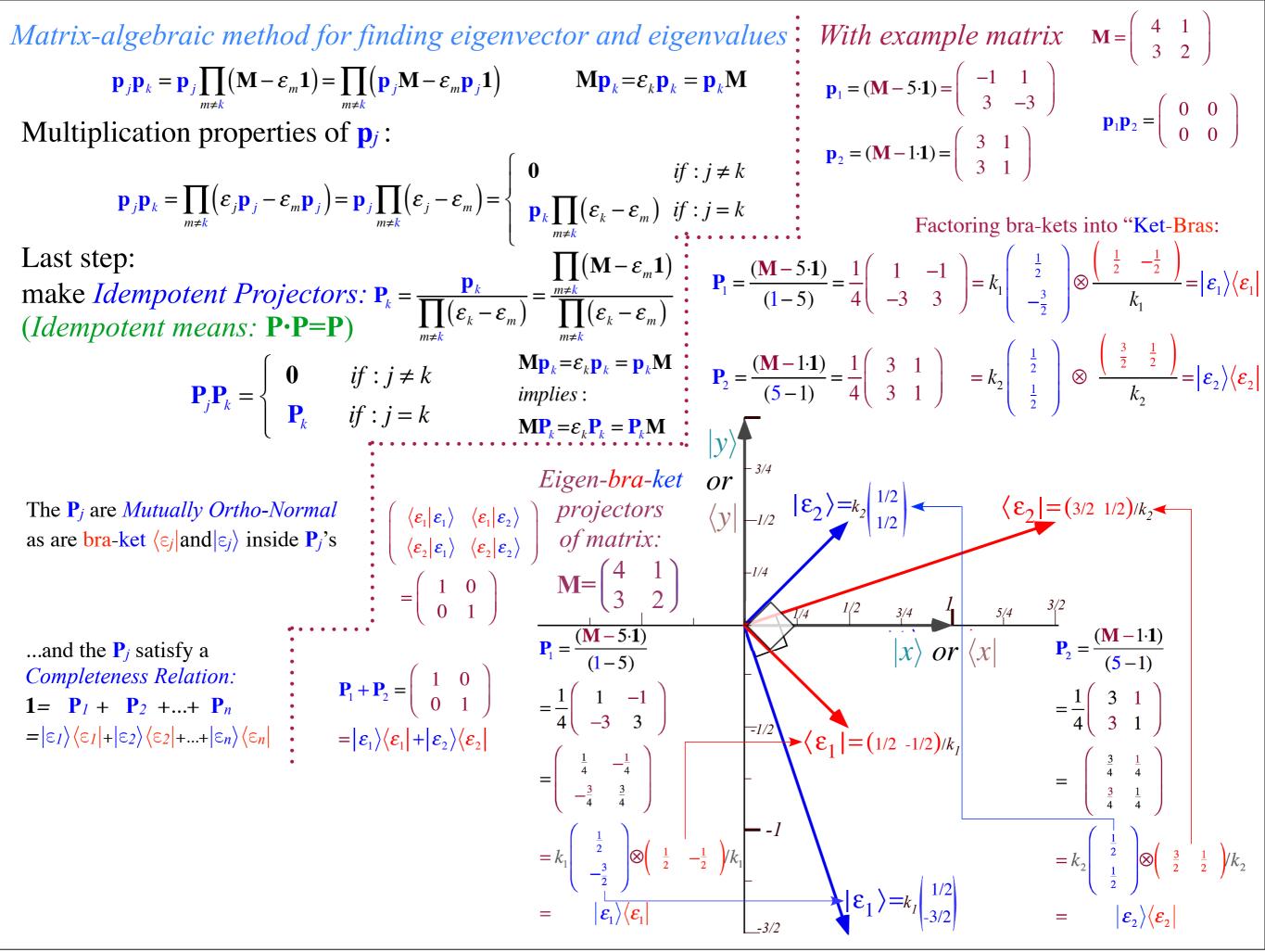
 Idempotent projectors (how eigenvalues⇒eigenvectors)

 Operator orthonormality and Completeness

Spectral Decompositions

Functional spectral decomposition Orthonormality vs. Completeness vis-a`-vis Operator vs. State Lagrange functional interpolation formula Proof that completeness relation is "Truer-than-true"





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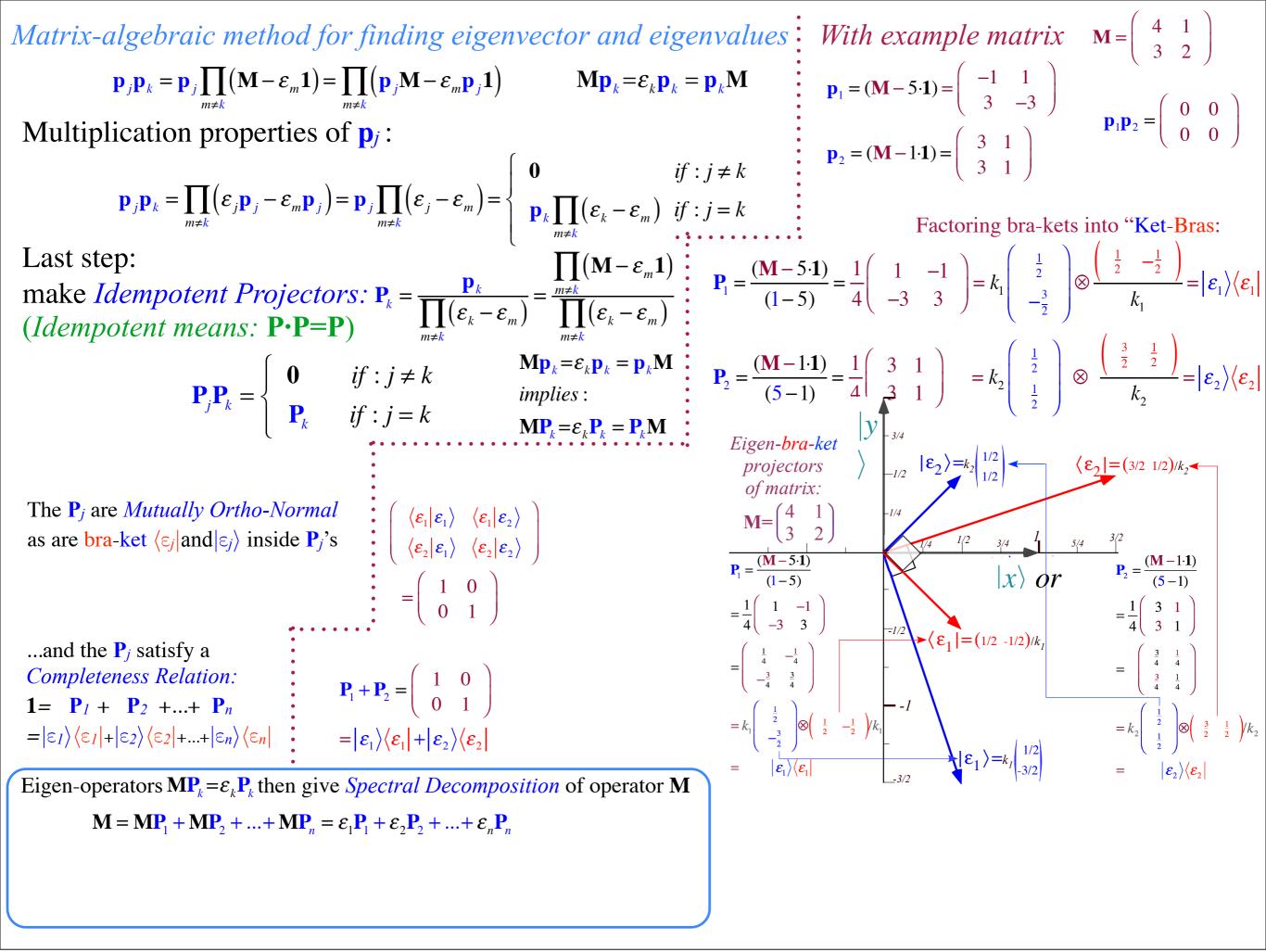
 $\begin{array}{l} Matrix-algebraic\ eigensolutions\ with\ example\ M=\begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}\\ Hamilton-Cayley\ equation\ and\ projectors\\ Idempotent\ projectors\ (how\ eigenvalues \Rightarrow eigenvectors)\\ Operator\ orthonormality\ and\ Completeness\end{array}$

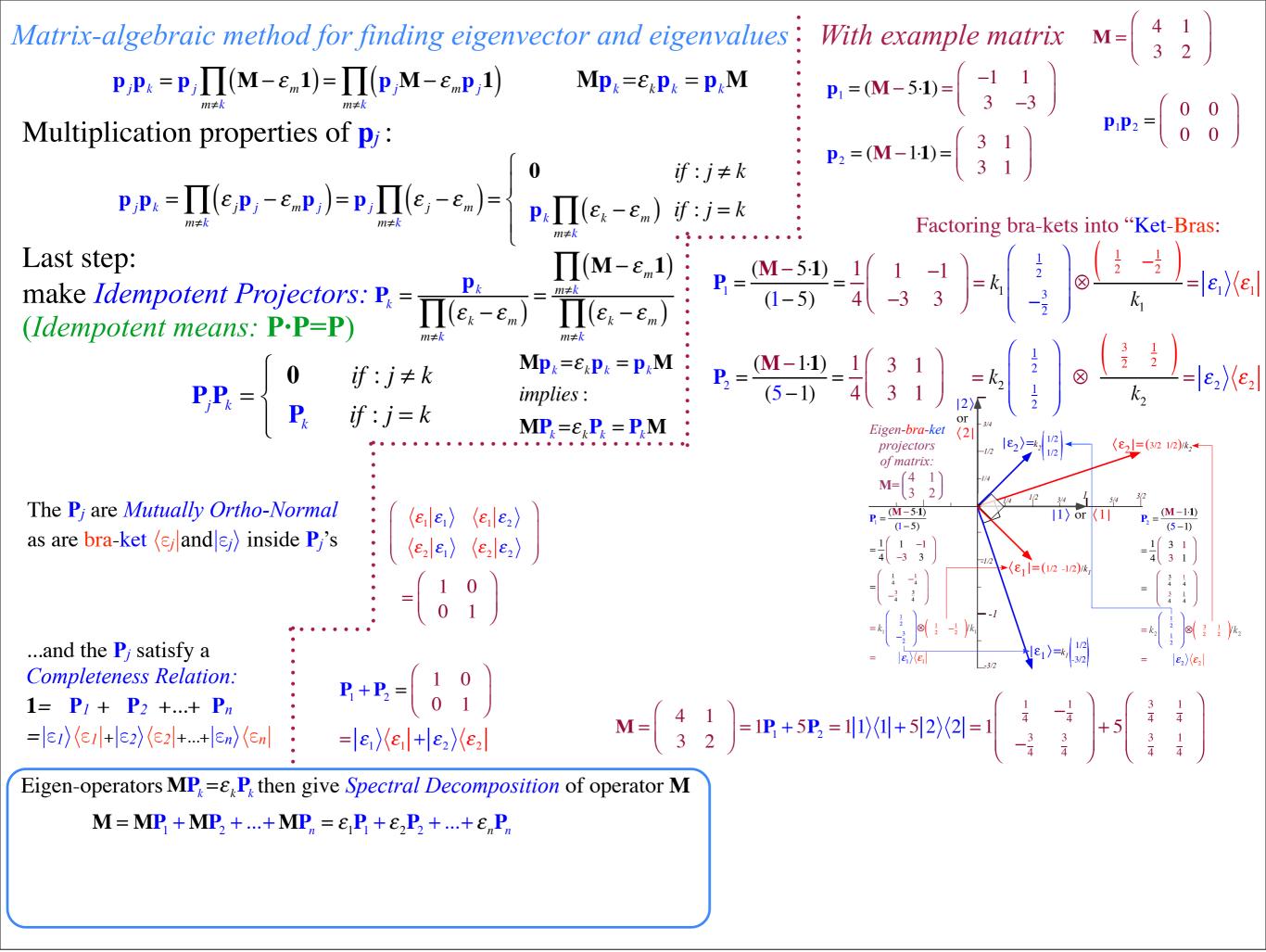
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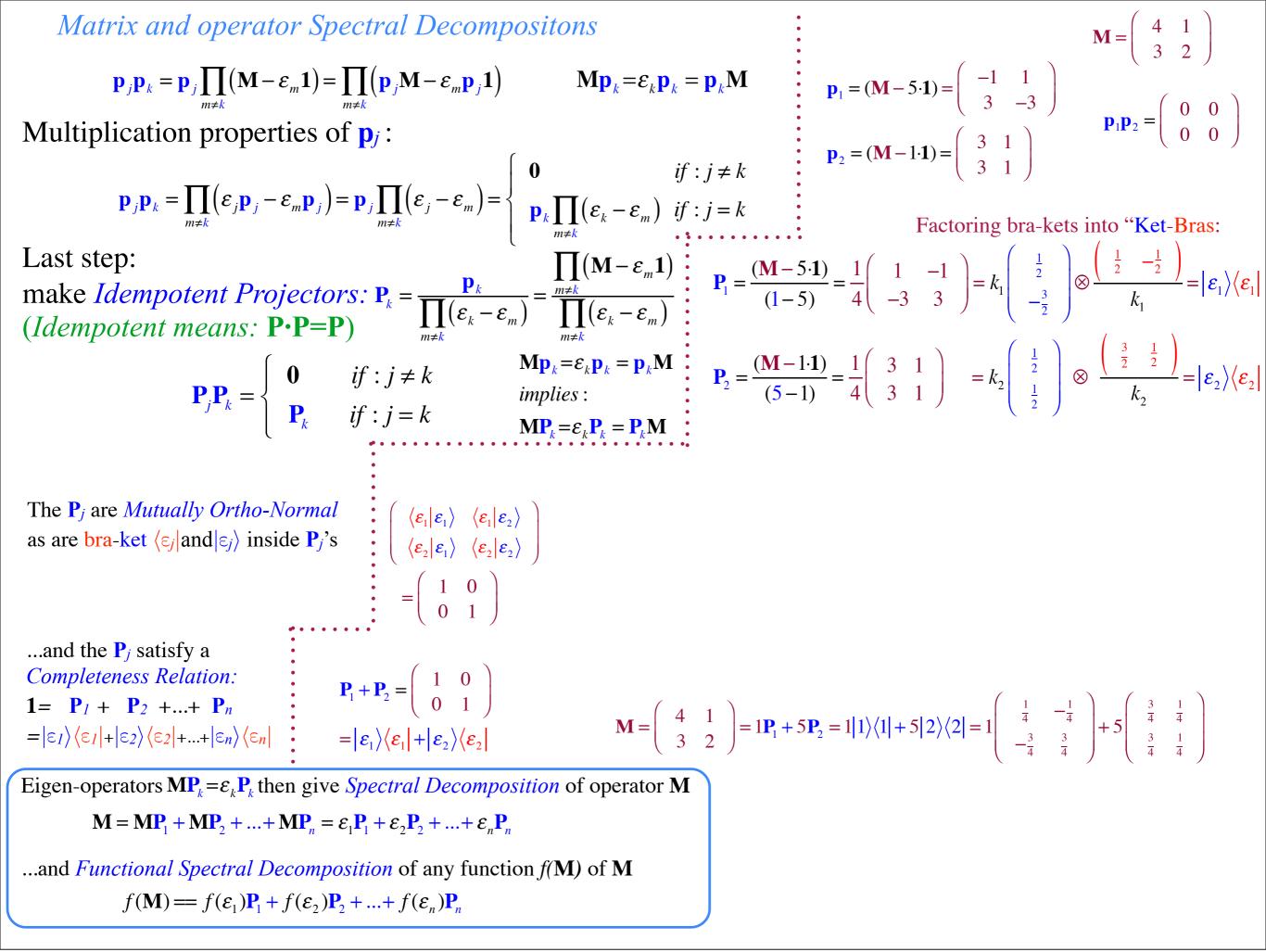
Spectral Decompositions

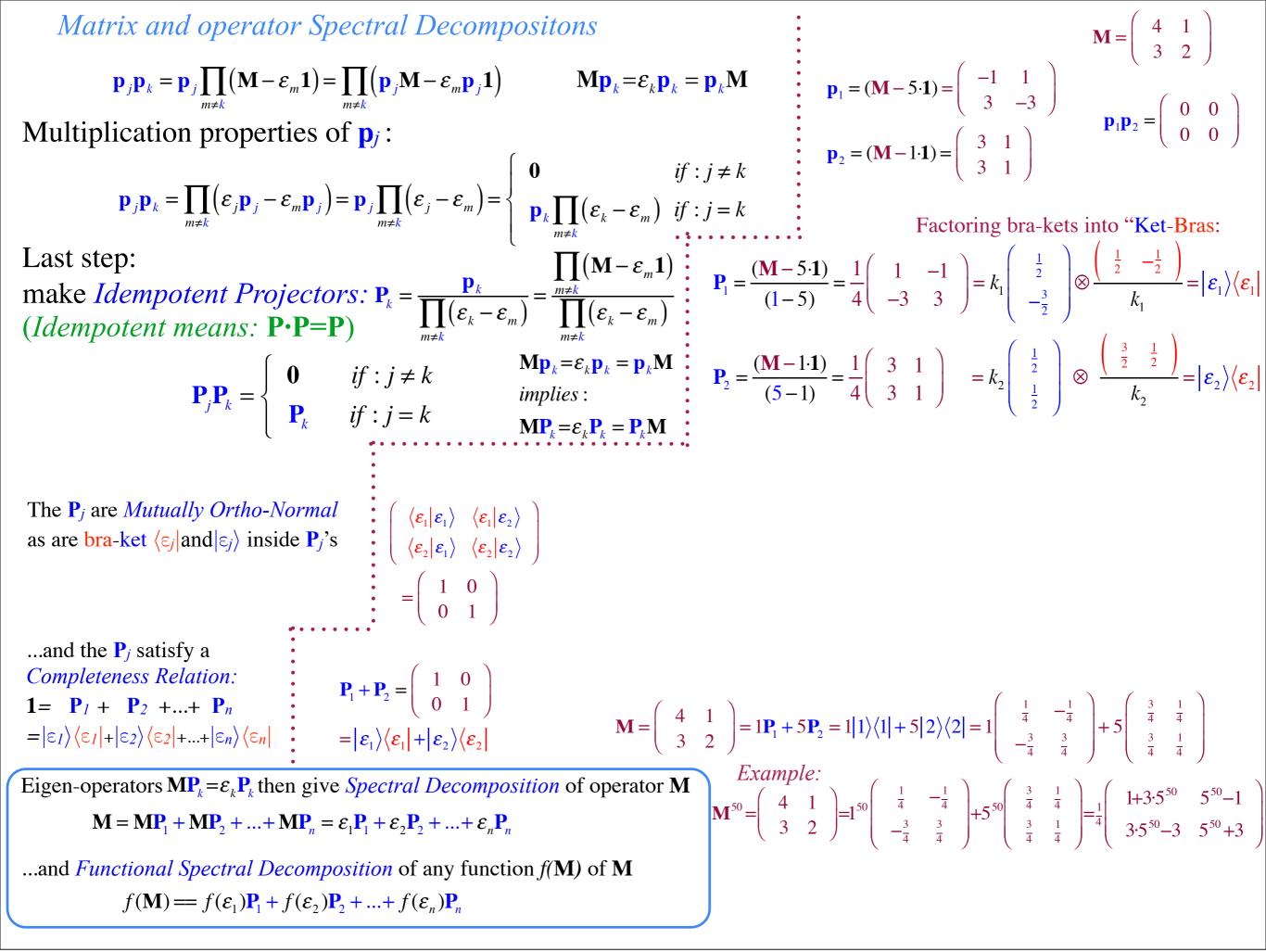
Functional spectral decomposition Orthonormality vs. Completeness vis-a`-vis Operator vs. State Lagrange functional interpolation formula

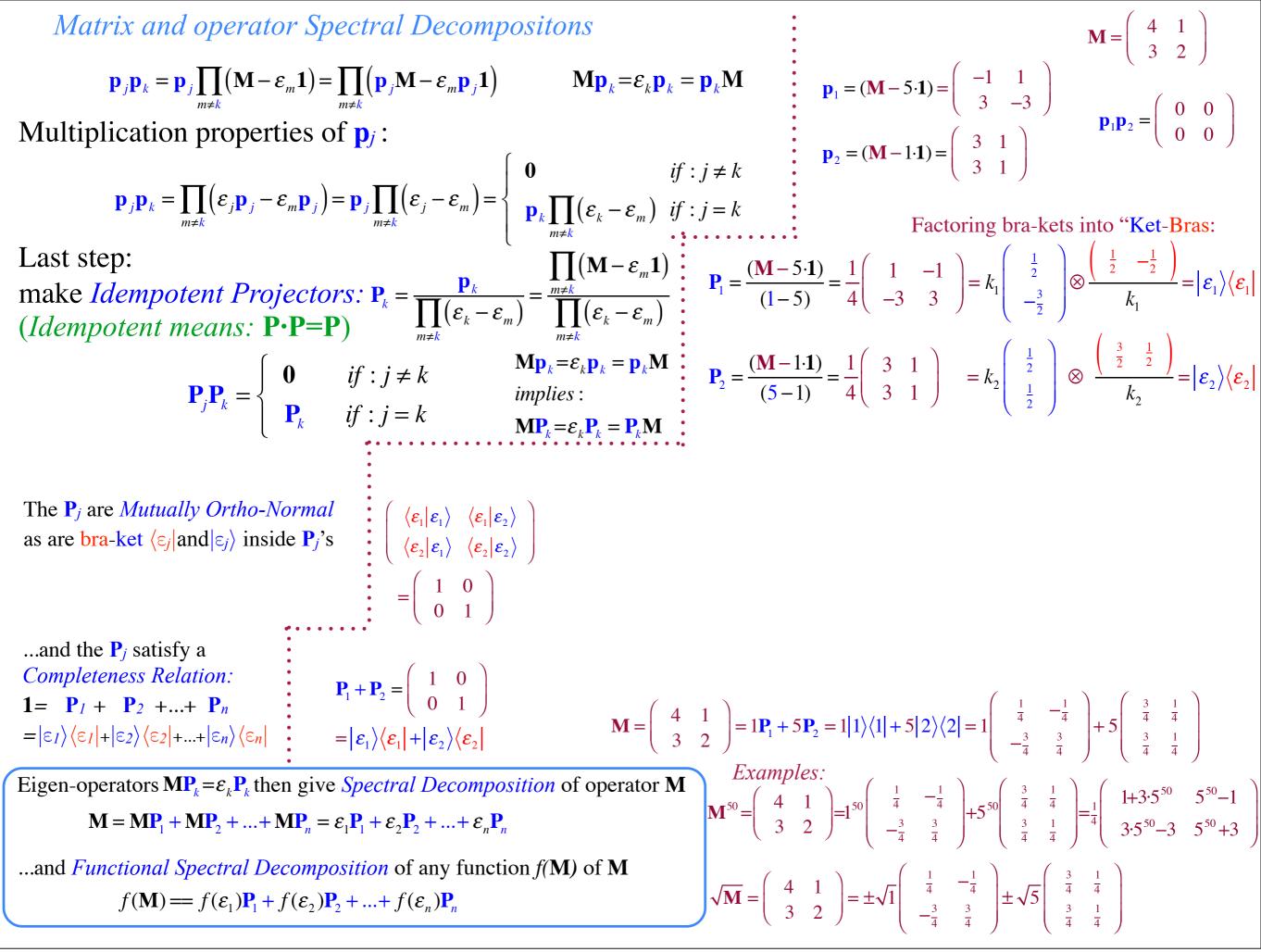
Proof that completeness relation is "Truer-than-true"











Geometric visualization of real symmetric matrices and eigenvectors Circle-to-ellipse mapping Ellipse-to-ellipse mapping (Normal space vs. tangent space) Eigensolutions as stationary extreme-values (Lagrange λ -multipliers)

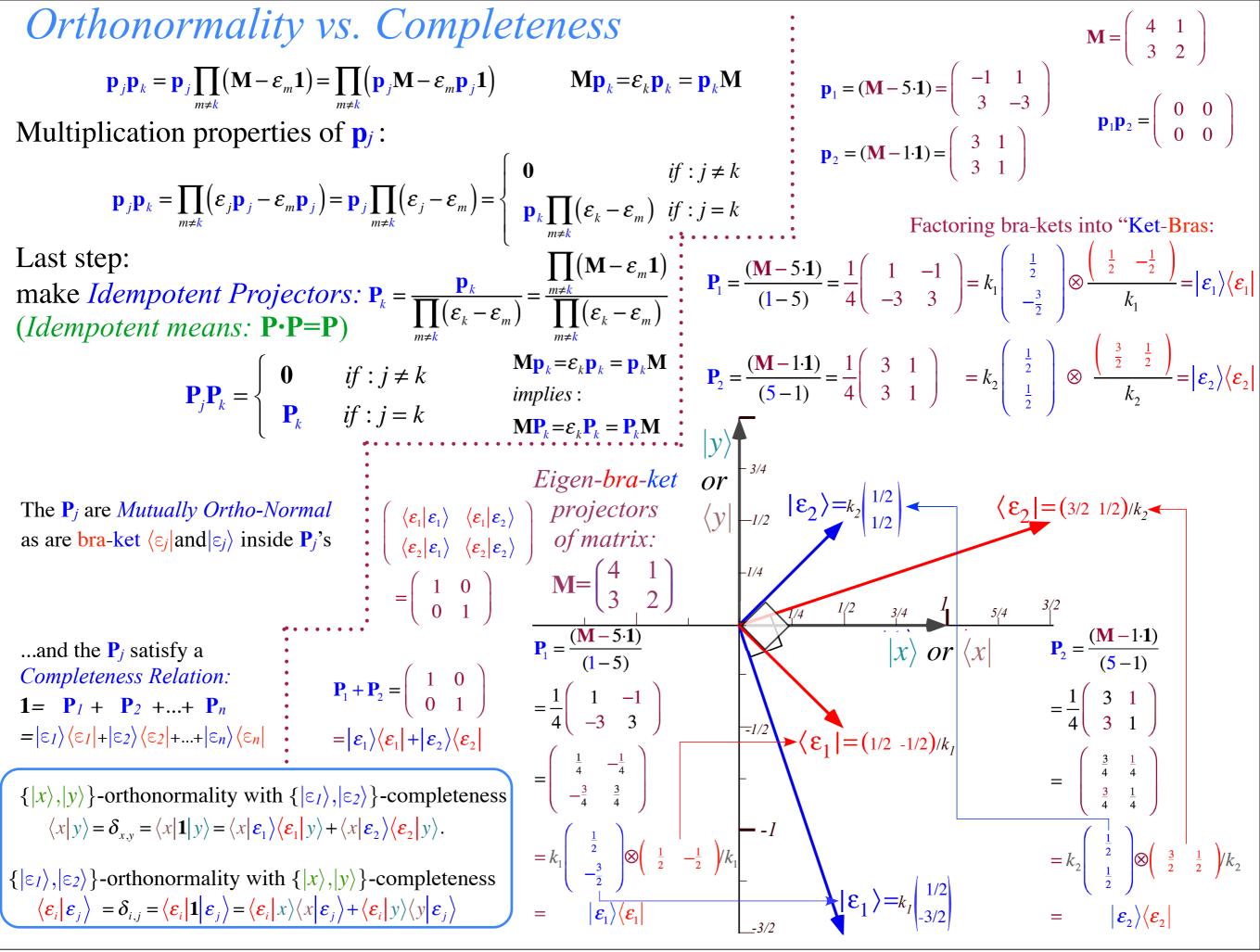
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Spectral Decompositions



Functional spectral decomposition Orthonormality vs. Completeness vis-a`-vis Operator vs. State Lagrange functional interpolation formula Proof that completeness relation is "Truer-than-true"





Orthonormality vs. Completeness vis-a`-vis Operator vs. State Operator expressions for orthonormality appear quite different from expressions for completeness. $\mathbf{P}_{j}\mathbf{P}_{k} = \delta_{jk}\mathbf{P}_{k} = \begin{cases} \mathbf{0} & if: j \neq k \\ \mathbf{P}_{k} & if: j = k \end{cases} \qquad \mathbf{1} = \mathbf{P}_{1} + \mathbf{P}_{2} + \dots + \mathbf{P}_{n}$ Orthonormality vs. Completeness vis-a`-vis Operator vs. State Operator expressions for orthonormality appear quite different from expressions for completeness. $\mathbf{P}_{j}\mathbf{P}_{k} = \delta_{jk}\mathbf{P}_{k} = \begin{cases} \mathbf{0} & if: j \neq k \\ \mathbf{P}_{k} & if: j = k \end{cases} \qquad \mathbf{1} = \mathbf{P}_{1} + \mathbf{P}_{2} + \dots + \mathbf{P}_{n}$

 $|\varepsilon_{j}\rangle\langle\varepsilon_{j}|\varepsilon_{k}\rangle\langle\varepsilon_{k}|=\delta_{jk}|\varepsilon_{k}\rangle\langle\varepsilon_{k}| \text{ or: } \langle\varepsilon_{j}|\varepsilon_{k}\rangle=\delta_{jk} \qquad \mathbf{1}=|\varepsilon_{I}\rangle\langle\varepsilon_{I}|+|\varepsilon_{2}\rangle\langle\varepsilon_{2}|+...+|\varepsilon_{n}\rangle\langle\varepsilon_{n}|$

Orthonormality vs. Completeness vis-a`-vis Operator vs. State

Operator expressions for orthonormality appear quite different from expressions for completeness.

$$\mathbf{P}_{j}\mathbf{P}_{k} = \delta_{jk}\mathbf{P}_{k} = \begin{cases} \mathbf{0} & if: j \neq k \\ \mathbf{P}_{k} & if: j = k \end{cases} \qquad \mathbf{1} = \mathbf{P}_{1} + \mathbf{P}_{2} + \dots + \mathbf{P}_{n} \\ \epsilon_{j} \langle \epsilon_{j} | \epsilon_{k} \rangle \langle \epsilon_{k} | = \delta_{jk} | \epsilon_{k} \rangle \langle \epsilon_{k} | \quad \text{or:} \quad \langle \epsilon_{j} | \epsilon_{k} \rangle = \delta_{jk} \qquad \mathbf{1} = |\epsilon_{1} \rangle \langle \epsilon_{1} | + |\epsilon_{2} \rangle \langle \epsilon_{2} | + \dots + |\epsilon_{n} \rangle \langle \epsilon_{n} \rangle$$

State vector representations of orthonormality are quite **similar** to representations of completeness. *Like 2-sides of the same coin.*

 $\{|x\rangle, |y\rangle\} \text{-orthonormality with } \{|\varepsilon_1\rangle, |\varepsilon_2\rangle\} \text{-completeness}$ $\langle x|y\rangle = \delta_{x,y} = \langle x|\mathbf{1}|y\rangle = \langle x|\varepsilon_1\rangle \langle \varepsilon_1|y\rangle + \langle x|\varepsilon_2\rangle \langle \varepsilon_2|y\rangle.$

 $\{|\varepsilon_{I}\rangle, |\varepsilon_{2}\rangle\} \text{-orthonormality with } \{|x\rangle, |y\rangle\} \text{-completeness}$ $\langle \varepsilon_{i}|\varepsilon_{j}\rangle = \delta_{i,j} = \langle \varepsilon_{i}|\mathbf{1}|\varepsilon_{j}\rangle = \langle \varepsilon_{i}|x\rangle\langle x|\varepsilon_{j}\rangle + \langle \varepsilon_{i}|y\rangle\langle y|\varepsilon_{j}\rangle$

Orthonormality vs. Completeness vis-a`-vis Operator vs. State

Operator expressions for orthonormality appear quite different from expressions for completeness.

$$\mathbf{P}_{j}\mathbf{P}_{k} = \delta_{jk}\mathbf{P}_{k} = \begin{cases} \mathbf{0} & if: j \neq k \\ \mathbf{P}_{k} & if: j = k \end{cases} \qquad \mathbf{1} = \mathbf{P}_{1} + \mathbf{P}_{2} + \dots + \mathbf{P}_{n} \\ if: j = k \qquad \mathbf{1} = |\mathbf{e}_{1}\rangle\langle \mathbf{e}_{k}| = \delta_{jk}|\mathbf{e}_{k}\rangle\langle \mathbf{e}_{k}| \quad \text{or:} \quad \langle \mathbf{e}_{j}|\mathbf{e}_{k}\rangle = \delta_{jk} \qquad \mathbf{1} = |\mathbf{e}_{1}\rangle\langle \mathbf{e}_{1}| + |\mathbf{e}_{2}\rangle\langle \mathbf{e}_{2}| + \dots + |\mathbf{e}_{n}\rangle\langle \mathbf{e}_{n} \end{cases}$$

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However Schrodinger wavefunction notation $\psi(x) = \langle x | \psi \rangle$ shows quite a difference...

Orthonormality vs. Completeness vis-a`-vis Operator vs. State

Operator expressions for orthonormality appear quite different from expressions for completeness.

$$\mathbf{P}_{j}\mathbf{P}_{k} = \delta_{jk}\mathbf{P}_{k} = \begin{cases} \mathbf{0} & if: j \neq k \\ \mathbf{P}_{k} & if: j = k \end{cases} \qquad \mathbf{1} = \mathbf{P}_{1} + \mathbf{P}_{2} + \dots + \mathbf{P}_{n} \\ \epsilon_{j} \langle \epsilon_{j} | \epsilon_{k} \rangle \langle \epsilon_{k} | = \delta_{jk} | \epsilon_{k} \rangle \langle \epsilon_{k} | \quad \text{or:} \quad \langle \epsilon_{j} | \epsilon_{k} \rangle = \delta_{jk} \qquad \mathbf{1} = |\epsilon_{1} \rangle \langle \epsilon_{1} | + |\epsilon_{2} \rangle \langle \epsilon_{2} | + \dots + |\epsilon_{n} \rangle \langle \epsilon_{n} \rangle$$

State vector representations of orthonormality are quite **similar** to representations of completeness. Like 2-sides of the same coin.

> $\{|x\rangle, |y\rangle\} \text{-orthonormality with } \{|\varepsilon_{I}\rangle, |\varepsilon_{2}\rangle\} \text{-completeness}$ $\langle x|y\rangle = \delta_{x,y} = \langle x|\mathbf{1}|y\rangle = \langle x|\varepsilon_{1}\rangle\langle\varepsilon_{1}|y\rangle + \langle x|\varepsilon_{2}\rangle\langle\varepsilon_{2}|y\rangle.$ $\langle x|y\rangle = \delta(x,y) = \psi_{I}(x)\psi_{I}^{*}(y) + \psi_{2}(x)\psi_{2}^{*}(y) + ...$ $Dirac \delta\text{-function}$ $\{|\varepsilon_{I}\rangle, |\varepsilon_{2}\rangle\} \text{-orthonormality with } \{|x\rangle, |y\rangle\} \text{-completeness}$ $\langle \varepsilon_{i}|\varepsilon_{j}\rangle = \delta_{i,j} = \langle \varepsilon_{i}|\mathbf{1}|\varepsilon_{j}\rangle = \langle \varepsilon_{i}|x\rangle\langle x|\varepsilon_{j}\rangle + \langle \varepsilon_{i}|y\rangle\langle y|\varepsilon_{j}\rangle$ $\langle \varepsilon_{i}|\varepsilon_{j}\rangle = \delta_{i,j} = ... + \psi_{i}^{*}(x)\psi_{j}(x) + \psi_{2}(y)\psi_{2}^{*}(y) + ... \rightarrow \int dx\psi_{i}^{*}(x)\psi_{j}(x)$

However Schrodinger wavefunction notation $\psi(x) = \langle x | \psi \rangle$ shows quite a difference... ...particularly in the orthonormality integral.

Geometric visualization of real symmetric matrices and eigenvectors Circle-to-ellipse mapping Ellipse-to-ellipse mapping (Normal space vs. tangent space) Eigensolutions as stationary extreme-values (Lagrange λ -multipliers)

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Spectral Decompositions

Functional spectral decomposition Orthonormality vs. Completeness vis-a`-vis Operator vs. State Lagrange functional interpolation formula Proof that completeness relation is "Truer-than-true"



$$\mathbf{1} = \mathbf{P}_{1} + \mathbf{P}_{2} + \dots + \mathbf{P}_{n} = \sum_{\boldsymbol{\varepsilon}_{k}} \mathbf{P}_{k} = \sum_{\boldsymbol{\varepsilon}_{k}} \frac{\prod_{m \neq k} (\mathbf{M} - \boldsymbol{\varepsilon}_{m} \mathbf{1})}{\prod_{m \neq k} (\boldsymbol{\varepsilon}_{k} - \boldsymbol{\varepsilon}_{m})} \qquad f(\mathbf{M}) = f(\boldsymbol{\varepsilon}_{1})\mathbf{P}_{1} + f(\boldsymbol{\varepsilon}_{2})\mathbf{P}_{2} + \dots + f(\boldsymbol{\varepsilon}_{n})\mathbf{P}_{n} = \sum_{\boldsymbol{\varepsilon}_{k}} f(\boldsymbol{\varepsilon}_{k})\mathbf{P}_{k} = \sum_{\boldsymbol{\varepsilon}_{k}} f(\boldsymbol{\varepsilon}_{k})\frac{\prod_{m \neq k} (\mathbf{M} - \boldsymbol{\varepsilon}_{m} \mathbf{1})}{\prod_{m \neq k} (\boldsymbol{\varepsilon}_{k} - \boldsymbol{\varepsilon}_{m})}$$

with *Lagrange interpolation formula* of function f(x) approximated by its value at N points x_1, x_2, \ldots, x_N .

$$L(f(x)) = \sum_{k=1}^{N} f(x_k) \cdot P_k(x) \quad \text{where: } P_k(x) = \frac{\prod_{j \neq k}^{N} (x - x_j)}{\prod_{j \neq k}^{N} (x_k - x_j)}$$

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Each polynomial term $P_m(x)$ has zeros at each point $x=x_j$ except where $x=x_m$. Then $P_m(x_m)=1$.

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If f(x) happens to be a polynomial of degree N-1 or less, then L(f(x)) = f(x) may be exact everywhere.

$$1 = \sum_{m=1}^{N} P_m(x) \qquad x = \sum_{m=1}^{N} x_m P_m(x) \qquad x^2 = \sum_{m=1}^{N} x_m^2 P_m(x)$$

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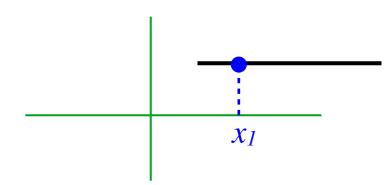
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One point determines a constant level line,



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A Proof of Projector Completeness (Truer-than-true)

Compare matrix *completeness relation* and *functional spectral decompositions* $\Pi(\mathbf{M} < \mathbf{1})$

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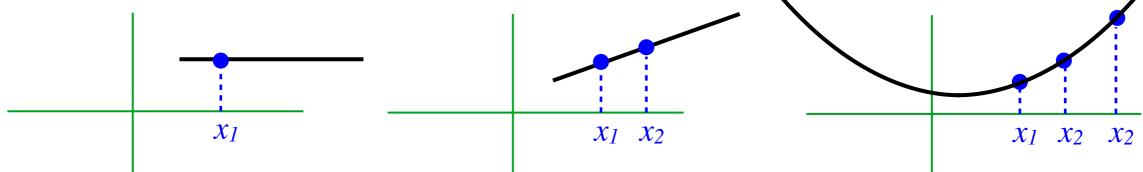
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$$\mathbf{P}_{1} + \mathbf{P}_{2} = \frac{\prod_{j \neq 1} \left(\mathbf{M} - \varepsilon_{j} \mathbf{1} \right)}{\prod_{j \neq 1} \left(\varepsilon_{1} - \varepsilon_{j} \right)} + \frac{\prod_{j \neq 1} \left(\mathbf{M} - \varepsilon_{j} \mathbf{1} \right)}{\prod_{j \neq 1} \left(\varepsilon_{2} - \varepsilon_{j} \right)} = \frac{\left(\mathbf{M} - \varepsilon_{2} \mathbf{1} \right)}{\left(\varepsilon_{1} - \varepsilon_{2} \right)} + \frac{\left(\mathbf{M} - \varepsilon_{1} \mathbf{1} \right)}{\left(\varepsilon_{2} - \varepsilon_{1} \right)} = \frac{\left(\mathbf{M} - \varepsilon_{2} \mathbf{1} \right) - \left(\mathbf{M} - \varepsilon_{1} \mathbf{1} \right)}{\left(\varepsilon_{1} - \varepsilon_{2} \right)} = \frac{-\varepsilon_{2} \mathbf{1} + \varepsilon_{1} \mathbf{1}}{\left(\varepsilon_{1} - \varepsilon_{2} \right)} = \mathbf{1} \text{ (for all } \varepsilon_{j})$$

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However, only *select* values ε_k work for eigen-forms $\mathbf{MP}_k = \varepsilon_k \mathbf{P}_k$ or orthonormality $\mathbf{P}_j \mathbf{P}_k = \delta_{jk} \mathbf{P}_k$.

Unitary operators and matrices that change state vectors ...and eigenstates ("ownstates) that are mostly immune

Geometric visualization of real symmetric matrices and eigenvectors Circle-to-ellipse mapping Ellipse-to-ellipse mapping (Normal space vs. tangent space) Eigensolutions as stationary extreme-values (Lagrange λ -multipliers)

 $\begin{array}{l} Matrix-algebraic\ eigensolutions\ with\ example\ M=\begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}\\ Hamilton-Cayley\ equation\ and\ projectors\\ Idempotent\ projectors\ (how\ eigenvalues \Rightarrow eigenvectors)\\ Operator\ orthonormality\ and\ Completeness\end{array}$

Spectral Decompositions

Functional spectral decomposition Orthonormality vs. Completeness vis-a`-vis Operator vs. State Lagrange functional interpolation formula Proof that completeness relation is "Truer-than-true"



Diagonalizing Transformations (D-Ttran) from projectors Eigensolutions for active analyzers

Spectral Decompositions with degeneracy Functional spectral decomposition Diagonalizing Transformations (D-Ttran) from projectors Given our eigenvectors and their Projectors. $\mathbf{P}_{1} = \frac{(\mathbf{M} - 5 \cdot \mathbf{l})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_{1} \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\left(\frac{1}{2} & -\frac{1}{2}\right)}{k_{1}} = |\boldsymbol{\varepsilon}_{1}\rangle\langle\boldsymbol{\varepsilon}_{1}|$ $\mathbf{P}_{2} = \frac{(\mathbf{M} - 1 \cdot \mathbf{l})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_{2} \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\left(\frac{3}{2} & \frac{1}{2}\right)}{k_{2}} = |\boldsymbol{\varepsilon}_{2}\rangle\langle\boldsymbol{\varepsilon}_{2}|$ Diagonalizing Transformations (D-Ttran) from projectors Given our eigenvectors and their Projectors. $\mathbf{P}_{1} = \frac{(\mathbf{M} - 5 \cdot \mathbf{l})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_{1} \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\left(\frac{1}{2} & -\frac{1}{2}\right)}{k_{1}} = |\boldsymbol{\varepsilon}_{1}\rangle\langle\boldsymbol{\varepsilon}_{1}|$ $\mathbf{P}_{2} = \frac{(\mathbf{M} - 1 \cdot \mathbf{l})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_{2} \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\left(\frac{3}{2} & \frac{1}{2}\right)}{k_{2}} = |\boldsymbol{\varepsilon}_{2}\rangle\langle\boldsymbol{\varepsilon}_{2}|$

Load distinct bras $\langle \varepsilon_1 |$ and $\langle \varepsilon_2 |$ into d-tran rows, kets $|\varepsilon_1 \rangle$ and $|\varepsilon_2 \rangle$ into inverse d-tran columns.

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$$\left\{ \left\langle \boldsymbol{\varepsilon}_{1} \right| = \left(\begin{array}{cc} \frac{1}{2} & -\frac{1}{2} \end{array} \right), \left\langle \boldsymbol{\varepsilon}_{2} \right| = \left(\begin{array}{cc} \frac{3}{2} & \frac{1}{2} \end{array} \right) \right\} , \quad \left\{ \left| \boldsymbol{\varepsilon}_{1} \right\rangle = \left(\begin{array}{cc} \frac{1}{2} \\ -\frac{3}{2} \end{array} \right), \left| \boldsymbol{\varepsilon}_{2} \right\rangle = \left(\begin{array}{cc} \frac{1}{2} \\ \frac{1}{2} \end{array} \right) \right\} \right\}$$

 $\begin{array}{c} (\boldsymbol{\varepsilon}_{1},\boldsymbol{\varepsilon}_{2}) \leftarrow (1,2) \ d\text{-Tran matrix} \\ \begin{pmatrix} \left\langle \boldsymbol{\varepsilon}_{1} \middle| x \right\rangle & \left\langle \boldsymbol{\varepsilon}_{1} \middle| y \right\rangle \\ \left\langle \boldsymbol{\varepsilon}_{2} \middle| x \right\rangle & \left\langle \boldsymbol{\varepsilon}_{2} \middle| y \right\rangle \end{array} \end{pmatrix} = \left(\begin{array}{c} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{array} \right) \\ \begin{pmatrix} \left\langle x \middle| \boldsymbol{\varepsilon}_{1} \right\rangle & \left\langle x \middle| \boldsymbol{\varepsilon}_{2} \right\rangle \\ \left\langle y \middle| \boldsymbol{\varepsilon}_{1} \right\rangle & \left\langle y \middle| \boldsymbol{\varepsilon}_{2} \right\rangle \end{array} \right) = \left(\begin{array}{c} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{array} \right) \\ \end{array}$

 $\begin{array}{ll} (\boldsymbol{\varepsilon}_{1},\boldsymbol{\varepsilon}_{2}) \leftarrow (1,2) \ d-Tran \ matrix \\ \begin{pmatrix} \langle \boldsymbol{\varepsilon}_{1} | x \rangle & \langle \boldsymbol{\varepsilon}_{1} | y \rangle \\ \langle \boldsymbol{\varepsilon}_{2} | x \rangle & \langle \boldsymbol{\varepsilon}_{2} | y \rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{pmatrix} , \quad \begin{pmatrix} \langle x | \boldsymbol{\varepsilon}_{1} \rangle & \langle x | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle y | \boldsymbol{\varepsilon}_{1} \rangle & \langle y | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{pmatrix} \\ \text{Use Dirac labeling for all components so transformation is OK} \\ \begin{pmatrix} \langle \boldsymbol{\varepsilon}_{1} | x \rangle & \langle \boldsymbol{\varepsilon}_{1} | y \rangle \\ \langle \boldsymbol{\varepsilon}_{2} | x \rangle & \langle \boldsymbol{\varepsilon}_{2} | y \rangle \end{pmatrix} \cdot \begin{pmatrix} \langle x | \mathbf{K} | x \rangle & \langle x | \mathbf{K} | y \rangle \\ \langle y | \mathbf{K} | x \rangle & \langle y | \mathbf{K} | y \rangle \end{pmatrix} \cdot \begin{pmatrix} \langle x | \mathbf{K} | x \rangle & \langle x | \mathbf{K} | y \rangle \\ \langle y | \mathbf{K} | x \rangle & \langle y | \mathbf{K} | y \rangle \end{pmatrix} \cdot \begin{pmatrix} \langle x | \boldsymbol{\varepsilon}_{1} \rangle & \langle x | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle y | \boldsymbol{\varepsilon}_{1} \rangle & \langle y | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix} = \begin{pmatrix} \langle \boldsymbol{\varepsilon}_{1} | \mathbf{K} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{1} | \mathbf{K} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{\varepsilon}_{2} | \mathbf{K} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{2} | \mathbf{K} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix} \\ \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{pmatrix} & \cdot \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} & \cdot \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 5 \end{pmatrix} \end{array}$

Diagonalizing Transformations (D-Ttran) from projectors Given our eigenvectors and their Projectors. $\mathbf{P}_{1} = \frac{(\mathbf{M} - 5 \cdot \mathbf{I})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_{1} \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}}{k_{1}} = |\boldsymbol{\varepsilon}_{1}\rangle\langle\boldsymbol{\varepsilon}_{1}|$ $\mathbf{P}_{2} = \frac{(\mathbf{M} - 1 \cdot \mathbf{1})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_{2} \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix}}{k_{2}} = |\boldsymbol{\varepsilon}_{2}\rangle \langle \boldsymbol{\varepsilon}_{2}|$ Load distinct bras $\langle \varepsilon_1 |$ and $\langle \varepsilon_2 |$ into d-tran rows, kets $|\varepsilon_1 \rangle$ and $|\varepsilon_2 \rangle$ into <u>inverse</u> d-tran columns. $\left\{ \left\langle \boldsymbol{\varepsilon}_{1} \right| = \left(\begin{array}{cc} \frac{1}{2} & -\frac{1}{2} \end{array} \right), \left\langle \boldsymbol{\varepsilon}_{2} \right| = \left(\begin{array}{cc} \frac{3}{2} & \frac{1}{2} \end{array} \right) \right\}, \quad \left\{ \left| \boldsymbol{\varepsilon}_{1} \right\rangle = \left| \begin{array}{cc} \frac{1}{2} \\ -\frac{3}{2} \end{array} \right|, \left| \boldsymbol{\varepsilon}_{2} \right\rangle = \left| \begin{array}{cc} \frac{1}{2} \\ \frac{1}{2} \end{array} \right| \right\}$ $(\boldsymbol{\varepsilon}_1, \boldsymbol{\varepsilon}_2) \leftarrow (1, 2) d$ -Tran matrix $(1,2) \leftarrow (\varepsilon_1, \varepsilon_2)$ INVERSE *d*-Tran matrix $\begin{pmatrix} \langle \boldsymbol{\varepsilon}_1 | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_1 | \boldsymbol{y} \rangle \\ \langle \boldsymbol{\varepsilon}_2 | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_2 | \boldsymbol{y} \rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{pmatrix} , \quad \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_1 \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_2 \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_1 \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_2 \rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{pmatrix}$ Use Dirac labeling for all components so transformation is OK $\begin{pmatrix} \langle \boldsymbol{\varepsilon}_{1} | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_{1} | \boldsymbol{y} \rangle \\ \langle \boldsymbol{\varepsilon}_{2} | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_{2} | \boldsymbol{y} \rangle \end{pmatrix} \cdot \begin{pmatrix} \langle \boldsymbol{x} | \mathbf{K} | \boldsymbol{x} \rangle & \langle \boldsymbol{x} | \mathbf{K} | \boldsymbol{y} \rangle \\ \langle \boldsymbol{y} | \mathbf{K} | \boldsymbol{x} \rangle & \langle \boldsymbol{y} | \mathbf{K} | \boldsymbol{y} \rangle \end{pmatrix} \cdot \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix} = \begin{pmatrix} \langle \boldsymbol{\varepsilon}_{1} | \mathbf{K} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{1} | \mathbf{K} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{\varepsilon}_{2} | \mathbf{K} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{2} | \mathbf{K} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}$ $\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{pmatrix} \qquad \cdot \qquad \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} \qquad \cdot \qquad \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{pmatrix} \qquad = \qquad \begin{pmatrix} 1 & 0 \\ 0 & 5 \end{pmatrix}$ Check inverse-d-tran is really inverse of your d-tran. $\begin{array}{c|c} \langle \boldsymbol{\varepsilon}_1 | 1 \rangle & \langle \boldsymbol{\varepsilon}_1 | 2 \rangle \\ \langle \boldsymbol{\varepsilon}_2 | 1 \rangle & \langle \boldsymbol{\varepsilon}_2 | 2 \rangle \end{array} \end{array} \right) \cdot \left(\begin{array}{c} \langle 1 | \boldsymbol{\varepsilon}_1 \rangle & \langle 1 | \boldsymbol{\varepsilon}_2 \rangle \\ \langle 2 | \boldsymbol{\varepsilon}_1 \rangle & \langle 2 | \boldsymbol{\varepsilon}_2 \rangle \end{array} \right) = \left(\begin{array}{c} \langle \boldsymbol{\varepsilon}_1 | 1 | \boldsymbol{\varepsilon}_1 \rangle & \langle \boldsymbol{\varepsilon}_1 | 1 | \boldsymbol{\varepsilon}_2 \rangle \\ \langle \boldsymbol{\varepsilon}_2 | 1 | \boldsymbol{\varepsilon}_1 \rangle & \langle \boldsymbol{\varepsilon}_2 | 1 | \boldsymbol{\varepsilon}_2 \rangle \end{array} \right)$

Thursday, January 24, 2013

 $\begin{bmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{bmatrix} \quad \cdot \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{bmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$

Diagonalizing Transformations (D-Ttran) from projectors Given our eigenvectors and their Projectors. $\mathbf{P}_{1} = \frac{(\mathbf{M} - 5 \cdot \mathbf{I})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_{1} \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}}{k_{1}} = |\boldsymbol{\varepsilon}_{1}\rangle\langle\boldsymbol{\varepsilon}_{1}|$ $\mathbf{P}_{2} = \frac{(\mathbf{M} - 1 \cdot \mathbf{1})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_{2} \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix}}{k_{2}} = |\boldsymbol{\varepsilon}_{2}\rangle\langle\boldsymbol{\varepsilon}_{2}|$ Load distinct bras $\langle \varepsilon_1 |$ and $\langle \varepsilon_2 |$ into d-tran rows, kets $|\varepsilon_1 \rangle$ and $|\varepsilon_2 \rangle$ into <u>inverse</u> d-tran columns. $\left\{ \left\langle \boldsymbol{\varepsilon}_{1} \right| = \left(\begin{array}{cc} \frac{1}{2} & -\frac{1}{2} \end{array} \right), \left\langle \boldsymbol{\varepsilon}_{2} \right| = \left(\begin{array}{cc} \frac{3}{2} & \frac{1}{2} \end{array} \right) \right\}, \quad \left\{ \left| \boldsymbol{\varepsilon}_{1} \right\rangle = \left| \begin{array}{cc} \frac{1}{2} \\ -\frac{3}{2} \end{array} \right|, \left| \boldsymbol{\varepsilon}_{2} \right\rangle = \left| \begin{array}{cc} \frac{1}{2} \\ \frac{1}{2} \end{array} \right| \right\}$ $(\boldsymbol{\varepsilon}_1, \boldsymbol{\varepsilon}_2) \leftarrow (1, 2) d$ -Tran matrix $(1,2) \leftarrow (\boldsymbol{\varepsilon}_1, \boldsymbol{\varepsilon}_2)$ INVERSE *d*-Tran matrix $\begin{pmatrix} \langle \boldsymbol{\varepsilon}_1 | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_1 | \boldsymbol{y} \rangle \\ \langle \boldsymbol{\varepsilon}_2 | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_2 | \boldsymbol{y} \rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{pmatrix} , \quad \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_1 \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_2 \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_1 \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_2 \rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{pmatrix}$ Use Dirac labeling for all components so transformation is OK $\begin{pmatrix} \langle \boldsymbol{\varepsilon}_{1} | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_{1} | \boldsymbol{y} \rangle \\ \langle \boldsymbol{\varepsilon}_{2} | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_{2} | \boldsymbol{y} \rangle \end{pmatrix} \cdot \begin{pmatrix} \langle \boldsymbol{x} | \mathbf{K} | \boldsymbol{x} \rangle & \langle \boldsymbol{x} | \mathbf{K} | \boldsymbol{y} \rangle \\ \langle \boldsymbol{y} | \mathbf{K} | \boldsymbol{x} \rangle & \langle \boldsymbol{y} | \mathbf{K} | \boldsymbol{y} \rangle \end{pmatrix} \cdot \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix} = \begin{pmatrix} \langle \boldsymbol{\varepsilon}_{1} | \mathbf{K} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{1} | \mathbf{K} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{\varepsilon}_{2} | \mathbf{K} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{2} | \mathbf{K} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}$ $\left(\begin{array}{ccc} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{array}\right) \qquad \cdot \qquad \left(\begin{array}{ccc} 4 & 1 \\ 3 & 2 \end{array}\right) \qquad \cdot \qquad \left(\begin{array}{ccc} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{array}\right) \qquad = \qquad \left(\begin{array}{ccc} 1 & 0 \\ 0 & 5 \end{array}\right)$ Check inverse-d-tran is really inverse of your d-tran. In standard quantum matrices inverses are "easy" $\begin{pmatrix} \langle \boldsymbol{\varepsilon}_{1} | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_{1} | \boldsymbol{y} \rangle \\ \langle \boldsymbol{\varepsilon}_{2} | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_{2} | \boldsymbol{y} \rangle \end{pmatrix} \cdot \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix} = \begin{pmatrix} \langle \boldsymbol{\varepsilon}_{1} | \boldsymbol{1} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{\varepsilon}_{1} | \boldsymbol{1} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{\varepsilon}_{2} | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_{2} | \boldsymbol{y} \rangle \end{pmatrix} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{z}_{2} | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_{2} | \boldsymbol{z} \rangle \end{pmatrix} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{\varepsilon}_{2} | \boldsymbol{x} \rangle & \langle \boldsymbol{\varepsilon}_{2} | \boldsymbol{y} \rangle \end{pmatrix} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle & \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{1} \rangle & \langle \boldsymbol{x} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{y} | \boldsymbol{\varepsilon}_{2} \rangle & \langle \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon}_{2} \rangle & \langle \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon}_{2} \rangle & \langle \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon}_{2} \rangle \\ \langle \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon}_{2} \rangle & \langle \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon}_{2} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} \rangle \end{pmatrix}^{\dagger} = \begin{pmatrix} \langle \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol{\varepsilon} | \boldsymbol$ Unitary operators and matrices that change state vectors ...and eigenstates ("ownstates) that are mostly immune

Geometric visualization of real symmetric matrices and eigenvectors Circle-to-ellipse mapping Ellipse-to-ellipse mapping (Normal space vs. tangent space) Eigensolutions as stationary extreme-values (Lagrange λ -multipliers)

 $\begin{array}{l} Matrix-algebraic\ eigensolutions\ with\ example\ M=\begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}\\ Hamilton-Cayley\ equation\ and\ projectors\\ Idempotent\ projectors\ (how\ eigenvalues \Rightarrow eigenvectors)\\ Operator\ orthonormality\ and\ Completeness\end{array}$

Spectral Decompositions

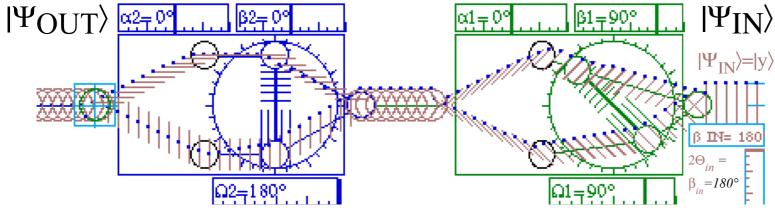
Functional spectral decomposition Orthonormality vs. Completeness vis-a`-vis Operator vs. State Lagrange functional interpolation formula Proof that completeness relation is "Truer-than-true"

Diagonalizing Transformations (D-Ttran) from projectors Eigensolutions for active analyzers

Spectral Decompositions with degeneracy Functional spectral decomposition

Matrix products and eigensolutions for active analyzers

Consider a 45° tilted ($\theta_1 = \beta_1/2 = \pi/4$ or $\beta_1 = 90^\circ$) analyzer followed by a untilted ($\beta_2 = 0$) analyzer. Active analyzers have both paths open and a phase shift $e^{-i\Omega}$ between each path. Here the first analyzer has $\Omega_1 = 90^\circ$. The second has $\Omega_2 = 180^\circ$.



The transfer matrix for each analyzer is a sum of projection operators for each open path multiplied by the phase factor that is active at that path. Apply phase factor $e^{-i\Omega 1} = e^{-i\pi/2}$ to top path in the first analyzer and the factor $e^{-i\Omega 2} = e^{-i\pi}$ to the top path in the second analyzer.

$$T(2) = e^{-i\pi} |x\rangle\langle x| + |y\rangle\langle y| = \begin{pmatrix} e^{-i\pi} & 0\\ 0 & 1 \end{pmatrix} \qquad T(1) = e^{-i\pi/2} |x'\rangle\langle x'| + |y'\rangle\langle y'| = e^{-i\pi/2} \begin{pmatrix} \frac{1}{2} & \frac{1}{2}\\ \frac{1}{2} & \frac{1}{2} \end{pmatrix} + \begin{pmatrix} \frac{1}{2} & \frac{-1}{2}\\ \frac{-1}{2} & \frac{1}{2} \end{pmatrix} = \begin{pmatrix} \frac{1-i}{2} & \frac{-1-i}{2}\\ \frac{-1-i}{2} & \frac{1-i}{2} \end{pmatrix}$$

The matrix product T(total) = T(2)T(1) relates input states $|\Psi_{IN}\rangle$ to output states: $|\Psi_{OUT}\rangle = T(total)|\Psi_{IN}\rangle$

$$T(total) = T(2)T(1) = \begin{pmatrix} -1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \frac{1-i}{2} & \frac{-1-i}{2} \\ \frac{-1-i}{2} & \frac{1-i}{2} \end{pmatrix} = \begin{pmatrix} \frac{-1+i}{2} & \frac{1+i}{2} \\ \frac{-1-i}{2} & \frac{1-i}{2} \end{pmatrix} = e^{-i\pi/4} \begin{pmatrix} \frac{-1}{\sqrt{2}} & \frac{i}{\sqrt{2}} \\ \frac{-i}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{-i}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix} \sim \begin{pmatrix} \frac{-1}{\sqrt{2}} & \frac{i}{\sqrt{2}} \\ \frac{-i}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{-i}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix}$$

We drop the overall phase $e^{-i\pi/4}$ since it is unobservable. T(total) yields two eigenvalues and projectors.

$$\lambda^{2} - 0\lambda - 1 = 0, \text{ or: } \lambda = +1, -1$$
, gives projectors
$$P_{+1} = \underbrace{\begin{pmatrix} -i & i \\ \sqrt{2} & 1 \\ \sqrt{2} & \sqrt{2} \end{pmatrix}}_{1 - (-1)} = \underbrace{\begin{pmatrix} -1 + \sqrt{2} & i \\ -i & 1 + \sqrt{2} \end{pmatrix}}_{2\sqrt{2}}, P_{-1} = \underbrace{\begin{pmatrix} 1 + \sqrt{2} & -i \\ i & -1 + \sqrt{2} \end{pmatrix}}_{2\sqrt{2}}$$

