

Group Theory in Quantum Mechanics

Lecture 4 (1.27.17)

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)

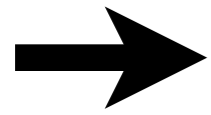
Matrix-algebraic eigensolutions *with example* $M = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}$
Secular equation
Hamilton-Cayley equation and projectors
Idempotent projectors (how eigenvalues \Rightarrow eigenvectors)
Operator orthonormality and completeness

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



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Unitary operators and matrices that change state vectors

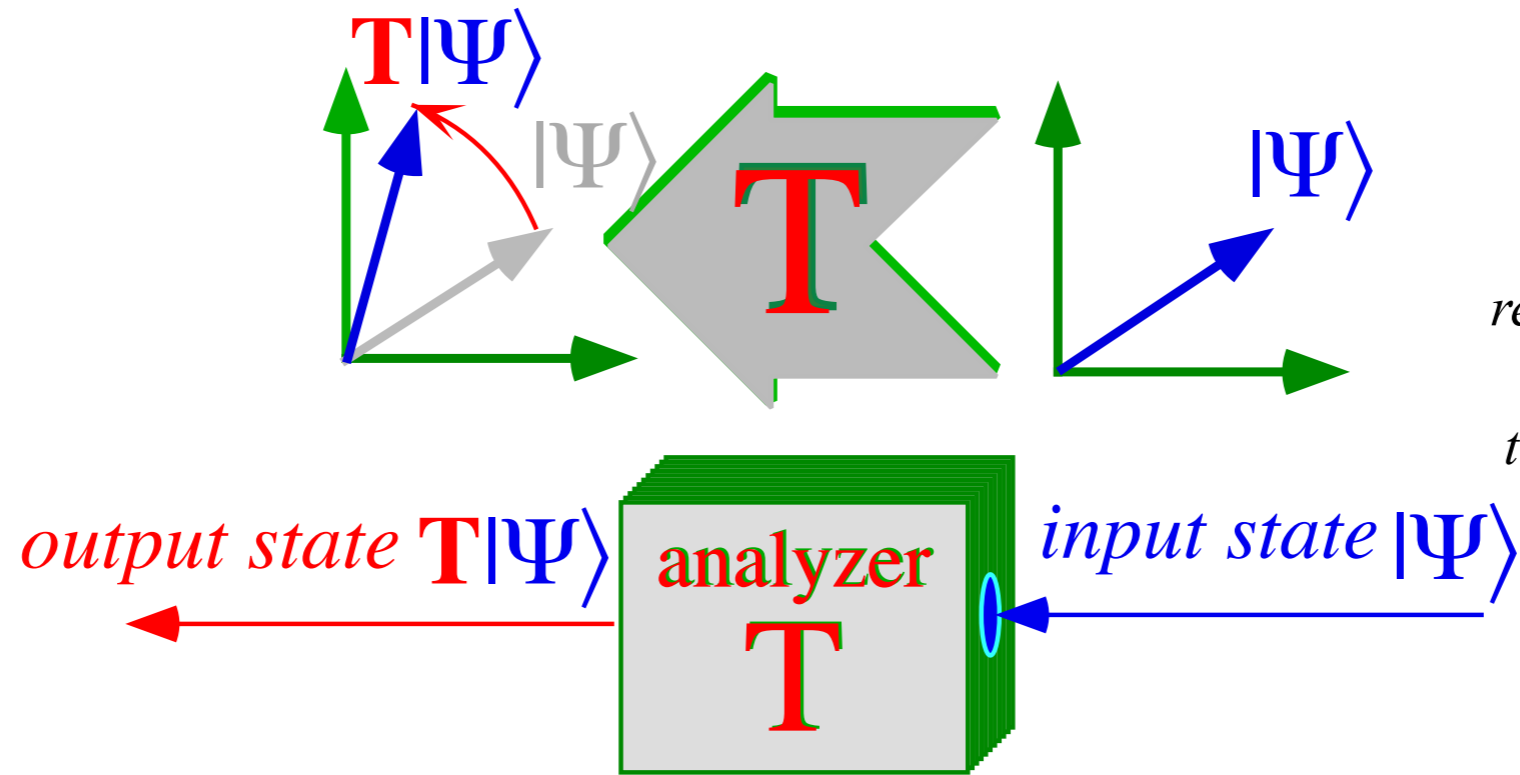


Fig. 3.1.1 Effect of analyzer represented by ket vector transformation of $|\Psi\rangle$ to new ket vector $\mathbf{T}|\Psi\rangle$.

Unitary operators and matrices that change state vectors...

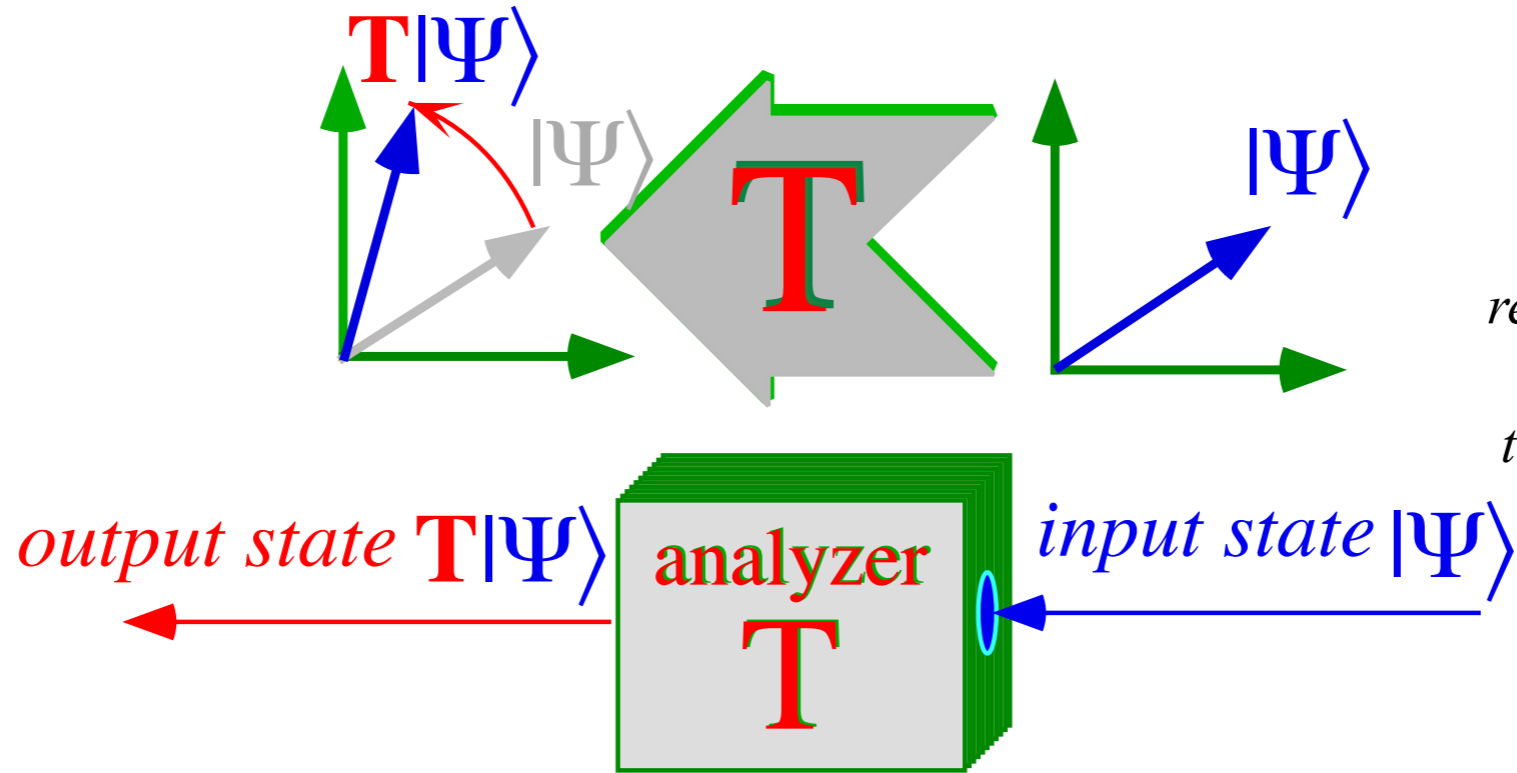


Fig. 3.1.1 Effect of analyzer represented by ket vector transformation of $|\Psi\rangle$ to new ket vector $T|\Psi\rangle$.

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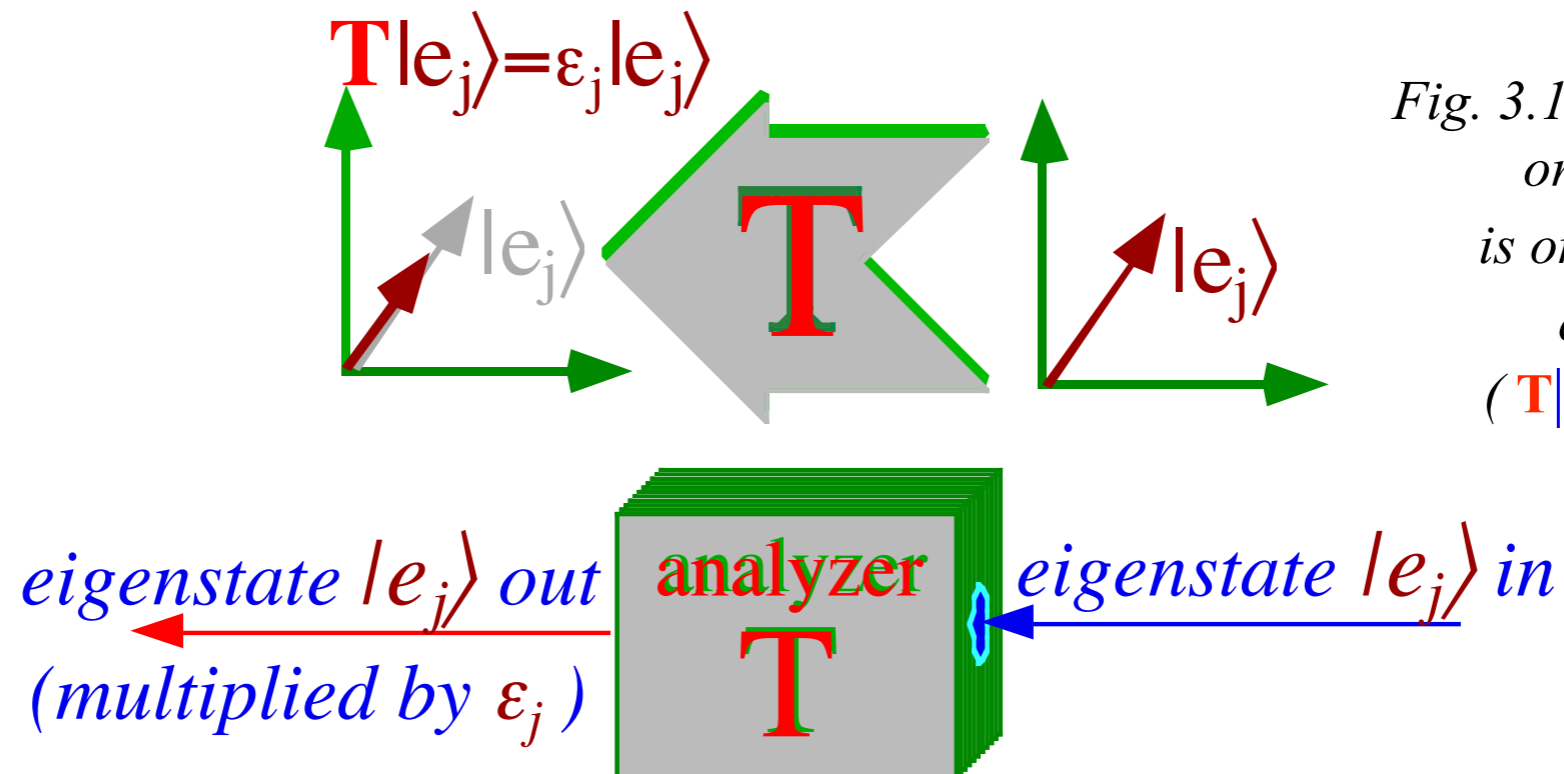



Fig. 3.1.2 Effect of analyzer on eigenket $|e_j\rangle$ is only to multiply by eigenvalue ϵ_j ($T|e_j\rangle = \epsilon_j |e_j\rangle$).

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

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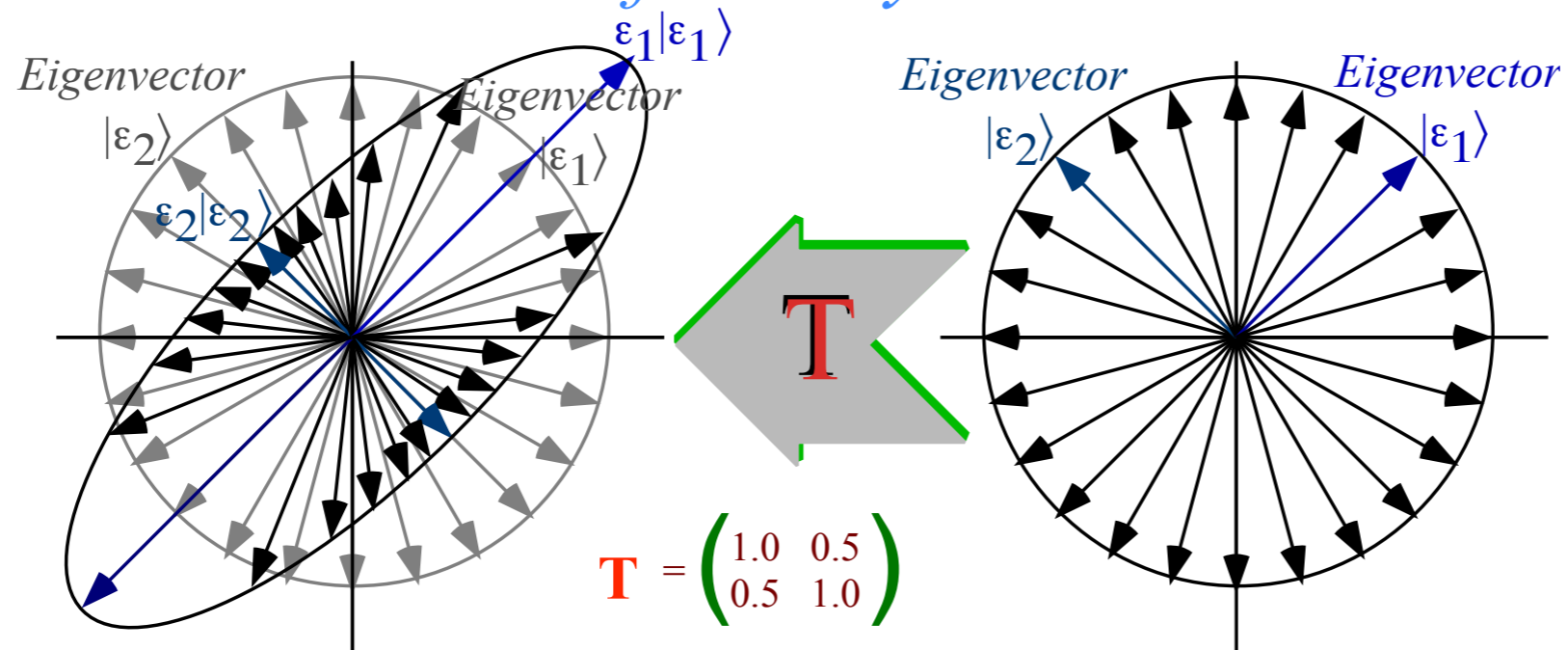
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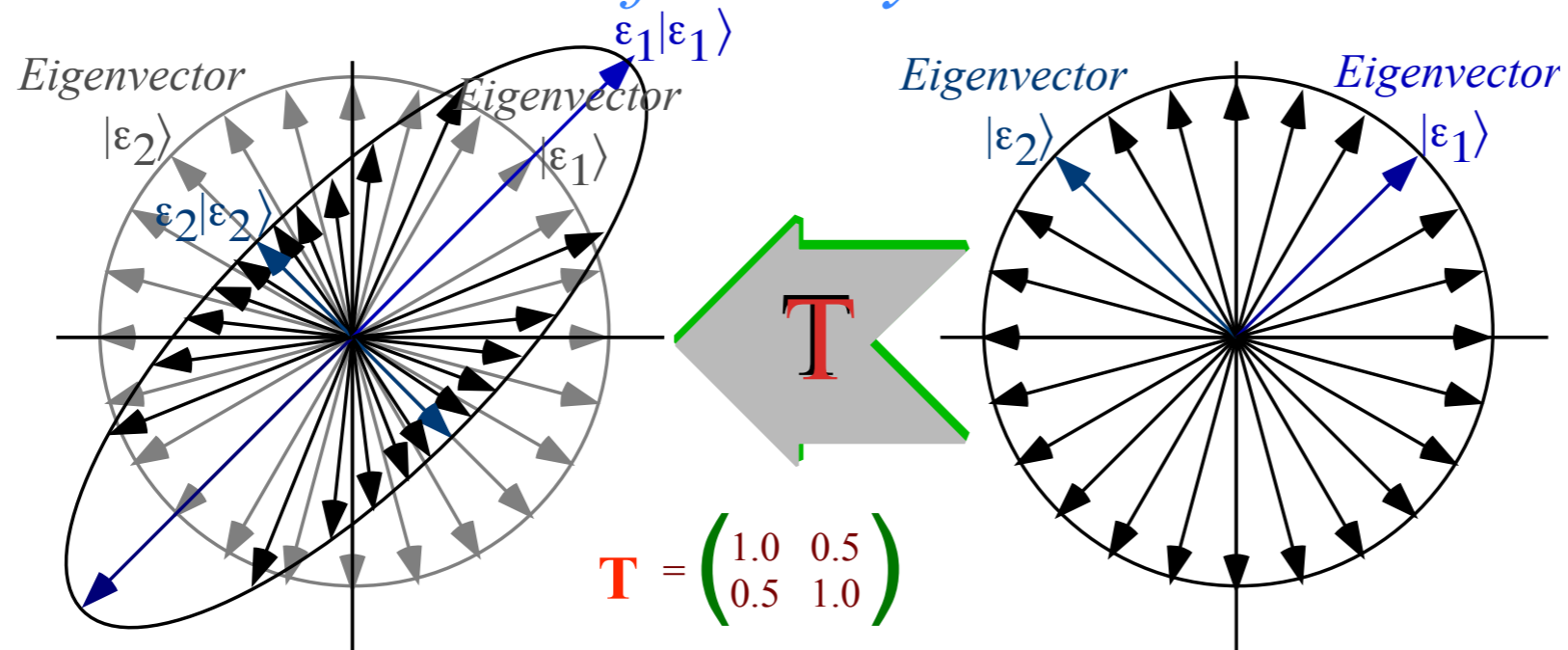


Circle-to-ellipse mapping

Study a real symmetric matrix \mathbf{T} by applying it to a circular array of unit vectors \mathbf{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



Circle-to-ellipse mapping

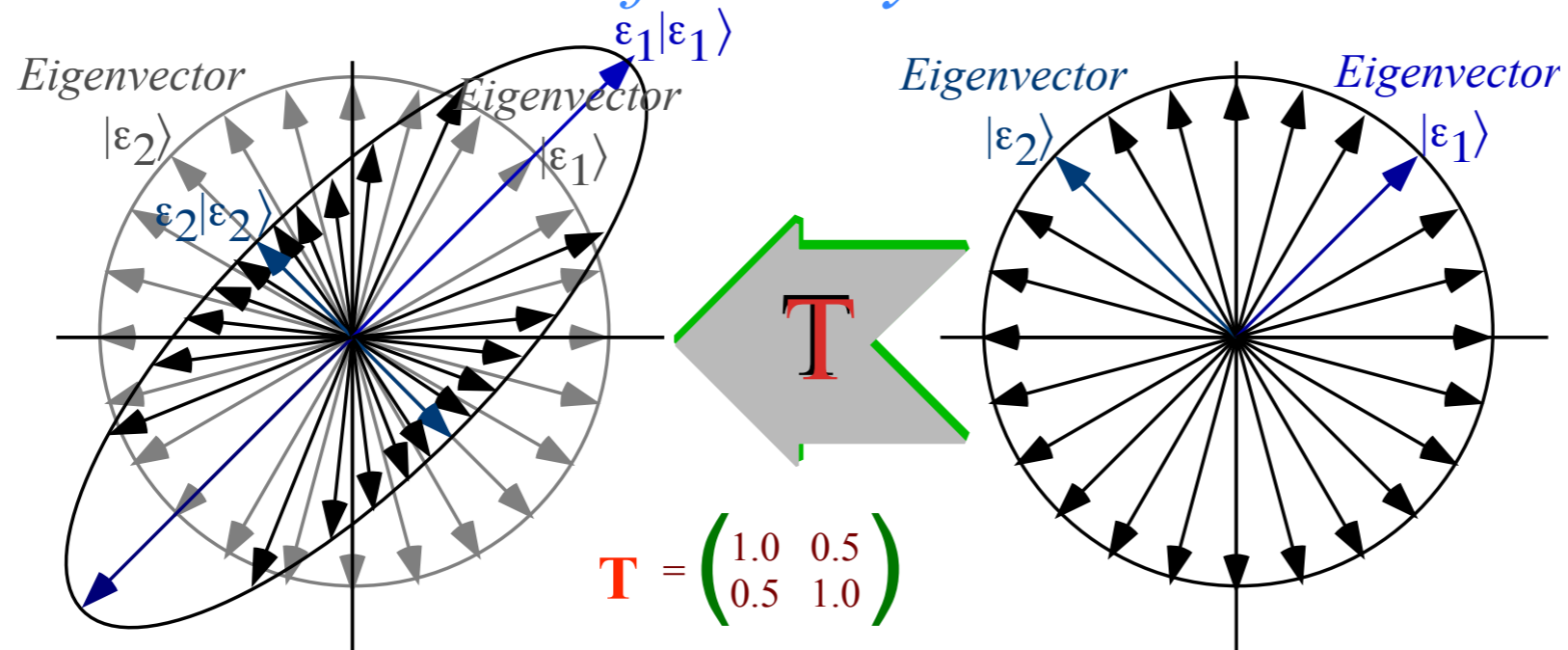
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Two vectors in the upper half plane survive \mathbf{T} without changing direction. These lucky vectors are the *eigenvectors of matrix \mathbf{T}* .

$$|\epsilon_1\rangle = \begin{pmatrix} 1 \\ 1 \end{pmatrix} / \sqrt{2}, \quad |\epsilon_2\rangle = \begin{pmatrix} -1 \\ 1 \end{pmatrix} / \sqrt{2}$$

Geometric visualization of real symmetric matrices and eigenvectors



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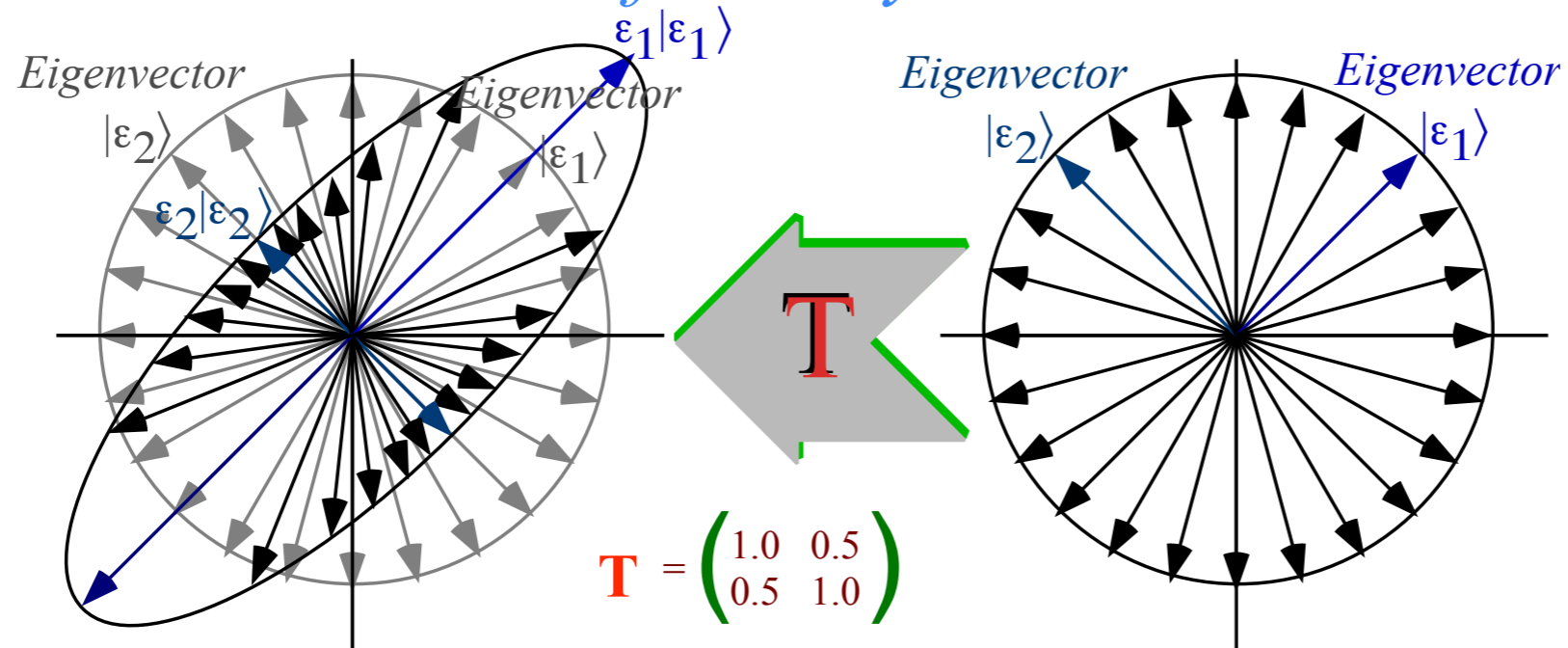
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They transform as follows: $\mathbf{T}|\epsilon_1\rangle = \epsilon_1|\epsilon_1\rangle = 1.5|\epsilon_1\rangle$, and $\mathbf{T}|\epsilon_2\rangle = \epsilon_2|\epsilon_2\rangle = 0.5|\epsilon_2\rangle$ to only suffer length change given by *eigenvalues* $\epsilon_1 = 1.5$ and $\epsilon_2 = 0.5$

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

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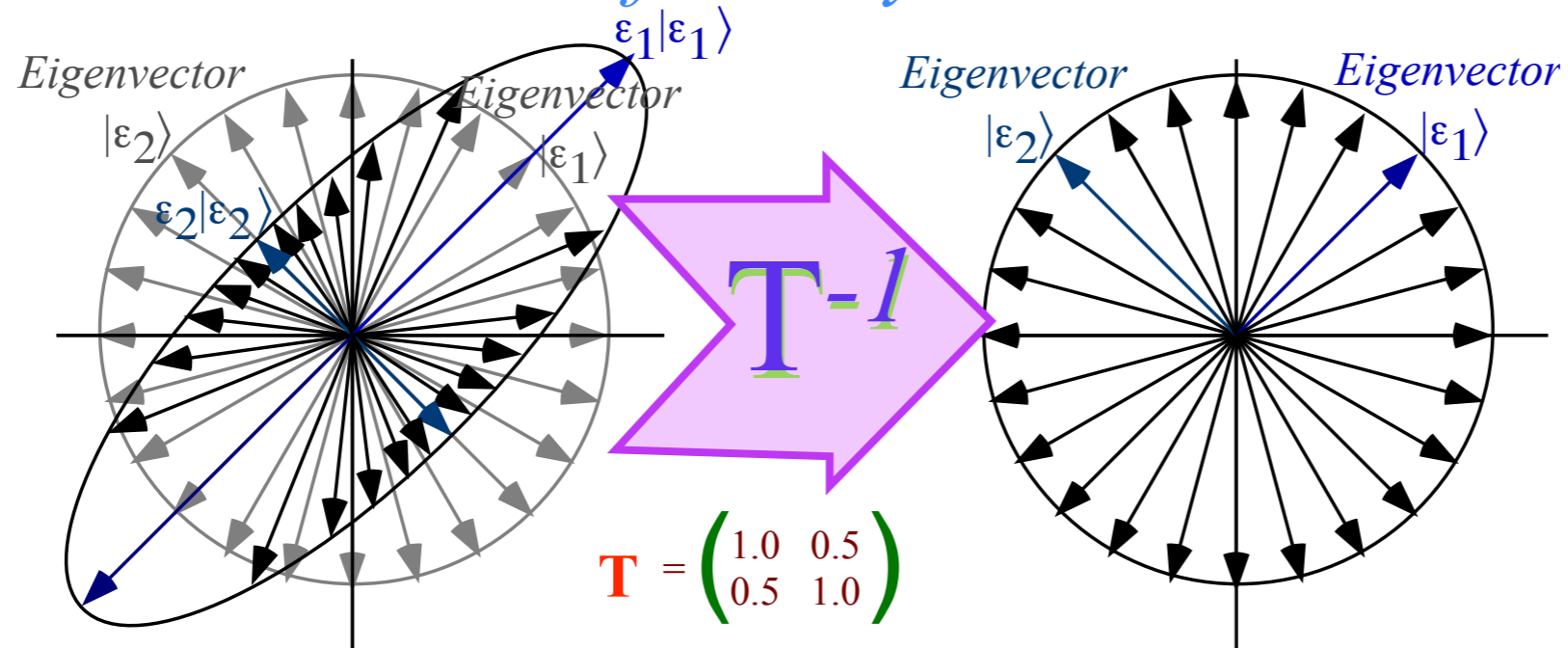
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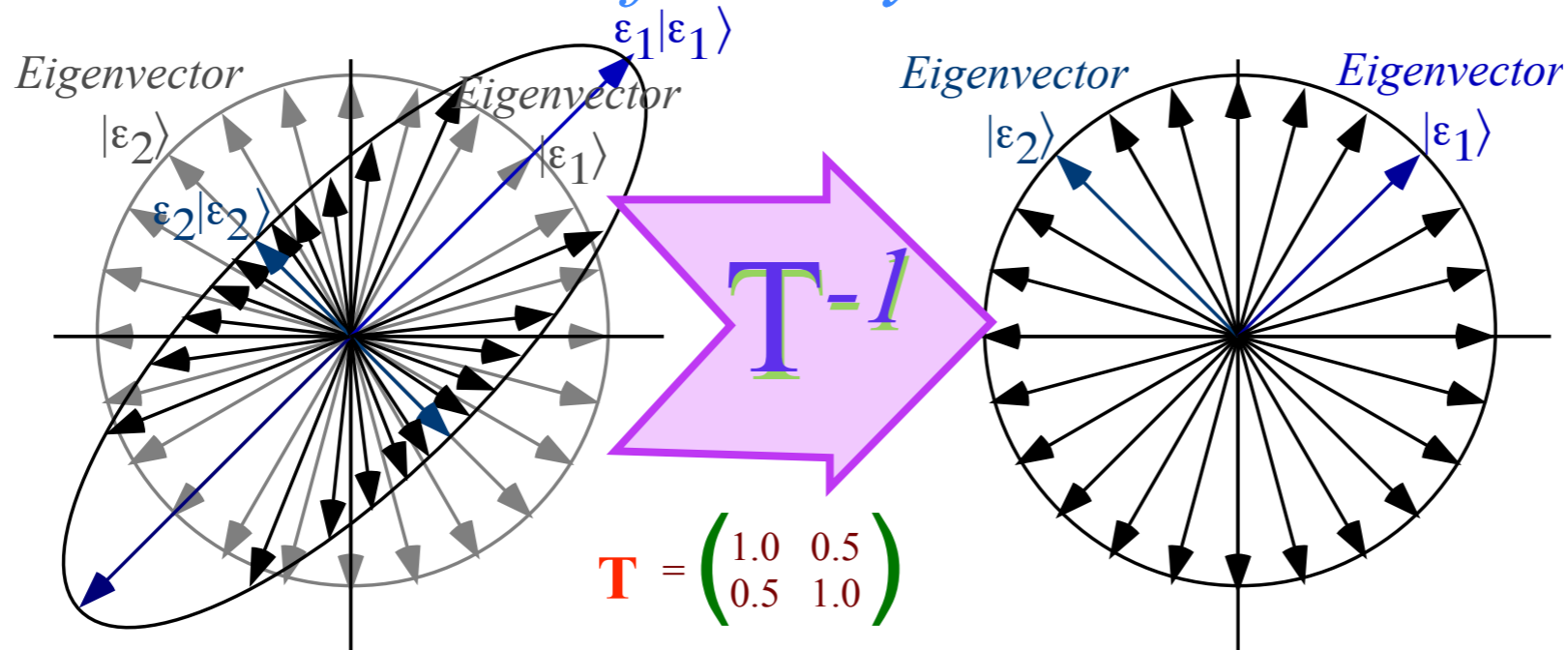
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Each vector $|\mathbf{r}\rangle$ on left ellipse maps back to vector $|\mathbf{c}\rangle = \mathbf{T}^{-1} |\mathbf{r}\rangle$ on right unit circle.

Each $|\mathbf{c}\rangle$ has unit length: $\langle \mathbf{c} | \mathbf{c} \rangle = 1 = \langle \mathbf{r} | \mathbf{T}^{-1} \mathbf{T}^{-1} | \mathbf{r} \rangle = \langle \mathbf{r} | \mathbf{T}^{-2} | \mathbf{r} \rangle$. (\mathbf{T} is real-symmetric: $\mathbf{T}^\dagger = \mathbf{T} = \mathbf{T}^T$.)

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

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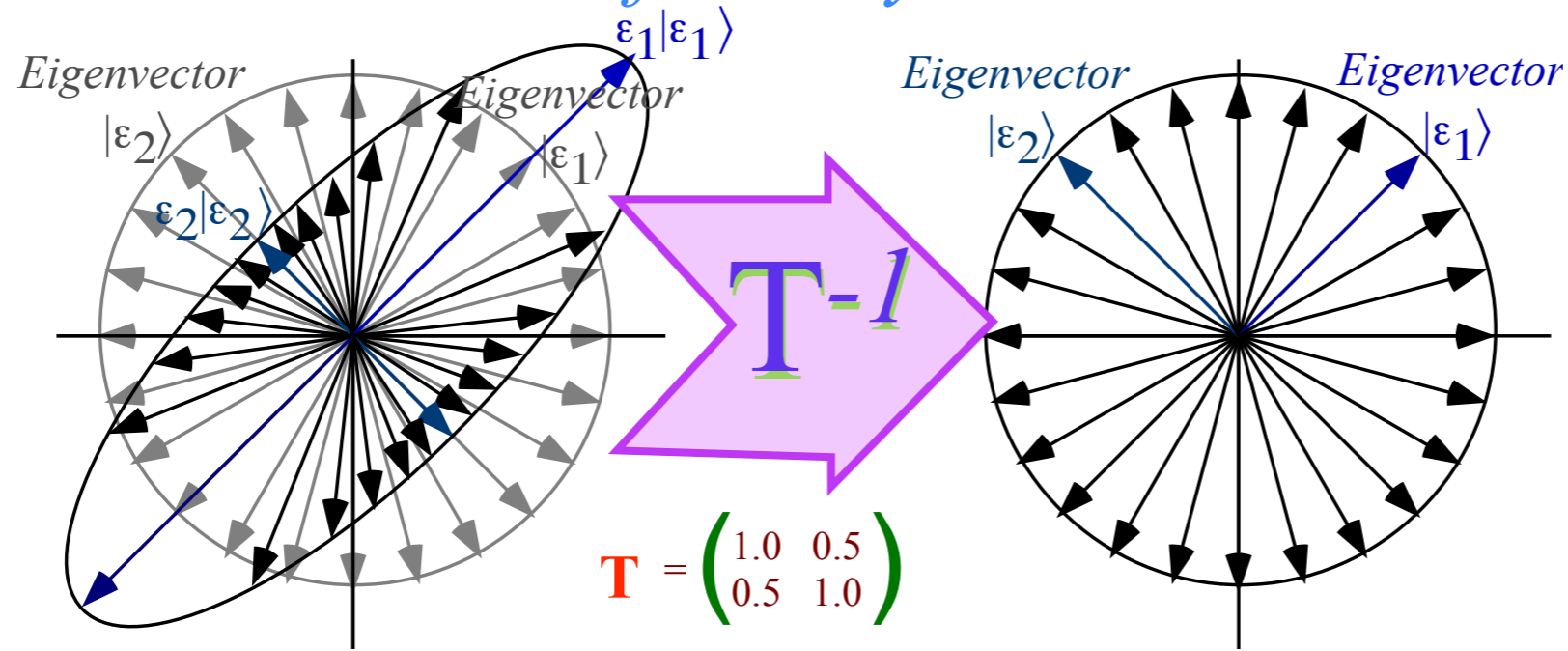
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This simplifies if rewritten in a coordinate system (x_1, x_2) of eigenvectors $|\epsilon_1\rangle$ and $|\epsilon_2\rangle$

where $\mathbf{T}^{-2} |\epsilon_1\rangle = \epsilon_1^{-2} |\epsilon_1\rangle$ and $\mathbf{T}^{-2} |\epsilon_2\rangle = \epsilon_2^{-2} |\epsilon_2\rangle$, that is, \mathbf{T} , \mathbf{T}^{-1} , and \mathbf{T}^{-2} are each diagonal.

$$\begin{pmatrix} \langle \epsilon_1 | \mathbf{T} | \epsilon_1 \rangle & \langle \epsilon_1 | \mathbf{T} | \epsilon_2 \rangle \\ \langle \epsilon_2 | \mathbf{T} | \epsilon_1 \rangle & \langle \epsilon_2 | \mathbf{T} | \epsilon_2 \rangle \end{pmatrix} = \begin{pmatrix} \epsilon_1 & 0 \\ 0 & \epsilon_2 \end{pmatrix}, \text{ and } \begin{pmatrix} \langle \epsilon_1 | \mathbf{T}^{-2} | \epsilon_1 \rangle & \langle \epsilon_1 | \mathbf{T}^{-2} | \epsilon_2 \rangle \\ \langle \epsilon_2 | \mathbf{T}^{-2} | \epsilon_1 \rangle & \langle \epsilon_2 | \mathbf{T}^{-2} | \epsilon_2 \rangle \end{pmatrix}^{-2} = \begin{pmatrix} \epsilon_1^{-2} & 0 \\ 0 & \epsilon_2^{-2} \end{pmatrix}$$

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$$\begin{pmatrix} \langle \epsilon_1 | \mathbf{T} | \epsilon_1 \rangle & \langle \epsilon_1 | \mathbf{T} | \epsilon_2 \rangle \\ \langle \epsilon_2 | \mathbf{T} | \epsilon_1 \rangle & \langle \epsilon_2 | \mathbf{T} | \epsilon_2 \rangle \end{pmatrix} = \begin{pmatrix} \epsilon_1 & 0 \\ 0 & \epsilon_2 \end{pmatrix}, \text{ and } \begin{pmatrix} \langle \epsilon_1 | \mathbf{T}^{-2} | \epsilon_1 \rangle & \langle \epsilon_1 | \mathbf{T}^{-2} | \epsilon_2 \rangle \\ \langle \epsilon_2 | \mathbf{T}^{-2} | \epsilon_1 \rangle & \langle \epsilon_2 | \mathbf{T}^{-2} | \epsilon_2 \rangle \end{pmatrix}^{-2} = \begin{pmatrix} \epsilon_1^{-2} & 0 \\ 0 & \epsilon_2^{-2} \end{pmatrix}$$

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

$$\mathbf{c} \cdot \mathbf{c} = 1 = \begin{pmatrix} x_1 & x_2 \end{pmatrix} \begin{pmatrix} \epsilon_1^{-2} & 0 \\ 0 & \epsilon_2^{-2} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \left(\frac{x_1}{\epsilon_1} \right)^2 + \left(\frac{x_2}{\epsilon_2} \right)^2$$

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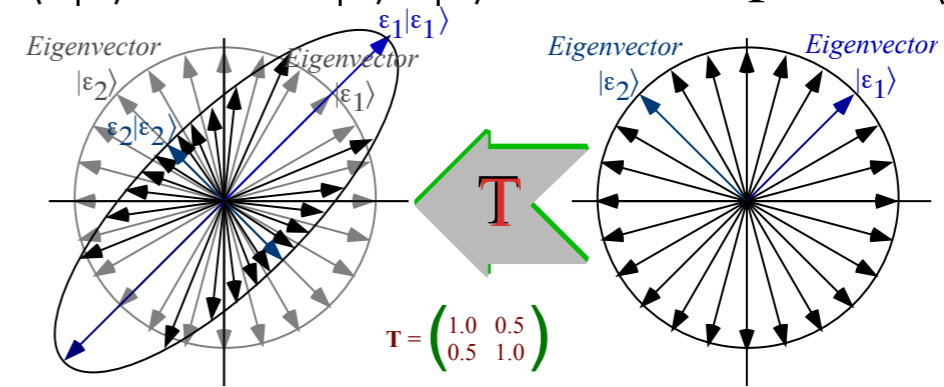
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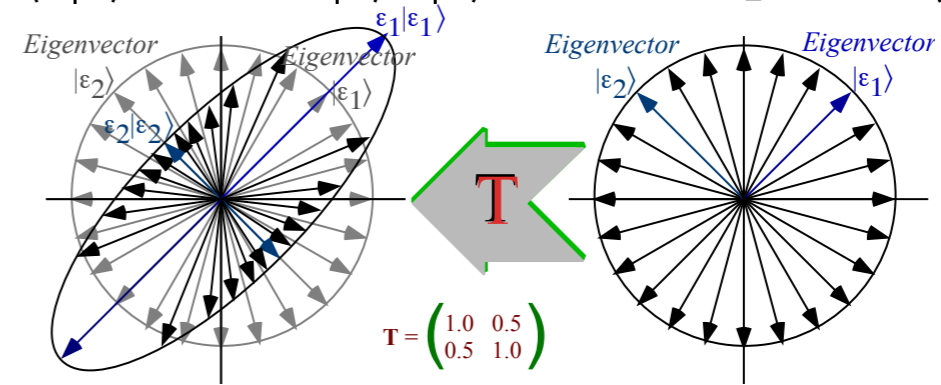
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Ellipse-to-ellipse mapping (Normal vs. tangent space)

Geometric visualization of real symmetric matrices and eigenvectors

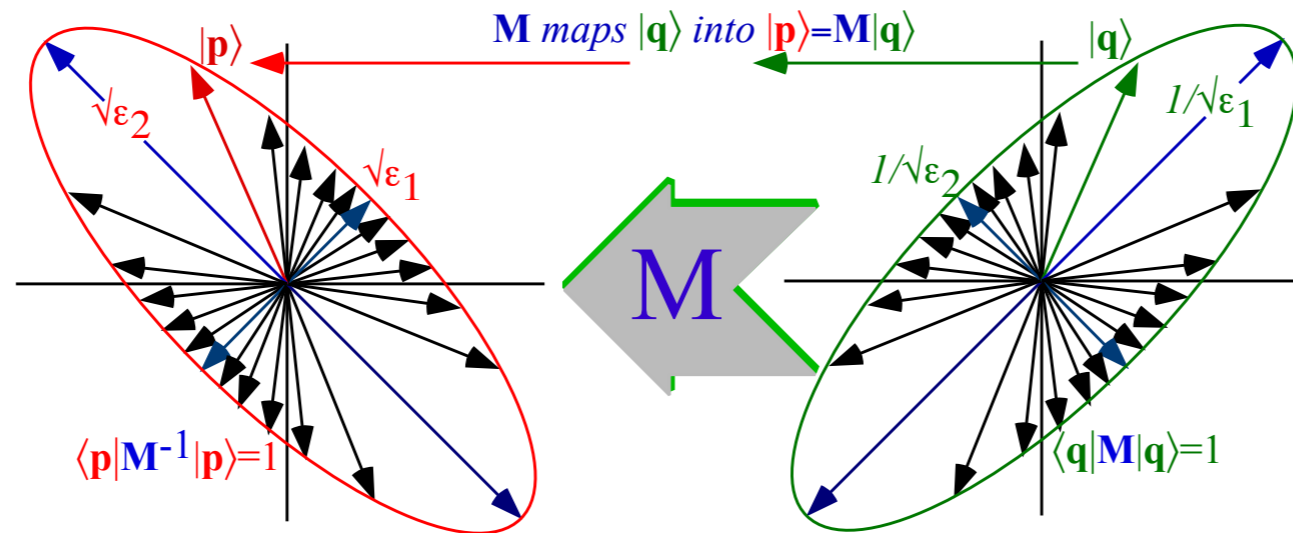
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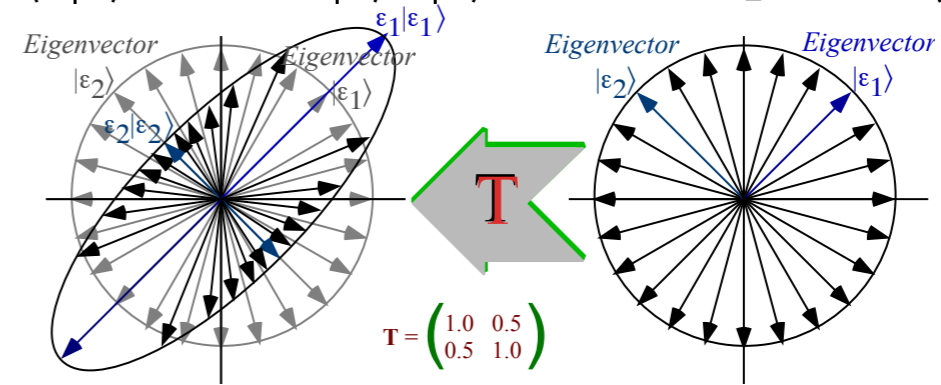
Now **M** maps vector $|\mathbf{q}\rangle$ from a *quadratic form* $1 = \langle \mathbf{q} | \mathbf{M} | \mathbf{q} \rangle$ to vector $|\mathbf{p}\rangle = \mathbf{M}|\mathbf{q}\rangle$ on surface $1 = \langle \mathbf{p} | \mathbf{M}^{-1} | \mathbf{p} \rangle$.

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



Geometric visualization of real symmetric matrices and eigenvectors

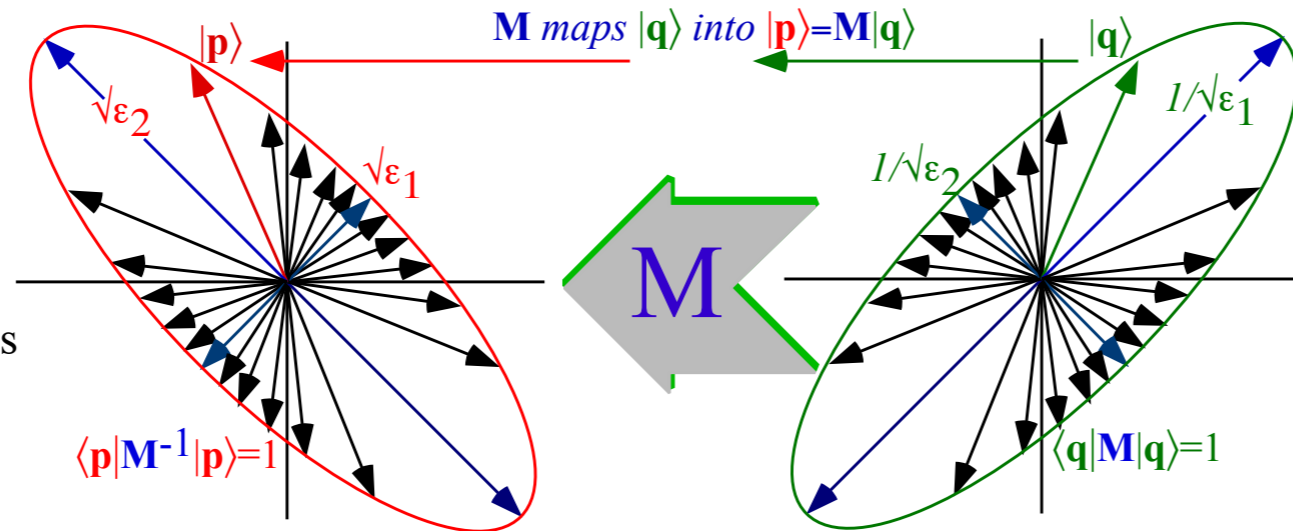
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Ellipse-to-ellipse mapping (Normal vs. tangent space)

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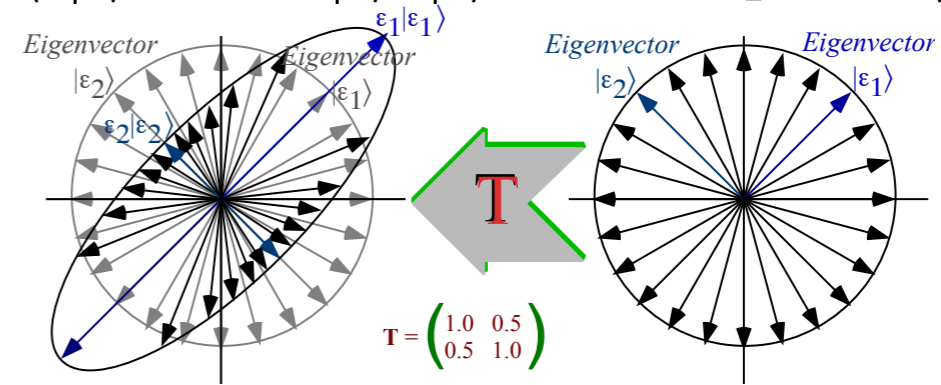


Radii of $|\mathbf{p}\rangle$ ellipse are square roots of eigenvalues $\sqrt{\epsilon_1}$ and $\sqrt{\epsilon_2}$

Radii of $|\mathbf{q}\rangle$ ellipse axes are inverse eigenvalue roots $1/\sqrt{\epsilon_1}$ and $1/\sqrt{\epsilon_2}$.

Geometric visualization of real symmetric matrices and eigenvectors

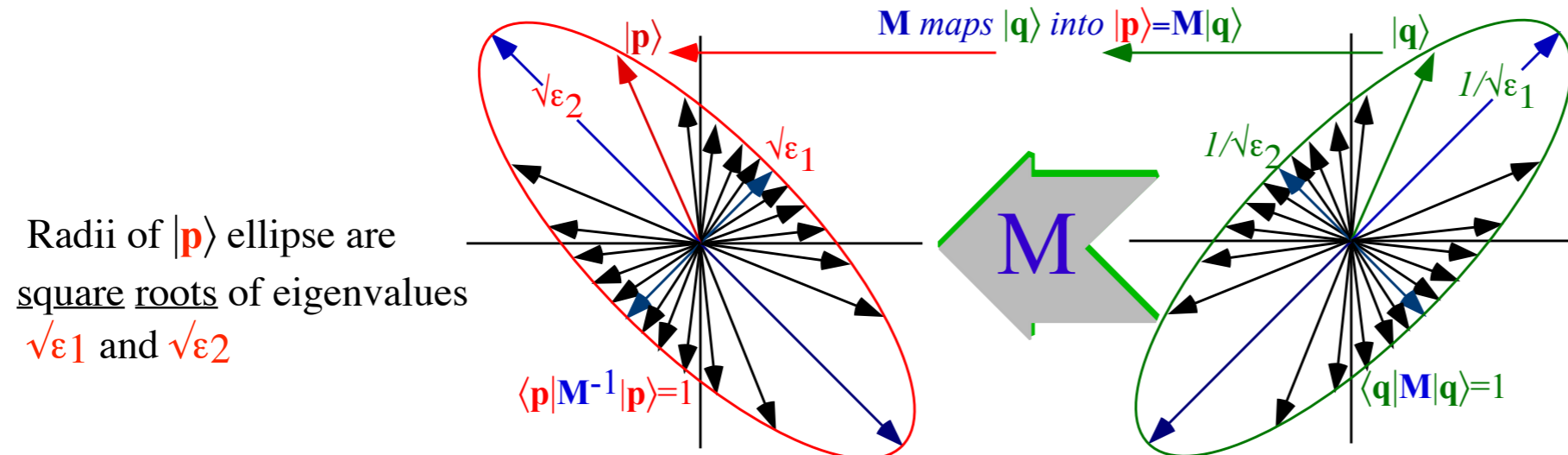
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Ellipse-to-ellipse mapping (Normal vs. tangent space)

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Radii of $|\mathbf{p}\rangle$ ellipse are square roots of eigenvalues $\sqrt{\epsilon_1}$ and $\sqrt{\epsilon_2}$

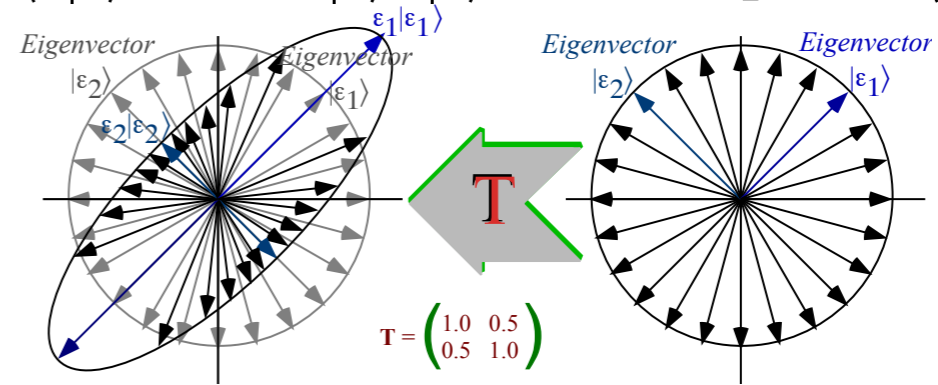
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Tangent-normal geometry of mapping is found by using gradient ∇ of quadratic curve $1 = \langle \mathbf{q} | \mathbf{M} | \mathbf{q} \rangle$.

$$\nabla(\langle \mathbf{q} | \mathbf{M} | \mathbf{q} \rangle) = \langle \mathbf{q} | \mathbf{M} + \mathbf{M} | \mathbf{q} \rangle = 2 \mathbf{M} | \mathbf{q} \rangle = 2 | \mathbf{p} \rangle$$

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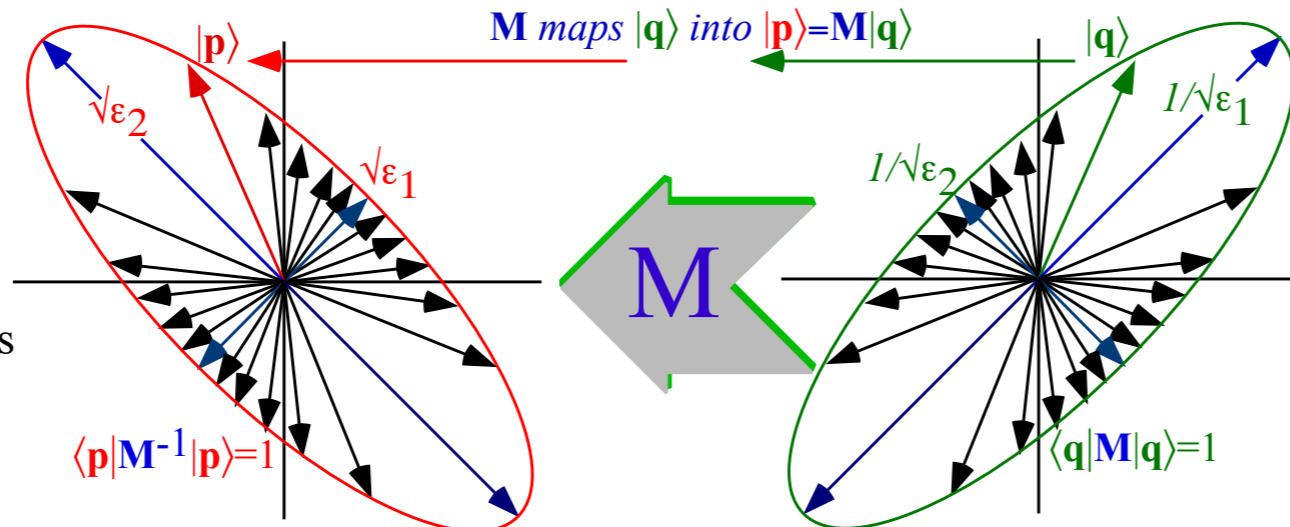


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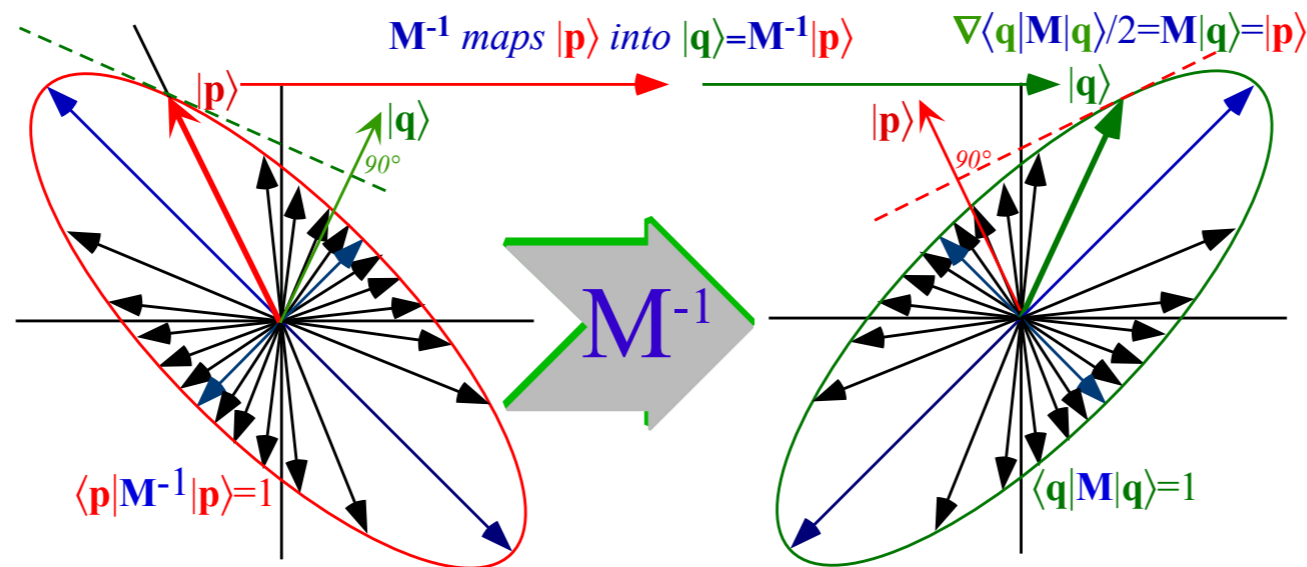
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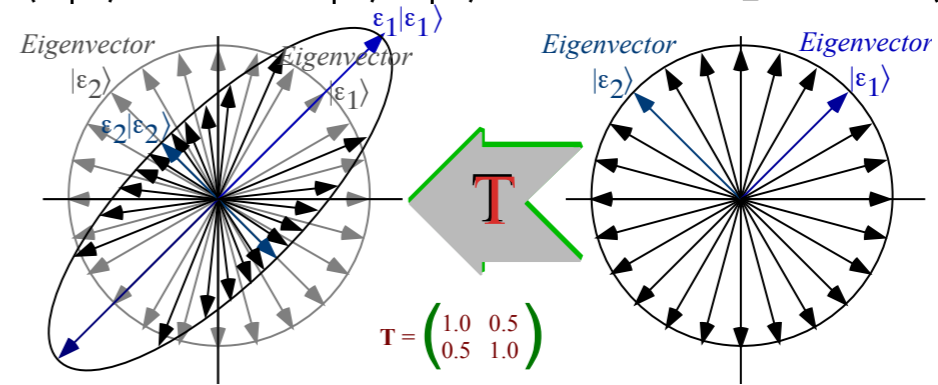
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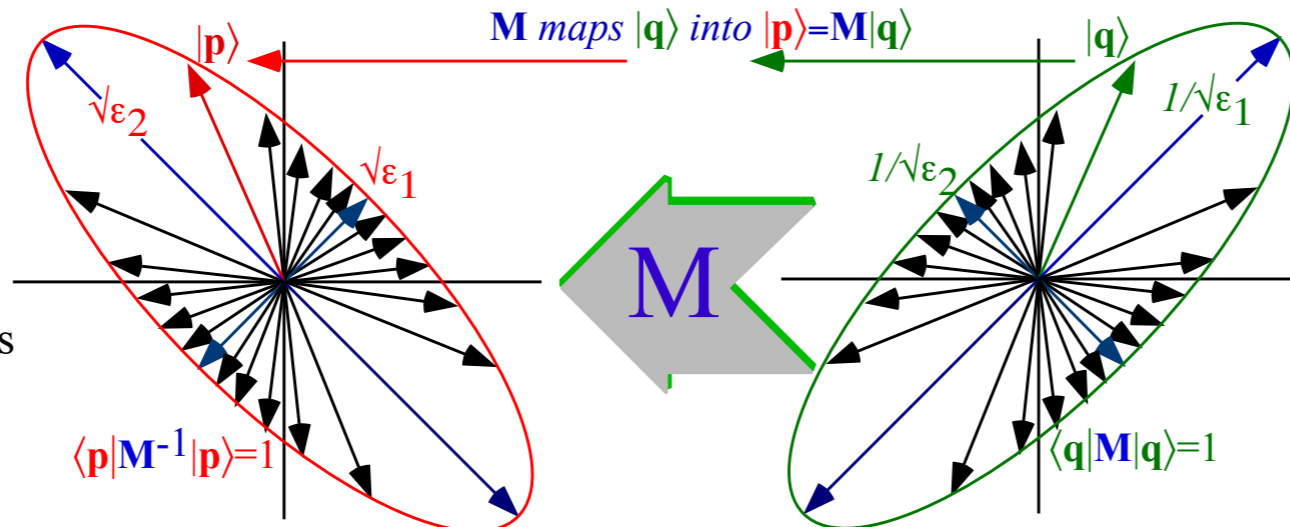


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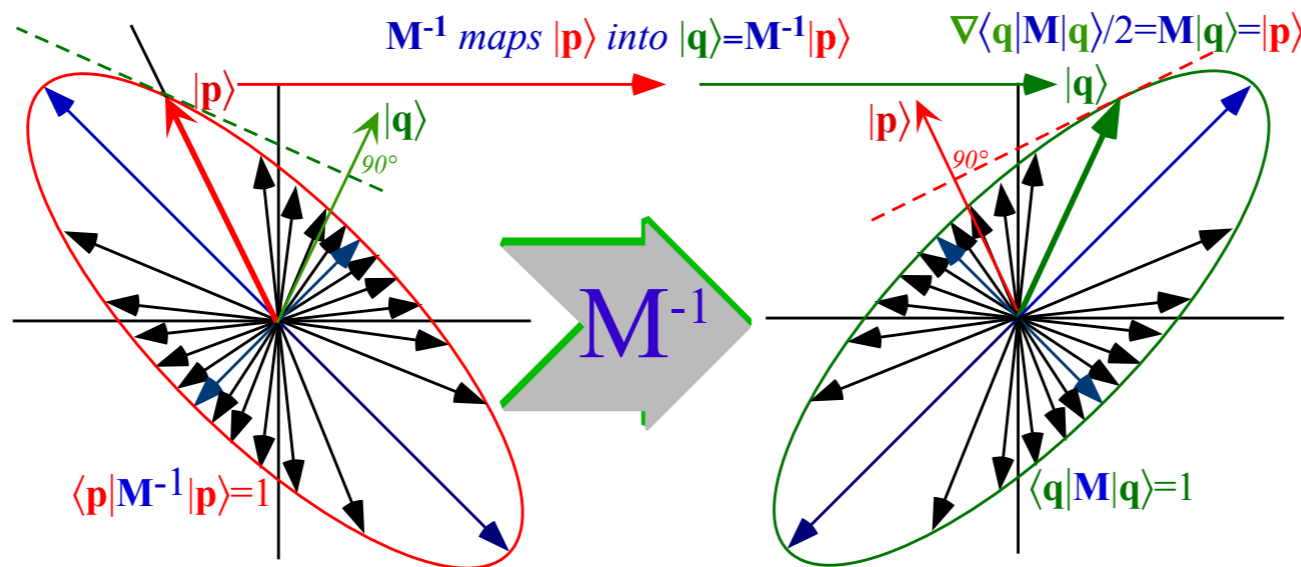


Radii of $|\mathbf{q}\rangle$ ellipse axes are inverse eigenvalue roots $1/\sqrt{\epsilon_1}$ and $1/\sqrt{\epsilon_2}$.

Tangent-normal geometry of mapping is found by using gradient ∇ of quadratic curve $1 = \langle \mathbf{q} | \mathbf{M} | \mathbf{q} \rangle$.

$$\nabla(\langle \mathbf{q} | \mathbf{M} | \mathbf{q} \rangle) = \langle \mathbf{q} | \mathbf{M} + \mathbf{M} | \mathbf{q} \rangle = 2 \mathbf{M} | \mathbf{q} \rangle = 2 |\mathbf{p}\rangle$$

Mapped vector $|\mathbf{p}\rangle$ lies on gradient $\nabla(\langle \mathbf{q} | \mathbf{M} | \mathbf{q} \rangle)$ that is normal to tangent to **original curve** at $|\mathbf{q}\rangle$.




Original vector $|\mathbf{q}\rangle$ lies on gradient $\nabla(\langle \mathbf{p} | \mathbf{M}^{-1} | \mathbf{p} \rangle)$ that is normal to tangent to **mapped curve** at $|\mathbf{p}\rangle$.

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

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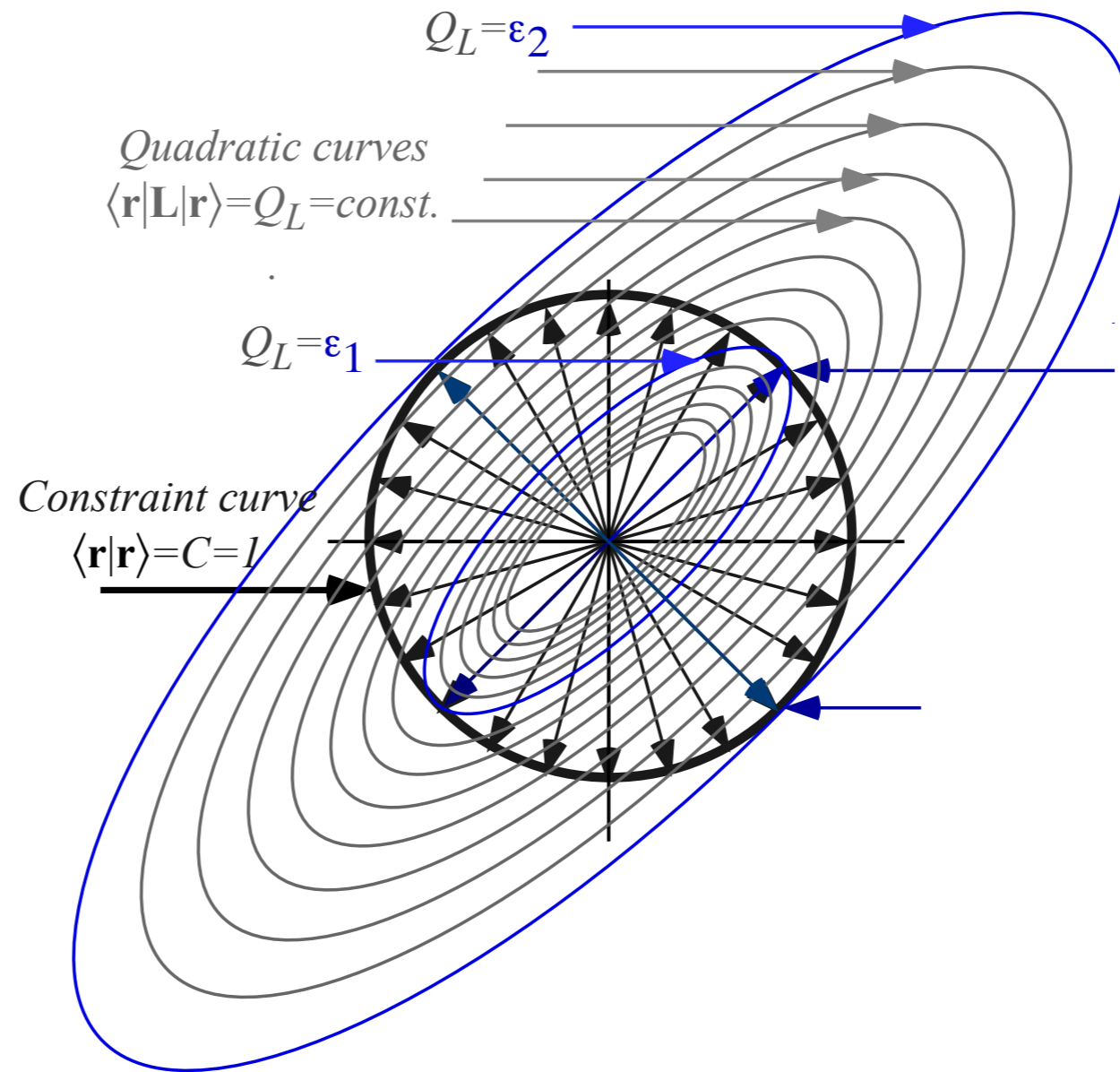
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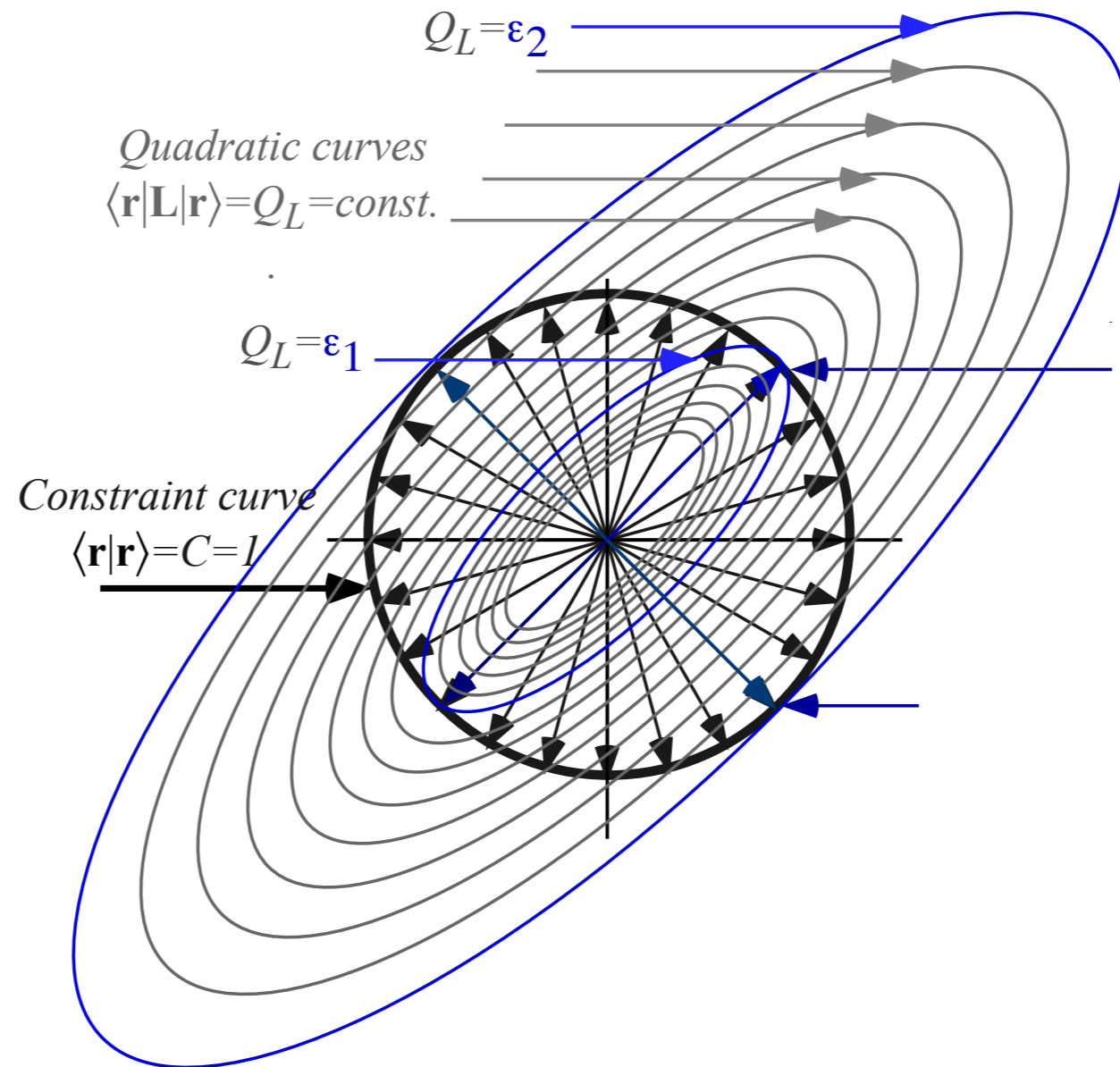


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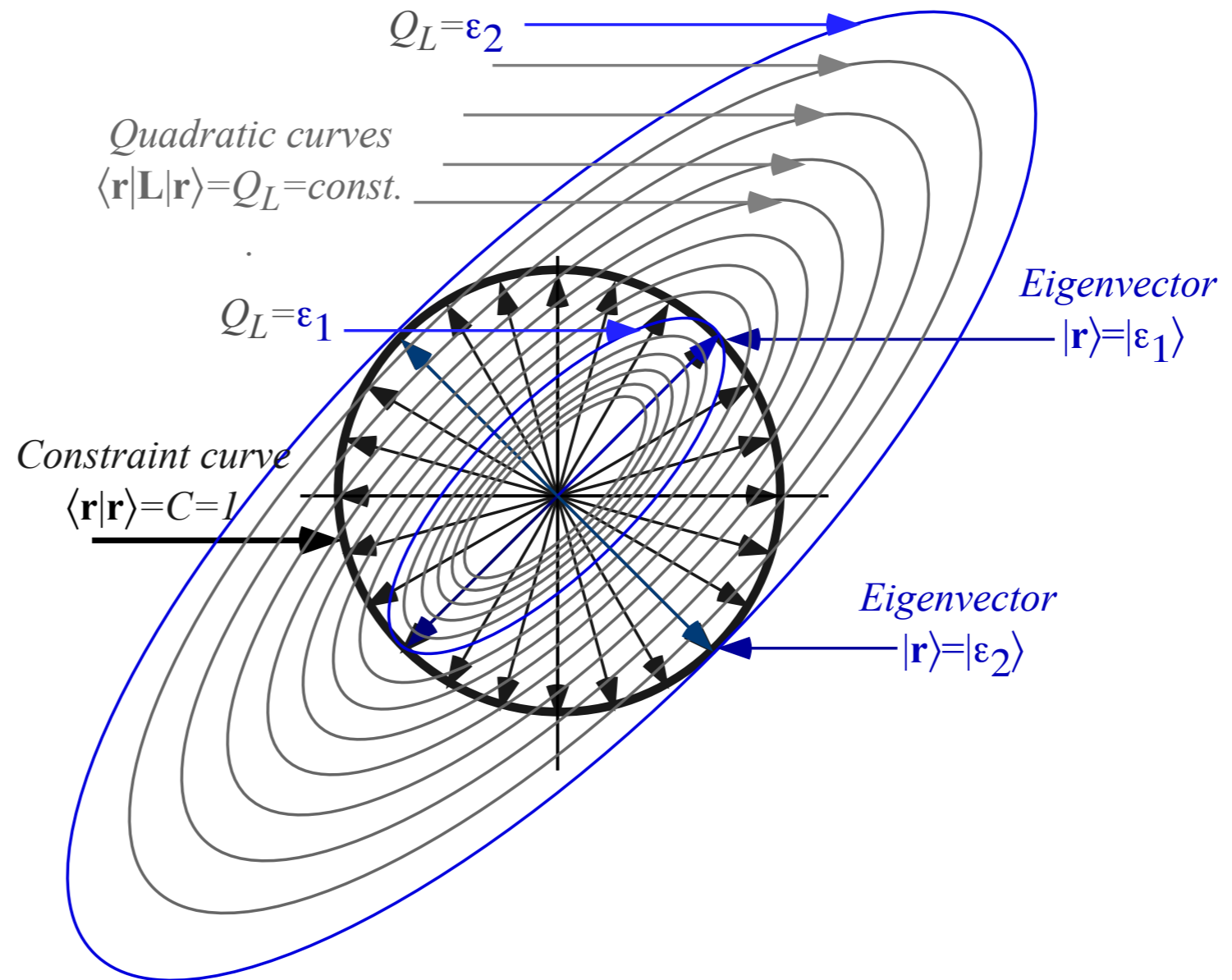
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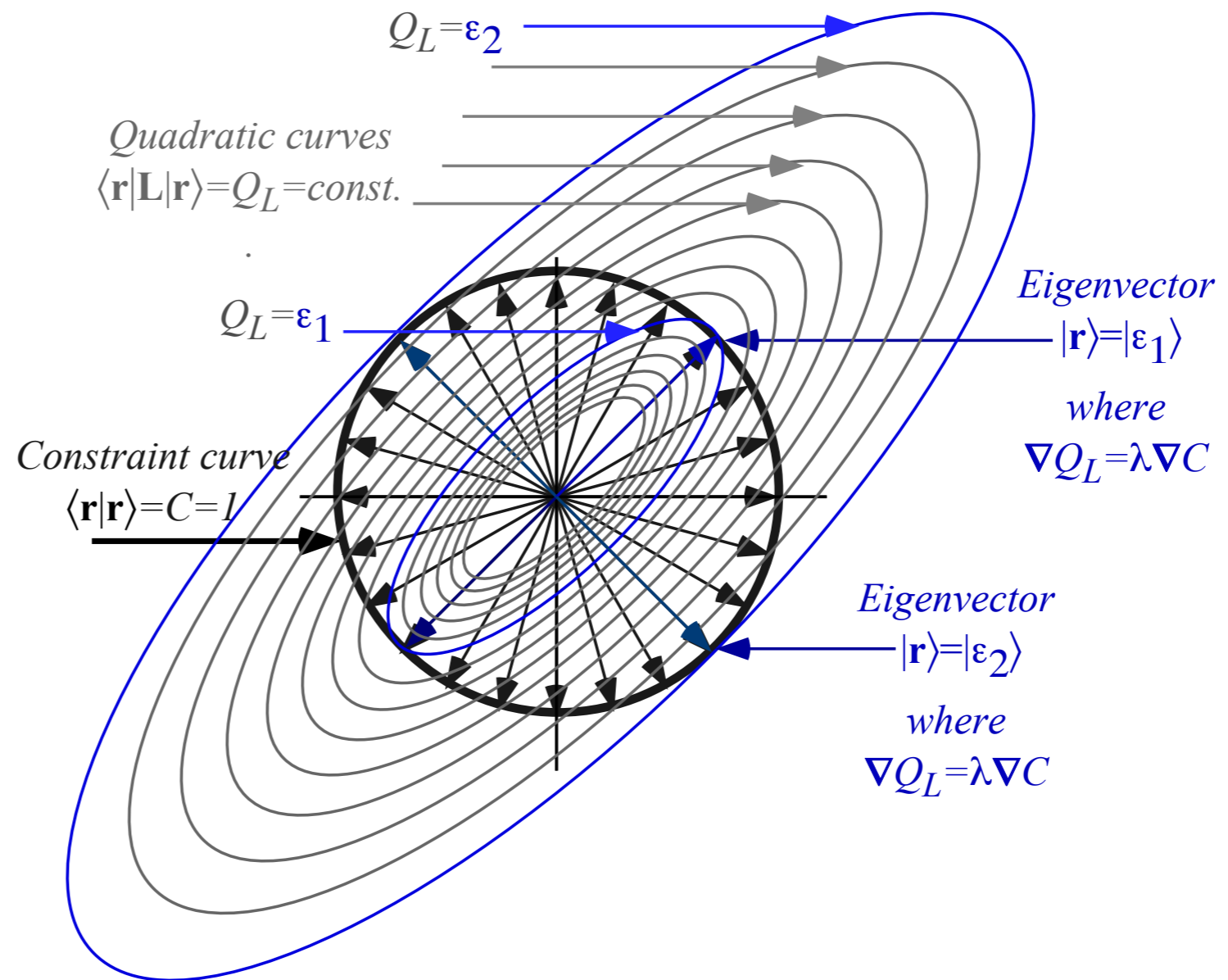
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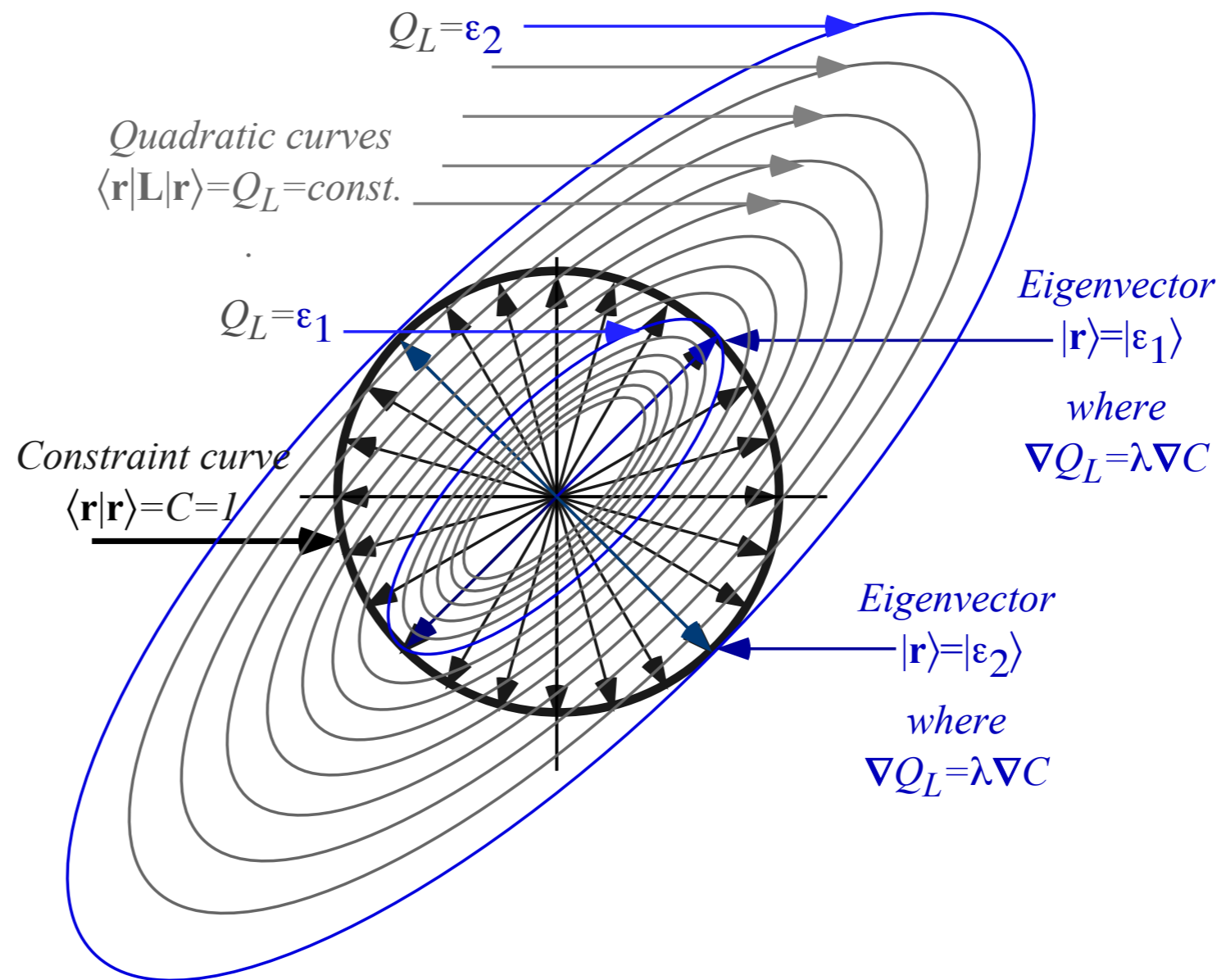
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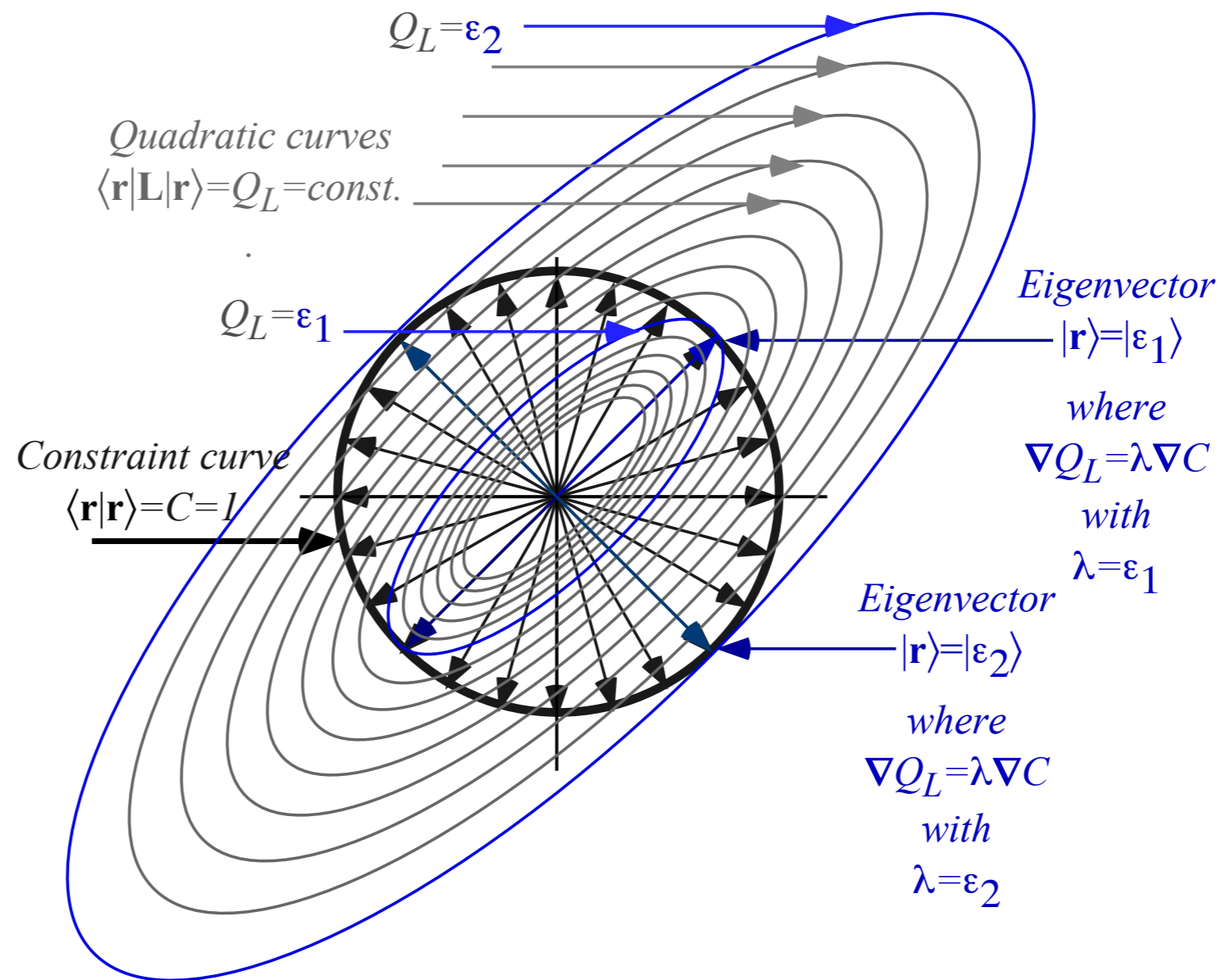
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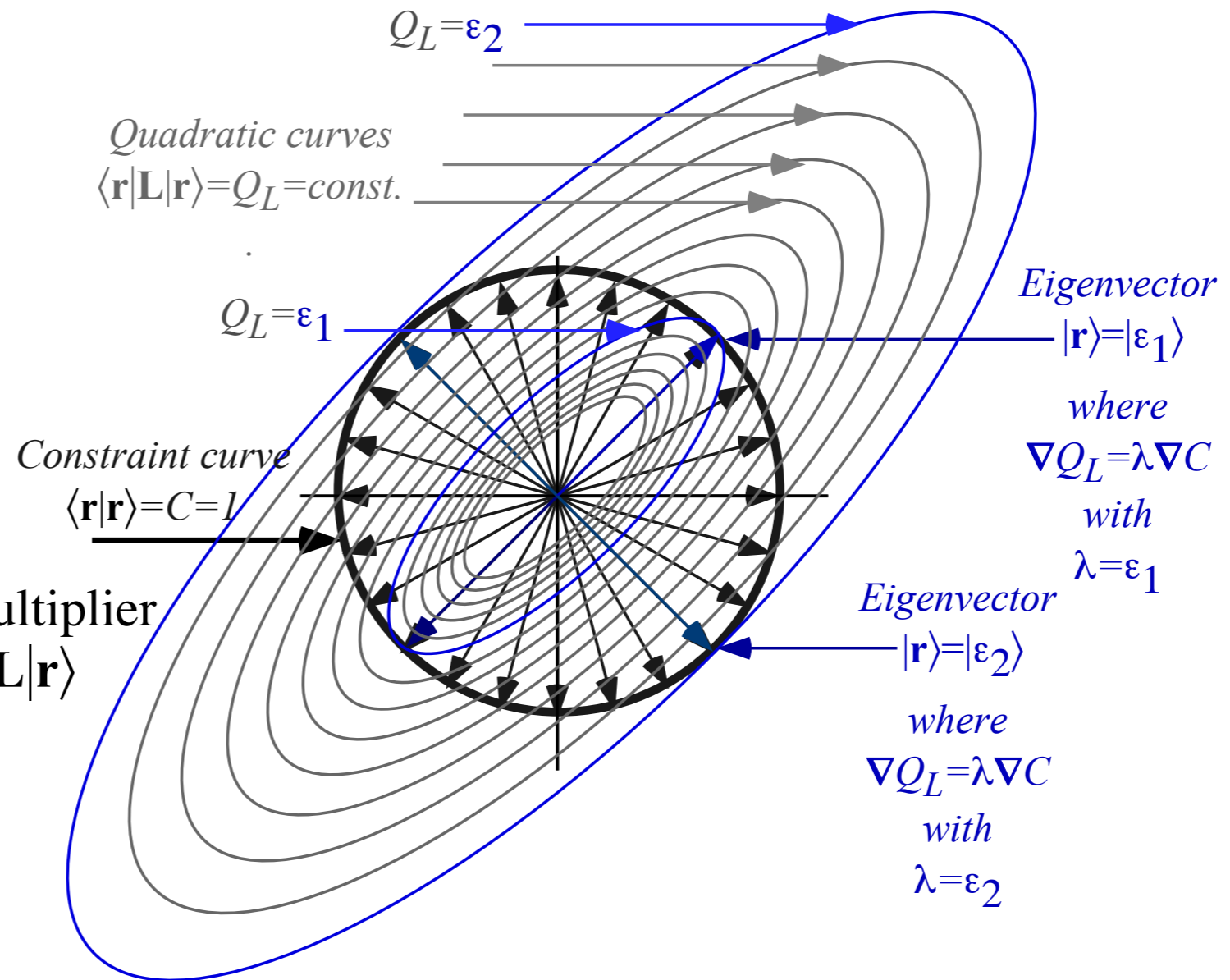
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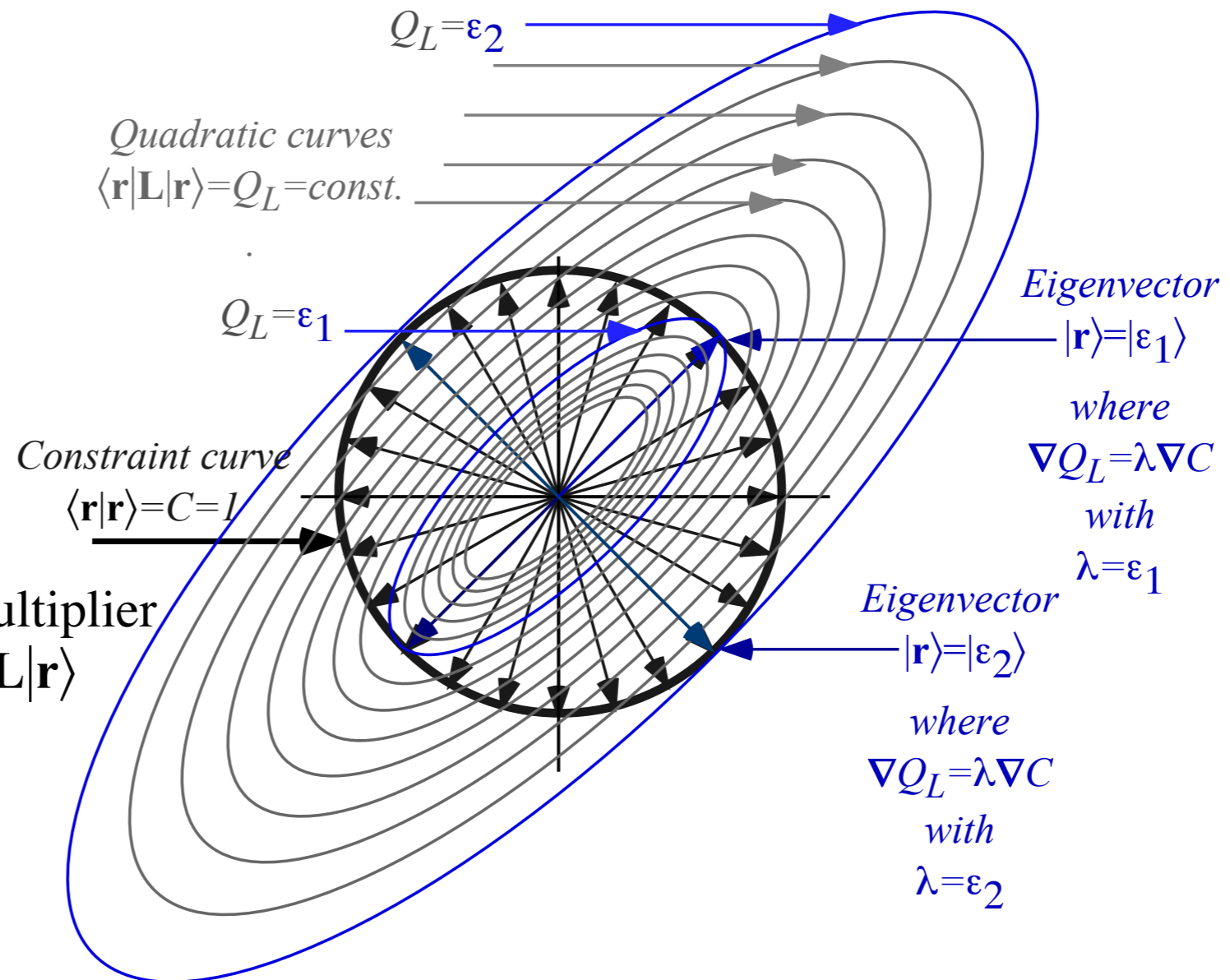
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$\langle\mathbf{r}|\mathbf{L}|\mathbf{r}\rangle$ is called a quantum *expectation value* of operator \mathbf{L} at \mathbf{r} .
Eigenvalues are extreme expectation values.

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

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

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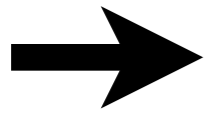
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An *eigenvector* $|\varepsilon_k\rangle$ of \mathbf{M} is in a direction that is left unchanged by \mathbf{M} .

$$\mathbf{M}|\varepsilon_k\rangle = \varepsilon_k|\varepsilon_k\rangle, \text{ or: } (\mathbf{M} - \varepsilon_k\mathbf{1})|\varepsilon_k\rangle = \mathbf{0}$$

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

$$\begin{pmatrix} \langle \varepsilon_1 | \mathbf{M} | \varepsilon_1 \rangle & \langle \varepsilon_1 | \mathbf{M} | \varepsilon_2 \rangle & \dots & \langle \varepsilon_1 | \mathbf{M} | \varepsilon_n \rangle \\ \langle \varepsilon_2 | \mathbf{M} | \varepsilon_1 \rangle & \langle \varepsilon_2 | \mathbf{M} | \varepsilon_2 \rangle & \dots & \langle \varepsilon_2 | \mathbf{M} | \varepsilon_n \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle \varepsilon_n | \mathbf{M} | \varepsilon_1 \rangle & \langle \varepsilon_n | \mathbf{M} | \varepsilon_2 \rangle & \dots & \langle \varepsilon_n | \mathbf{M} | \varepsilon_n \rangle \end{pmatrix} = \begin{pmatrix} \varepsilon_1 & 0 & \dots & 0 \\ 0 & \varepsilon_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \varepsilon_n \end{pmatrix}$$

First step in finding eigenvalues: Solve *secular equation*

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

where:

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

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

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

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

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

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

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

Trying to solve by Kramer's inversion:

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

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

$$0 = \det|\mathbf{M} - \varepsilon\mathbf{1}| = \det \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} - \varepsilon \det \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = \det \begin{pmatrix} 4-\varepsilon & 1 \\ 3 & 2-\varepsilon \end{pmatrix}$$

$$0 = (4-\varepsilon)(2-\varepsilon) - 1 \cdot 3 = 8 - 6\varepsilon + \varepsilon^2 - 3 = \varepsilon^2 - 6\varepsilon + 5$$

$$0 = \varepsilon^2 - \text{Trace}(\mathbf{M})\varepsilon + \det(\mathbf{M}) = \varepsilon^2 - 6\varepsilon + 5$$

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

$$0 = \mathbf{M}^2 - 6\mathbf{M} + 5\mathbf{1} = (\mathbf{M} - 1\mathbf{1})(\mathbf{M} - 5\mathbf{1})$$

$$\begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}^2 - 6 \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} + 5 \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

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1st step in finding eigenvalues: Solve *secular equation*

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Replace j^{th} HC-factor by $(\mathbf{1})$ to make *projection operators* $\mathbf{p}_k = \prod_{j \neq k} (\mathbf{M} - \varepsilon_j\mathbf{1})$.

$$\mathbf{p}_1 = (\mathbf{1})(\mathbf{M} - \varepsilon_2\mathbf{1}) \dots (\mathbf{M} - \varepsilon_n\mathbf{1})$$

$$\mathbf{p}_2 = (\mathbf{M} - \varepsilon_1\mathbf{1})(\mathbf{1}) \dots (\mathbf{M} - \varepsilon_n\mathbf{1}) \quad (\text{Assume distinct e-values here: Non-degeneracy clause})$$

\vdots

$$\varepsilon_j \neq \varepsilon_k \neq \dots$$

$$\mathbf{p}_n = (\mathbf{M} - \varepsilon_1\mathbf{1})(\mathbf{M} - \varepsilon_2\mathbf{1}) \dots (\mathbf{1})$$

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

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$$\begin{aligned} \mathbf{p}_1 &= (\mathbf{1})(\mathbf{M} - \varepsilon_2\mathbf{1}) \dots (\mathbf{M} - \varepsilon_n\mathbf{1}) \\ \mathbf{p}_2 &= (\mathbf{M} - \varepsilon_1\mathbf{1})(\mathbf{1}) \dots (\mathbf{M} - \varepsilon_n\mathbf{1}) \\ &\vdots \\ \mathbf{p}_n &= (\mathbf{M} - \varepsilon_1\mathbf{1})(\mathbf{M} - \varepsilon_2\mathbf{1}) \dots (\mathbf{1}) \end{aligned} \quad \begin{array}{l} \text{(Assume distinct e-values here: } \\ \text{Non-degeneracy clause)} \\ \varepsilon_j \neq \varepsilon_k \neq \dots \end{array}$$

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

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

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$$\mathbf{M}\mathbf{p}_1 = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} \cdot \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix} = 1 \cdot \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix} = 1 \cdot \mathbf{p}_1$$

$$\mathbf{M}\mathbf{p}_2 = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} \cdot \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = 5 \cdot \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = 5 \cdot \mathbf{p}_2$$

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
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Secular equation

Hamilton-Cayley equation and projectors

Idempotent projectors (how eigenvalues \Rightarrow eigenvectors)

Operator orthonormality and Completeness

Idempotent means: $\mathbf{P} \cdot \mathbf{P} = \mathbf{P}$

Spectral Decompositions

Functional spectral decomposition

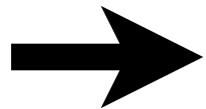
Orthonormality vs. Completeness vis-a`-vis Operator vs. State

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Spectral Decompositions with degeneracy

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

$$\mathbf{p}_j \mathbf{p}_k = \mathbf{p}_j \prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1}) = \prod_{m \neq k} (\mathbf{p}_j \mathbf{M} - \varepsilon_m \mathbf{p}_j \mathbf{1}) \quad \mathbf{M} \mathbf{p}_k = \varepsilon_k \mathbf{p}_k = \mathbf{p}_k \mathbf{M}$$

Multiplication properties of \mathbf{p}_j :

$$\mathbf{p}_j \mathbf{p}_k = \prod_{m \neq k} (\varepsilon_j \mathbf{p}_j - \varepsilon_m \mathbf{p}_j) = \mathbf{p}_j \prod_{m \neq k} (\varepsilon_j - \varepsilon_m) = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{p}_k \prod_{m \neq k} (\varepsilon_k - \varepsilon_m) & \text{if } j = k \end{cases}$$

$$\mathbf{p}_1 = (\mathbf{M} - 5 \cdot \mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix}$$

$$\mathbf{p}_2 = (\mathbf{M} - 1 \cdot \mathbf{1}) = \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix}$$

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Last step:

make *Idempotent Projectors*: $\mathbf{P}_k = \frac{\mathbf{p}_k}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)} = \frac{\prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1})}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)}$

(Idempotent means: $\mathbf{P} \cdot \mathbf{P} = \mathbf{P}$)

$$\mathbf{P}_1 = \frac{(\mathbf{M} - 5 \cdot \mathbf{1})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix}$$

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$$\mathbf{p}_j \mathbf{p}_k = \mathbf{p}_j \prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1}) = \prod_{m \neq k} (\mathbf{p}_j \mathbf{M} - \varepsilon_m \mathbf{p}_j \mathbf{1}) \quad \mathbf{M} \mathbf{p}_k = \varepsilon_k \mathbf{p}_k = \mathbf{p}_k \mathbf{M}$$

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implies:

$$\mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k = \mathbf{P}_k \mathbf{M}$$

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Factoring bra-kets
into “Ket-Bras:”

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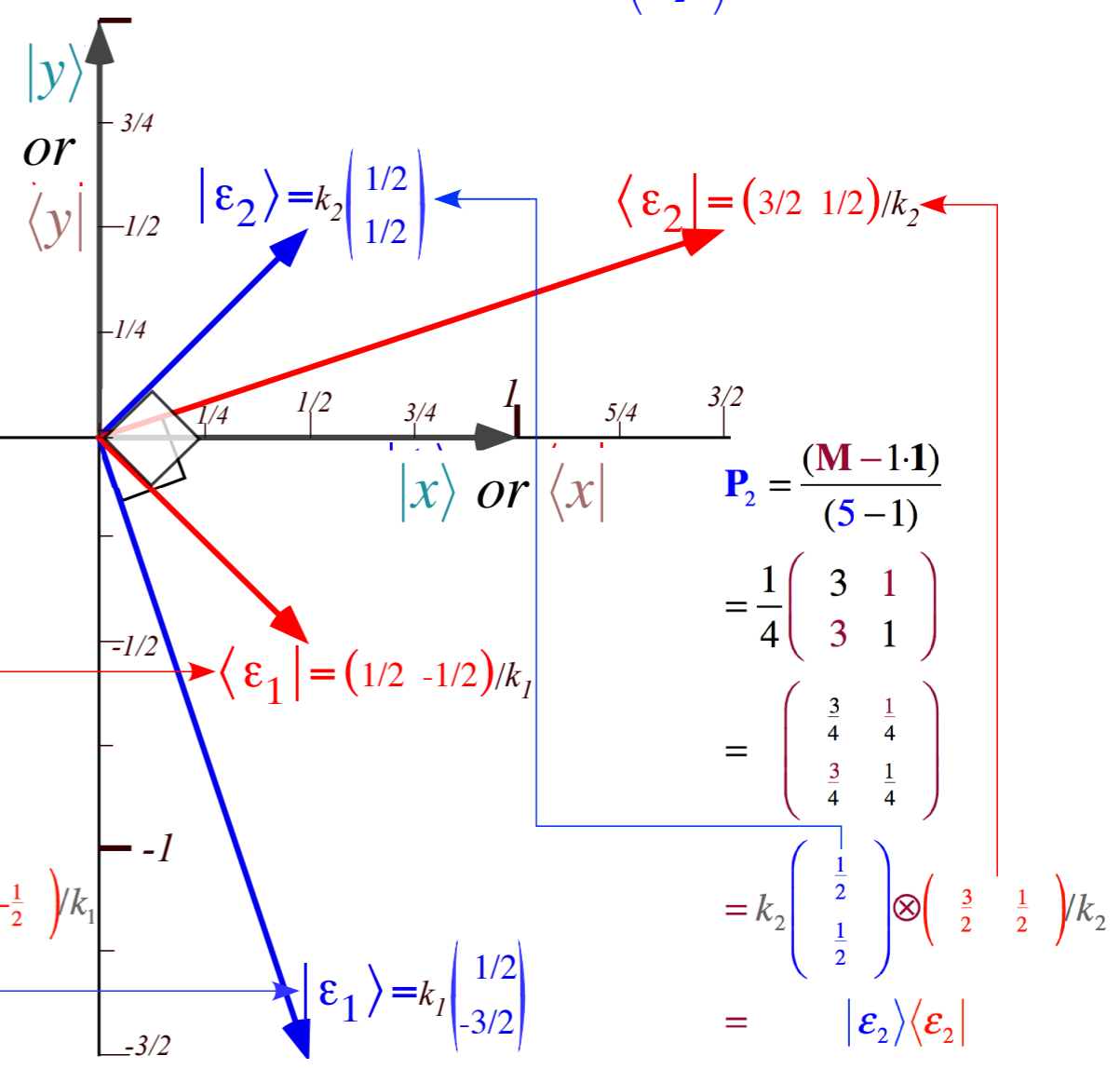
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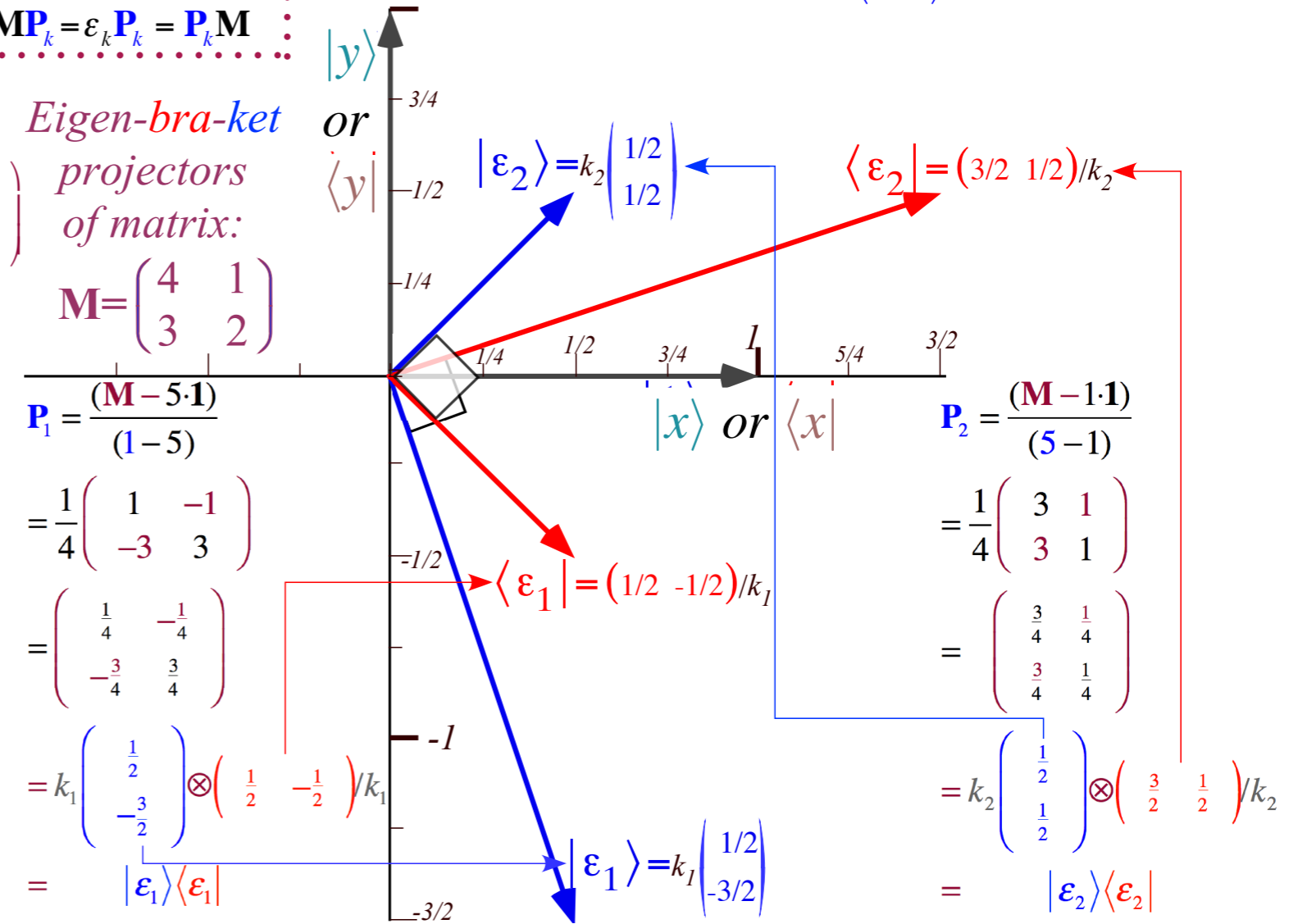
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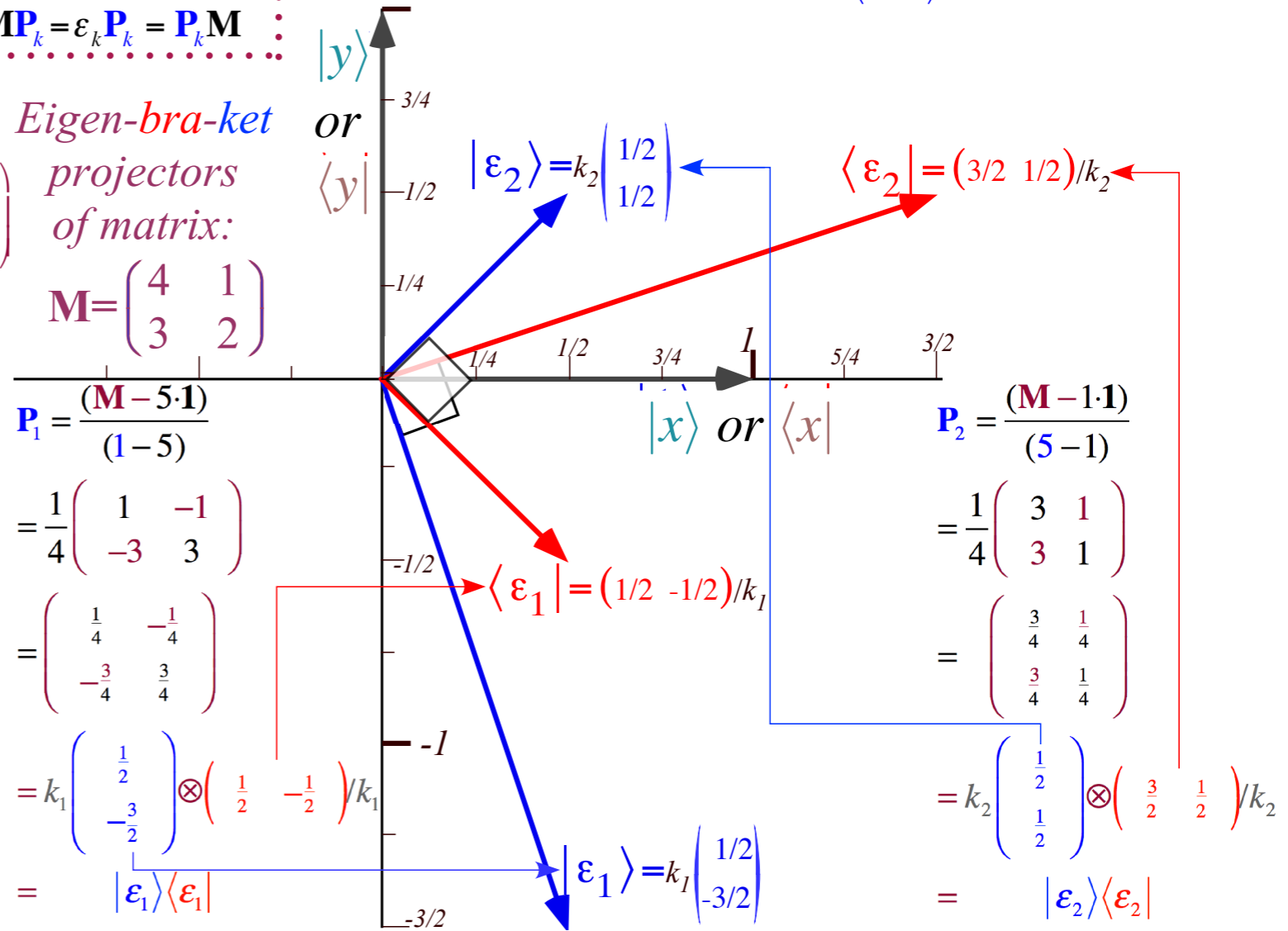
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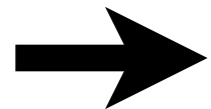
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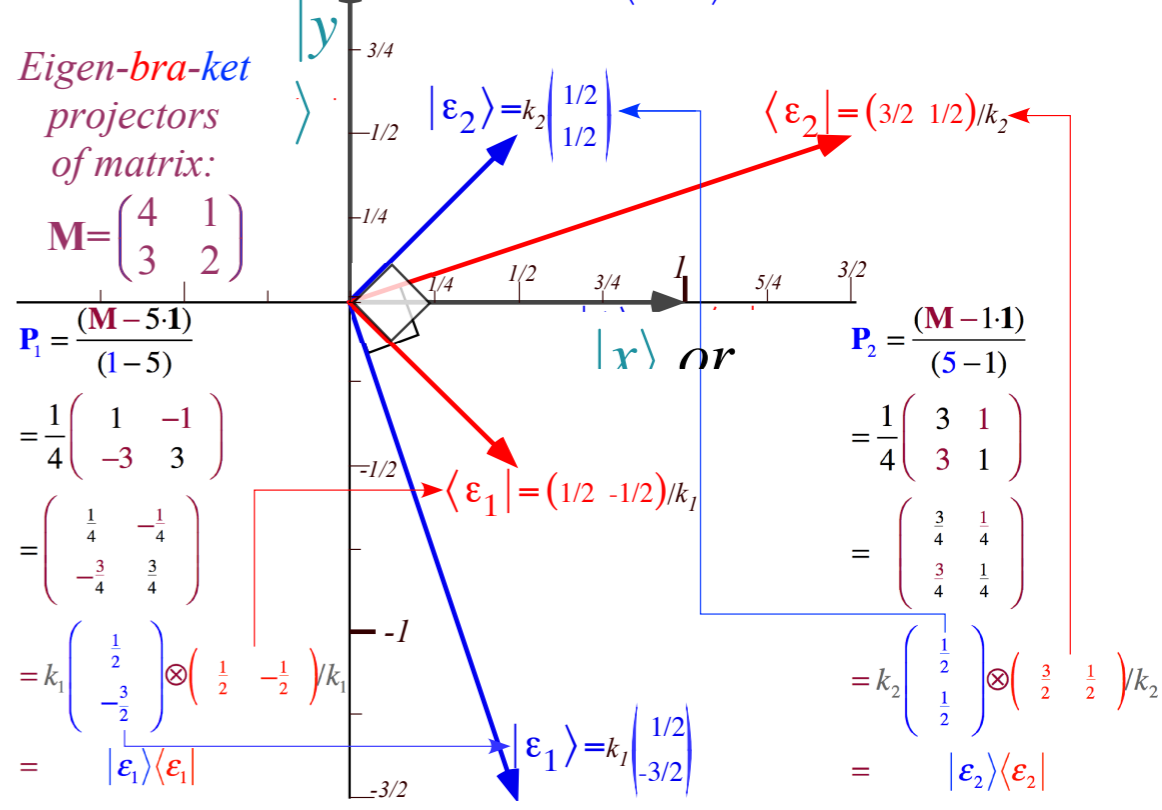
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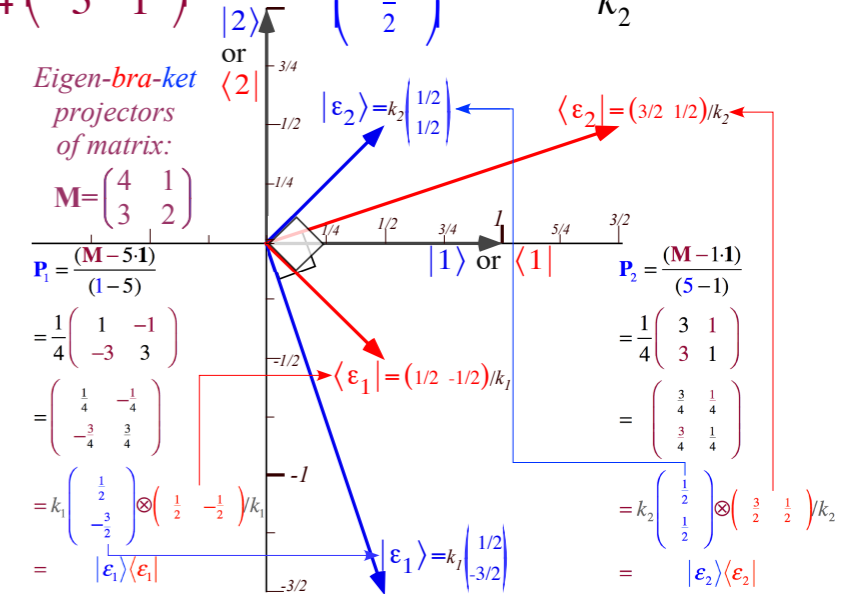
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$$M = M P_1 + M P_2 + \dots + M P_n = \epsilon_1 P_1 + \epsilon_2 P_2 + \dots + \epsilon_n P_n$$

Matrix and operator Spectral Decompositions

$$\mathbf{p}_j \mathbf{p}_k = \mathbf{p}_j \prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1}) = \prod_{m \neq k} (\mathbf{p}_j \mathbf{M} - \varepsilon_m \mathbf{p}_j \mathbf{1}) \quad \mathbf{M} \mathbf{p}_k = \varepsilon_k \mathbf{p}_k = \mathbf{p}_k \mathbf{M}$$

Multiplication properties of \mathbf{p}_j :

$$\mathbf{p}_j \mathbf{p}_k = \prod_{m \neq k} (\varepsilon_j \mathbf{p}_j - \varepsilon_m \mathbf{p}_j) = \mathbf{p}_j \prod_{m \neq k} (\varepsilon_j - \varepsilon_m) = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{p}_k \prod_{m \neq k} (\varepsilon_k - \varepsilon_m) & \text{if } j = k \end{cases}$$

Last step:

make *Idempotent Projectors*: $\mathbf{P}_k = \frac{\mathbf{p}_k}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)} = \frac{\prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1})}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)}$
(Idempotent means: $\mathbf{P} \cdot \mathbf{P} = \mathbf{P}$)

$$\mathbf{P}_j \mathbf{P}_k = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{P}_k & \text{if } j = k \end{cases} \quad \begin{array}{l} \mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k = \mathbf{P}_k \mathbf{M} \\ \text{implies:} \\ \mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k = \mathbf{P}_k \mathbf{M} \end{array}$$

The \mathbf{P}_j are *Mutually Ortho-Normal* as are bra-ket $\langle \varepsilon_j |$ and $|\varepsilon_j \rangle$ inside \mathbf{P}_j 's

$$\begin{pmatrix} \langle \varepsilon_1 | \varepsilon_1 \rangle & \langle \varepsilon_1 | \varepsilon_2 \rangle \\ \langle \varepsilon_2 | \varepsilon_1 \rangle & \langle \varepsilon_2 | \varepsilon_2 \rangle \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

...and the \mathbf{P}_j satisfy a *Completeness Relation*:

$$\mathbf{1} = \mathbf{P}_1 + \mathbf{P}_2 + \dots + \mathbf{P}_n = |\varepsilon_1 \rangle \langle \varepsilon_1 | + |\varepsilon_2 \rangle \langle \varepsilon_2 | + \dots + |\varepsilon_n \rangle \langle \varepsilon_n |$$

$$\mathbf{P}_1 + \mathbf{P}_2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = |\varepsilon_1 \rangle \langle \varepsilon_1 | + |\varepsilon_2 \rangle \langle \varepsilon_2 |$$

$$\mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} = 1\mathbf{P}_1 + 5\mathbf{P}_2 = 1|1\rangle\langle 1| + 5|2\rangle\langle 2| = 1 \begin{pmatrix} \frac{1}{4} & -\frac{1}{4} \\ -\frac{3}{4} & \frac{3}{4} \end{pmatrix} + 5 \begin{pmatrix} \frac{3}{4} & \frac{1}{4} \\ \frac{3}{4} & \frac{1}{4} \end{pmatrix}$$

$$\mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}$$

$$\mathbf{p}_1 = (\mathbf{M} - 5 \cdot \mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix}$$

$$\mathbf{p}_2 = (\mathbf{M} - 1 \cdot \mathbf{1}) = \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix}$$

$$\mathbf{p}_1 \mathbf{p}_2 = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$$

Factoring bra-kets into "Ket-Bras":

$$\mathbf{P}_1 = \frac{(\mathbf{M} - 5 \cdot \mathbf{1})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_1 \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}}{k_1} = |\varepsilon_1 \rangle \langle \varepsilon_1 |$$

$$\mathbf{P}_2 = \frac{(\mathbf{M} - 1 \cdot \mathbf{1})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_2 \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix}}{k_2} = |\varepsilon_2 \rangle \langle \varepsilon_2 |$$

Eigen-operators $\mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k$ then give *Spectral Decomposition* of operator \mathbf{M}

$$\mathbf{M} = \mathbf{M} \mathbf{P}_1 + \mathbf{M} \mathbf{P}_2 + \dots + \mathbf{M} \mathbf{P}_n = \varepsilon_1 \mathbf{P}_1 + \varepsilon_2 \mathbf{P}_2 + \dots + \varepsilon_n \mathbf{P}_n$$

...and *Functional Spectral Decomposition* of any function $f(\mathbf{M})$ of \mathbf{M}

$$f(\mathbf{M}) = f(\varepsilon_1) \mathbf{P}_1 + f(\varepsilon_2) \mathbf{P}_2 + \dots + f(\varepsilon_n) \mathbf{P}_n$$

Matrix and operator Spectral Decompositions

$$\mathbf{p}_j \mathbf{p}_k = \mathbf{p}_j \prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1}) = \prod_{m \neq k} (\mathbf{p}_j \mathbf{M} - \varepsilon_m \mathbf{p}_j \mathbf{1}) \quad \mathbf{M} \mathbf{p}_k = \varepsilon_k \mathbf{p}_k = \mathbf{p}_k \mathbf{M}$$

Multiplication properties of \mathbf{p}_j :

$$\mathbf{p}_j \mathbf{p}_k = \prod_{m \neq k} (\varepsilon_j \mathbf{p}_j - \varepsilon_m \mathbf{p}_j) = \mathbf{p}_j \prod_{m \neq k} (\varepsilon_j - \varepsilon_m) = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{p}_k \prod_{m \neq k} (\varepsilon_k - \varepsilon_m) & \text{if } j = k \end{cases}$$

Last step:

make *Idempotent Projectors*: $\mathbf{P}_k = \frac{\mathbf{p}_k}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)} = \frac{\prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1})}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)}$
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$$\mathbf{P}_j \mathbf{P}_k = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{P}_k & \text{if } j = k \end{cases} \quad \begin{array}{l} \mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k = \mathbf{P}_k \mathbf{M} \\ \text{implies:} \\ \mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k = \mathbf{P}_k \mathbf{M} \end{array}$$

The \mathbf{P}_j are *Mutually Ortho-Normal* as are bra-ket $\langle \varepsilon_j |$ and $|\varepsilon_j \rangle$ inside \mathbf{P}_j 's

$$\begin{pmatrix} \langle \varepsilon_1 | \varepsilon_1 \rangle & \langle \varepsilon_1 | \varepsilon_2 \rangle \\ \langle \varepsilon_2 | \varepsilon_1 \rangle & \langle \varepsilon_2 | \varepsilon_2 \rangle \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

...and the \mathbf{P}_j satisfy a *Completeness Relation*:

$$\mathbf{1} = \mathbf{P}_1 + \mathbf{P}_2 + \dots + \mathbf{P}_n = |\varepsilon_1 \rangle \langle \varepsilon_1 | + |\varepsilon_2 \rangle \langle \varepsilon_2 | + \dots + |\varepsilon_n \rangle \langle \varepsilon_n |$$

$$\mathbf{P}_1 + \mathbf{P}_2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = |\varepsilon_1 \rangle \langle \varepsilon_1 | + |\varepsilon_2 \rangle \langle \varepsilon_2 |$$

$$\mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} = 1\mathbf{P}_1 + 5\mathbf{P}_2 = 1|\varepsilon_1 \rangle \langle \varepsilon_1 | + 5|\varepsilon_2 \rangle \langle \varepsilon_2 | = 1 \begin{pmatrix} \frac{1}{4} & -\frac{1}{4} \\ -\frac{3}{4} & \frac{3}{4} \end{pmatrix} + 5 \begin{pmatrix} \frac{3}{4} & \frac{1}{4} \\ \frac{3}{4} & \frac{1}{4} \end{pmatrix}$$

Eigen-operators $\mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k$ then give *Spectral Decomposition* of operator \mathbf{M}

$$\mathbf{M} = \mathbf{M} \mathbf{P}_1 + \mathbf{M} \mathbf{P}_2 + \dots + \mathbf{M} \mathbf{P}_n = \varepsilon_1 \mathbf{P}_1 + \varepsilon_2 \mathbf{P}_2 + \dots + \varepsilon_n \mathbf{P}_n$$

...and *Functional Spectral Decomposition* of any function $f(\mathbf{M})$ of \mathbf{M}

$$f(\mathbf{M}) = f(\varepsilon_1) \mathbf{P}_1 + f(\varepsilon_2) \mathbf{P}_2 + \dots + f(\varepsilon_n) \mathbf{P}_n$$

$$\mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}$$

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Factoring bra-kets into "Ket-Bras:

$$\mathbf{P}_1 = \frac{(\mathbf{M} - 5 \cdot \mathbf{1})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_1 \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}}{k_1} = |\varepsilon_1 \rangle \langle \varepsilon_1 |$$

$$\mathbf{P}_2 = \frac{(\mathbf{M} - 1 \cdot \mathbf{1})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_2 \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix}}{k_2} = |\varepsilon_2 \rangle \langle \varepsilon_2 |$$

Example:

$$\mathbf{M}^{50} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} = 1^{50} \begin{pmatrix} \frac{1}{4} & -\frac{1}{4} \\ -\frac{3}{4} & \frac{3}{4} \end{pmatrix} + 5^{50} \begin{pmatrix} \frac{3}{4} & \frac{1}{4} \\ \frac{3}{4} & \frac{1}{4} \end{pmatrix} = \frac{1}{4} \begin{pmatrix} 1+3 \cdot 5^{50} & 5^{50}-1 \\ 3 \cdot 5^{50}-3 & 5^{50}+3 \end{pmatrix}$$

Matrix and operator Spectral Decompositions

$$\mathbf{p}_j \mathbf{p}_k = \mathbf{p}_j \prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1}) = \prod_{m \neq k} (\mathbf{p}_j \mathbf{M} - \varepsilon_m \mathbf{p}_j \mathbf{1}) \quad \mathbf{M} \mathbf{p}_k = \varepsilon_k \mathbf{p}_k = \mathbf{p}_k \mathbf{M}$$

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$$\mathbf{p}_j \mathbf{p}_k = \prod_{m \neq k} (\varepsilon_j \mathbf{p}_j - \varepsilon_m \mathbf{p}_j) = \mathbf{p}_j \prod_{m \neq k} (\varepsilon_j - \varepsilon_m) = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{p}_k \prod_{m \neq k} (\varepsilon_k - \varepsilon_m) & \text{if } j = k \end{cases}$$

Last step:

make *Idempotent Projectors*: $\mathbf{P}_k = \frac{\mathbf{p}_k}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)} = \frac{\prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1})}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)}$
(Idempotent means: $\mathbf{P} \cdot \mathbf{P} = \mathbf{P}$)

$$\mathbf{P}_j \mathbf{P}_k = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{P}_k & \text{if } j = k \end{cases} \quad \begin{array}{l} \mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k = \mathbf{P}_k \mathbf{M} \\ \text{implies:} \\ \mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k = \mathbf{P}_k \mathbf{M} \end{array}$$

The \mathbf{P}_j are *Mutually Ortho-Normal* as are bra-ket $\langle \varepsilon_j |$ and $|\varepsilon_j \rangle$ inside \mathbf{P}_j 's

$$\begin{pmatrix} \langle \varepsilon_1 | \varepsilon_1 \rangle & \langle \varepsilon_1 | \varepsilon_2 \rangle \\ \langle \varepsilon_2 | \varepsilon_1 \rangle & \langle \varepsilon_2 | \varepsilon_2 \rangle \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

...and the \mathbf{P}_j satisfy a *Completeness Relation*:

$$\mathbf{1} = \mathbf{P}_1 + \mathbf{P}_2 + \dots + \mathbf{P}_n = |\varepsilon_1 \rangle \langle \varepsilon_1 | + |\varepsilon_2 \rangle \langle \varepsilon_2 | + \dots + |\varepsilon_n \rangle \langle \varepsilon_n |$$

$$\mathbf{P}_1 + \mathbf{P}_2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = |\varepsilon_1 \rangle \langle \varepsilon_1 | + |\varepsilon_2 \rangle \langle \varepsilon_2 |$$

$$\mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} = 1\mathbf{P}_1 + 5\mathbf{P}_2 = 1|\varepsilon_1 \rangle \langle \varepsilon_1 | + 5|\varepsilon_2 \rangle \langle \varepsilon_2 | = 1 \begin{pmatrix} \frac{1}{4} & -\frac{1}{4} \\ -\frac{3}{4} & \frac{3}{4} \end{pmatrix} + 5 \begin{pmatrix} \frac{3}{4} & \frac{1}{4} \\ \frac{3}{4} & \frac{1}{4} \end{pmatrix}$$

Eigen-operators $\mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k$ then give *Spectral Decomposition* of operator \mathbf{M}

$$\mathbf{M} = \mathbf{M} \mathbf{P}_1 + \mathbf{M} \mathbf{P}_2 + \dots + \mathbf{M} \mathbf{P}_n = \varepsilon_1 \mathbf{P}_1 + \varepsilon_2 \mathbf{P}_2 + \dots + \varepsilon_n \mathbf{P}_n$$

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$$f(\mathbf{M}) = f(\varepsilon_1) \mathbf{P}_1 + f(\varepsilon_2) \mathbf{P}_2 + \dots + f(\varepsilon_n) \mathbf{P}_n$$

$$\mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}$$

$$\mathbf{p}_1 = (\mathbf{M} - 5 \cdot \mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix}$$

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$$\mathbf{p}_1 \mathbf{p}_2 = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$$

Factoring bra-kets into "Ket-Bras:

$$\mathbf{P}_1 = \frac{(\mathbf{M} - 5 \cdot \mathbf{1})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_1 \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}}{k_1} = |\varepsilon_1 \rangle \langle \varepsilon_1 |$$

$$\mathbf{P}_2 = \frac{(\mathbf{M} - 1 \cdot \mathbf{1})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_2 \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix}}{k_2} = |\varepsilon_2 \rangle \langle \varepsilon_2 |$$

Examples:

$$\mathbf{M}^{50} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} = 1^{50} \begin{pmatrix} \frac{1}{4} & -\frac{1}{4} \\ -\frac{3}{4} & \frac{3}{4} \end{pmatrix} + 5^{50} \begin{pmatrix} \frac{3}{4} & \frac{1}{4} \\ \frac{3}{4} & \frac{1}{4} \end{pmatrix} = \frac{1}{4} \begin{pmatrix} 1 + 3 \cdot 5^{50} & 5^{50} - 1 \\ 3 \cdot 5^{50} - 3 & 5^{50} + 3 \end{pmatrix}$$

$$\sqrt{\mathbf{M}} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} = \pm \sqrt{1} \begin{pmatrix} \frac{1}{4} & -\frac{1}{4} \\ -\frac{3}{4} & \frac{3}{4} \end{pmatrix} \pm \sqrt{5} \begin{pmatrix} \frac{3}{4} & \frac{1}{4} \\ \frac{3}{4} & \frac{1}{4} \end{pmatrix}$$

*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

Factoring bra-kets
into “Ket-Bras:

Spectral Decompositions

Functional spectral decomposition

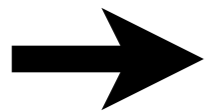
Orthonormality vs. Completeness vis-a`-vis Operator vs. State

Lagrange functional interpolation formula

Proof that completeness relation is “Truer-than-true”

Spectral Decompositions with degeneracy

Functional spectral decomposition



Orthonormality vs. Completeness

$$\mathbf{P}_j \mathbf{P}_k = \mathbf{P}_j \prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1}) = \prod_{m \neq k} (\mathbf{P}_j \mathbf{M} - \varepsilon_m \mathbf{P}_j \mathbf{1}) \quad \mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k = \mathbf{P}_k \mathbf{M}$$

Multiplication properties of \mathbf{P}_j :

$$\mathbf{P}_j \mathbf{P}_k = \prod_{m \neq k} (\varepsilon_j \mathbf{P}_j - \varepsilon_m \mathbf{P}_j) = \mathbf{P}_j \prod_{m \neq k} (\varepsilon_j - \varepsilon_m) = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{P}_k \prod_{m \neq k} (\varepsilon_k - \varepsilon_m) & \text{if } j = k \end{cases}$$

Last step:

make *Idempotent Projectors*: $\mathbf{P}_k = \frac{\mathbf{P}_k}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)} = \frac{\prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1})}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)}$
(Idempotent means: $\mathbf{P} \cdot \mathbf{P} = \mathbf{P}$)

$$\mathbf{P}_j \mathbf{P}_k = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{P}_k & \text{if } j = k \end{cases} \quad \begin{matrix} \mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k = \mathbf{P}_k \mathbf{M} \\ \text{implies:} \\ \mathbf{M} \mathbf{P}_k = \varepsilon_k \mathbf{P}_k = \mathbf{P}_k \mathbf{M} \end{matrix}$$

The \mathbf{P}_j are *Mutually Ortho-Normal* as are bra-ket $\langle \varepsilon_j |$ and $|\varepsilon_j \rangle$ inside \mathbf{P}_j 's

$$\begin{pmatrix} \langle \varepsilon_1 | \varepsilon_1 \rangle & \langle \varepsilon_1 | \varepsilon_2 \rangle \\ \langle \varepsilon_2 | \varepsilon_1 \rangle & \langle \varepsilon_2 | \varepsilon_2 \rangle \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

Eigen-bra-ket projectors of matrix:

$$\mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}$$

...and the \mathbf{P}_j satisfy a *Completeness Relation*:

$$\mathbf{1} = \mathbf{P}_1 + \mathbf{P}_2 + \dots + \mathbf{P}_n = |\varepsilon_1 \rangle \langle \varepsilon_1 | + |\varepsilon_2 \rangle \langle \varepsilon_2 | + \dots + |\varepsilon_n \rangle \langle \varepsilon_n |$$

$$\mathbf{P}_1 + \mathbf{P}_2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = |\varepsilon_1 \rangle \langle \varepsilon_1 | + |\varepsilon_2 \rangle \langle \varepsilon_2 |$$

$\{|x \rangle, |y \rangle\}$ -orthonormality with $\{|\varepsilon_1 \rangle, |\varepsilon_2 \rangle\}$ -completeness

$$\langle x | y \rangle = \delta_{x,y} = \langle x | \mathbf{1} | y \rangle = \langle x | \varepsilon_1 \rangle \langle \varepsilon_1 | y \rangle + \langle x | \varepsilon_2 \rangle \langle \varepsilon_2 | y \rangle.$$

$\{|\varepsilon_1 \rangle, |\varepsilon_2 \rangle\}$ -orthonormality with $\{|x \rangle, |y \rangle\}$ -completeness

$$\langle \varepsilon_i | \varepsilon_j \rangle = \delta_{i,j} = \langle \varepsilon_i | \mathbf{1} | \varepsilon_j \rangle = \langle \varepsilon_i | x \rangle \langle x | \varepsilon_j \rangle + \langle \varepsilon_i | y \rangle \langle y | \varepsilon_j \rangle$$

$$\mathbf{M} = \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix}$$

$$\mathbf{P}_1 = (\mathbf{M} - 5 \cdot \mathbf{1}) = \begin{pmatrix} -1 & 1 \\ 3 & -3 \end{pmatrix}$$

$$\mathbf{P}_1 \mathbf{P}_2 = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$$

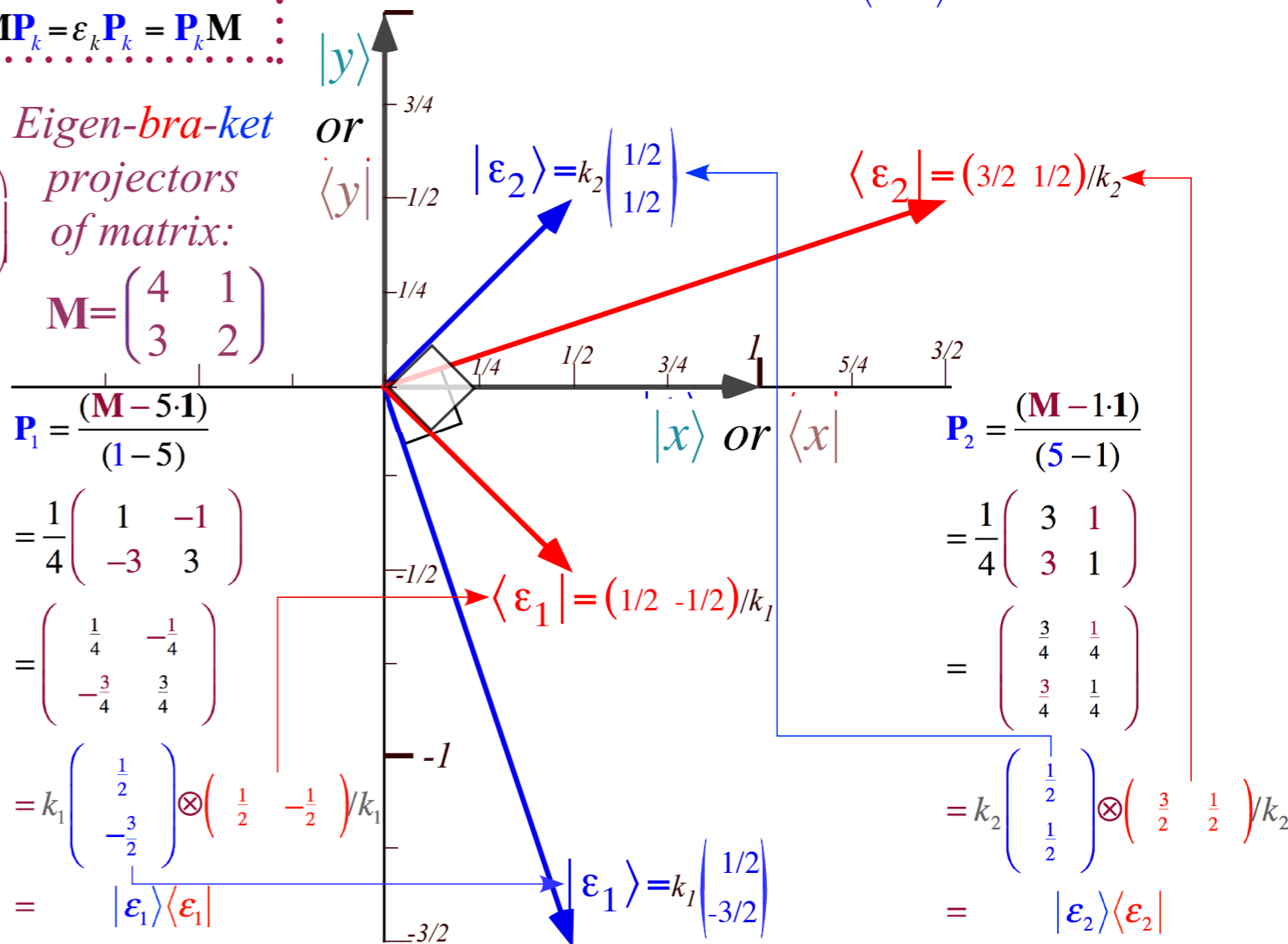
$$\mathbf{P}_2 = (\mathbf{M} - 1 \cdot \mathbf{1}) = \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix}$$

Factoring bra-kets into "Ket-Bras:

$$\mathbf{P}_1 = \frac{(\mathbf{M} - 5 \cdot \mathbf{1})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_1 \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}}{k_1} = |\varepsilon_1 \rangle \langle \varepsilon_1 |$$

"Gauge" scale factors that only affect plots

$$\mathbf{P}_2 = \frac{(\mathbf{M} - 1 \cdot \mathbf{1})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_2 \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix}}{k_2} = |\varepsilon_2 \rangle \langle \varepsilon_2 |$$



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

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

$$\mathbf{P}_j \mathbf{P}_k = \delta_{jk} \mathbf{P}_k = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{P}_k & \text{if } j = k \end{cases}$$

$$\mathbf{1} = \mathbf{P}_1 + \mathbf{P}_2 + \dots + \mathbf{P}_n$$

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

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$$\mathbf{P}_j \mathbf{P}_k = \delta_{jk} \mathbf{P}_k = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{P}_k & \text{if } j = k \end{cases}$$
$$|\varepsilon_j\rangle \langle \varepsilon_j | \varepsilon_k\rangle \langle \varepsilon_k| = \delta_{jk} |\varepsilon_k\rangle \langle \varepsilon_k| \quad \text{or:} \quad \langle \varepsilon_j | \varepsilon_k\rangle = \delta_{jk}$$
$$\mathbf{1} = \mathbf{P}_1 + \mathbf{P}_2 + \dots + \mathbf{P}_n$$
$$\mathbf{1} = |\varepsilon_1\rangle \langle \varepsilon_1| + |\varepsilon_2\rangle \langle \varepsilon_2| + \dots + |\varepsilon_n\rangle \langle \varepsilon_n|$$

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

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

$$\mathbf{P}_j \mathbf{P}_k = \delta_{jk} \mathbf{P}_k = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{P}_k & \text{if } j = k \end{cases} \qquad \mathbf{1} = \mathbf{P}_1 + \mathbf{P}_2 + \dots + \mathbf{P}_n$$
$$|\epsilon_j\rangle \langle \epsilon_j | \epsilon_k\rangle \langle \epsilon_k| = \delta_{jk} |\epsilon_k\rangle \langle \epsilon_k| \quad \text{or:} \quad \langle \epsilon_j | \epsilon_k\rangle = \delta_{jk} \qquad \mathbf{1} = |\epsilon_1\rangle \langle \epsilon_1| + |\epsilon_2\rangle \langle \epsilon_2| + \dots + |\epsilon_n\rangle \langle \epsilon_n|$$

State vector representations of orthonormality are quite **similar** to representations of completeness.

Like 2-sides of the same coin.

$\{|x\rangle, |y\rangle\}$ -orthonormality with $\{|\epsilon_1\rangle, |\epsilon_2\rangle\}$ -completeness

$$\langle x | y \rangle = \delta_{x,y} = \langle x | \mathbf{1} | y \rangle = \langle x | \epsilon_1 \rangle \langle \epsilon_1 | y \rangle + \langle x | \epsilon_2 \rangle \langle \epsilon_2 | y \rangle.$$

$\{|\epsilon_1\rangle, |\epsilon_2\rangle\}$ -orthonormality with $\{|x\rangle, |y\rangle\}$ -completeness

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

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

$$\mathbf{P}_j \mathbf{P}_k = \delta_{jk} \mathbf{P}_k = \begin{cases} \mathbf{0} & \text{if } j \neq k \\ \mathbf{P}_k & \text{if } j = k \end{cases} \qquad \mathbf{1} = \mathbf{P}_1 + \mathbf{P}_2 + \dots + \mathbf{P}_n$$

$$|\epsilon_j\rangle \langle \epsilon_j| \epsilon_k\rangle \langle \epsilon_k| = \delta_{jk} |\epsilon_k\rangle \langle \epsilon_k| \quad \text{or:} \quad \langle \epsilon_j | \epsilon_k \rangle = \delta_{jk} \qquad \mathbf{1} = |\epsilon_1\rangle \langle \epsilon_1| + |\epsilon_2\rangle \langle \epsilon_2| + \dots + |\epsilon_n\rangle \langle \epsilon_n|$$

State vector representations of orthonormality are quite **similar** to representations of completeness.

Like 2-sides of the same coin.

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Dirac δ -function

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

...particularly in the orthonormality integral.

*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

Factoring bra-kets
into “Ket-Bras:

Spectral Decompositions

Functional spectral decomposition

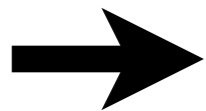
Orthonormality vs. Completeness vis-a`-vis Operator vs. State

Lagrange functional interpolation formula

Proof that completeness relation is “Truer-than-true”

Spectral Decompositions with degeneracy

Functional spectral decomposition



A Proof of Projector Completeness (Truer-than-true by Lagrange interpolation)

Compare matrix completeness relation and functional spectral decompositions

$$\mathbf{1} = \mathbf{P}_1 + \mathbf{P}_2 + \dots + \mathbf{P}_n = \sum_{\varepsilon_k} \mathbf{P}_k = \sum_{\varepsilon_k} \frac{\prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1})}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)} \quad f(\mathbf{M}) = f(\varepsilon_1)\mathbf{P}_1 + f(\varepsilon_2)\mathbf{P}_2 + \dots + f(\varepsilon_n)\mathbf{P}_n = \sum_{\varepsilon_k} f(\varepsilon_k)\mathbf{P}_k = \sum_{\varepsilon_k} f(\varepsilon_k) \frac{\prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1})}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)}$$

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

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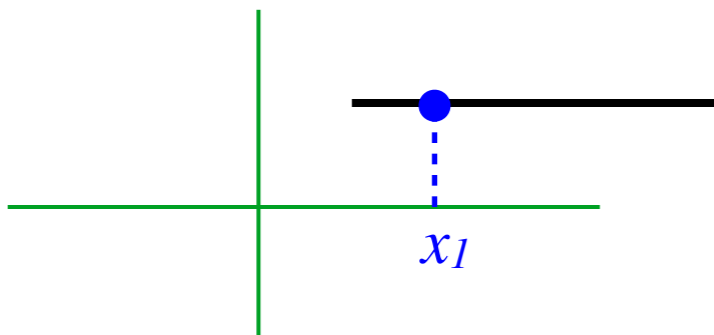
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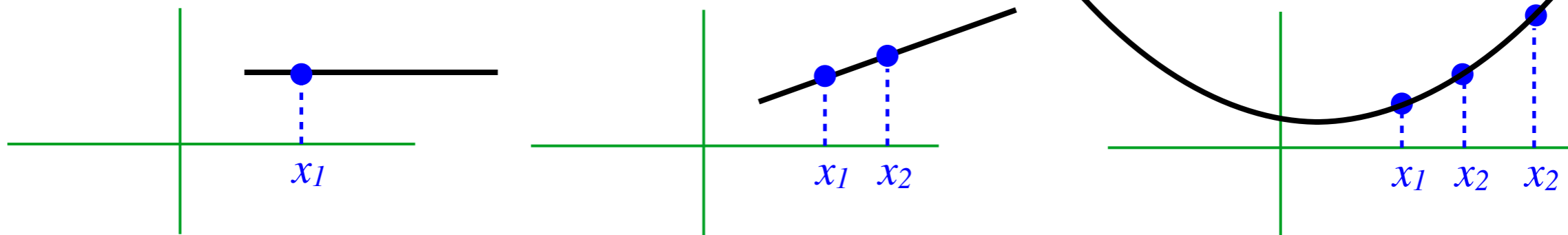
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All distinct values $\varepsilon_1 \neq \varepsilon_2 \neq \dots \neq \varepsilon_N$ satisfy $\sum \mathbf{P}_k = \mathbf{1}$. Completeness is *truer than true* as is seen for $N=2$.

$$\mathbf{P}_1 + \mathbf{P}_2 = \frac{\prod_{j \neq 1} (\mathbf{M} - \varepsilon_j \mathbf{1})}{\prod_{j \neq 1} (\varepsilon_1 - \varepsilon_j)} + \frac{\prod_{j \neq 2} (\mathbf{M} - \varepsilon_j \mathbf{1})}{\prod_{j \neq 2} (\varepsilon_2 - \varepsilon_j)} = \frac{(\mathbf{M} - \varepsilon_2 \mathbf{1})}{(\varepsilon_1 - \varepsilon_2)} + \frac{(\mathbf{M} - \varepsilon_1 \mathbf{1})}{(\varepsilon_2 - \varepsilon_1)} = \frac{(\mathbf{M} - \varepsilon_2 \mathbf{1}) - (\mathbf{M} - \varepsilon_1 \mathbf{1})}{(\varepsilon_1 - \varepsilon_2)} = \frac{-\varepsilon_2 \mathbf{1} + \varepsilon_1 \mathbf{1}}{(\varepsilon_1 - \varepsilon_2)} = \mathbf{1} \text{ (for all } \varepsilon_j \text{)}$$

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Compare matrix *completeness relation* and *functional spectral decompositions*

$$\mathbf{1} = \mathbf{P}_1 + \mathbf{P}_2 + \dots + \mathbf{P}_n = \sum_{\varepsilon_k} \mathbf{P}_k = \sum_{\varepsilon_k} \frac{\prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1})}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)} \quad f(\mathbf{M}) = f(\varepsilon_1)\mathbf{P}_1 + f(\varepsilon_2)\mathbf{P}_2 + \dots + f(\varepsilon_n)\mathbf{P}_n = \sum_{\varepsilon_k} f(\varepsilon_k)\mathbf{P}_k = \sum_{\varepsilon_k} f(\varepsilon_k) \frac{\prod_{m \neq k} (\mathbf{M} - \varepsilon_m \mathbf{1})}{\prod_{m \neq k} (\varepsilon_k - \varepsilon_m)}$$

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

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

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

So at each of these points this L-approximation becomes exact: $L(f(x_j))=f(x_j)$.

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

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

One point determines a constant level line, two separate points uniquely determine a sloping line, three separate points uniquely determine a parabola, etc.

Lagrange interpolation formula \rightarrow *Completeness formula* as $x \rightarrow \mathbf{M}$ and as $x_k \rightarrow \varepsilon_k$ and as $P_k(x_k) \rightarrow \mathbf{P}_k$

All distinct values $\varepsilon_1 \neq \varepsilon_2 \neq \dots \neq \varepsilon_N$ satisfy $\sum \mathbf{P}_k = \mathbf{1}$. Completeness is *truer than true* as is seen for $N=2$.

$$\mathbf{P}_1 + \mathbf{P}_2 = \frac{\prod_{j \neq 1} (\mathbf{M} - \varepsilon_j \mathbf{1})}{\prod_{j \neq 1} (\varepsilon_1 - \varepsilon_j)} + \frac{\prod_{j \neq 2} (\mathbf{M} - \varepsilon_j \mathbf{1})}{\prod_{j \neq 2} (\varepsilon_2 - \varepsilon_j)} = \frac{(\mathbf{M} - \varepsilon_2 \mathbf{1})}{(\varepsilon_1 - \varepsilon_2)} + \frac{(\mathbf{M} - \varepsilon_1 \mathbf{1})}{(\varepsilon_2 - \varepsilon_1)} = \frac{(\mathbf{M} - \varepsilon_2 \mathbf{1}) - (\mathbf{M} - \varepsilon_1 \mathbf{1})}{(\varepsilon_1 - \varepsilon_2)} = \frac{-\varepsilon_2 \mathbf{1} + \varepsilon_1 \mathbf{1}}{(\varepsilon_1 - \varepsilon_2)} = \mathbf{1} \text{ (for all } \varepsilon_j \text{)}$$

However, only *select* values ε_k work for eigen-forms $\mathbf{M}\mathbf{P}_k = \varepsilon_k \mathbf{P}_k$ 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)*

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

Factoring bra-kets
into “Ket-Bras:

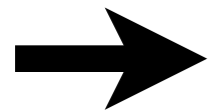
Spectral Decompositions

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.

$$\mathbf{P}_1 = \frac{(\mathbf{M} - 5 \cdot \mathbf{1})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_1 \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}}{k_1} = |\varepsilon_1\rangle\langle\varepsilon_1|$$

$$\mathbf{P}_2 = \frac{(\mathbf{M} - 1 \cdot \mathbf{1})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_2 \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix}}{k_2} = |\varepsilon_2\rangle\langle\varepsilon_2|$$

Diagonalizing Transformations (D-Ttran) from projectors

Given our eigenvectors and their Projectors. $\mathbf{P}_1 = \frac{(\mathbf{M} - 5 \cdot \mathbf{1})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_1 \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}}{k_1} = |\varepsilon_1\rangle\langle\varepsilon_1|$

$$\mathbf{P}_2 = \frac{(\mathbf{M} - 1 \cdot \mathbf{1})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_2 \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix}}{k_2} = |\varepsilon_2\rangle\langle\varepsilon_2|$$

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**.

Diagonalizing Transformations (D-Tran) from projectors

Given our eigenvectors and their Projectors.

$$\mathbf{P}_1 = \frac{(\mathbf{M} - 5 \cdot \mathbf{1})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_1 \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}}{k_1} = |\varepsilon_1\rangle\langle\varepsilon_1|$$

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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**.

$$\left\{ \langle\varepsilon_1| = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}, \langle\varepsilon_2| = \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix} \right\}, \quad \left\{ |\varepsilon_1\rangle = \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix}, |\varepsilon_2\rangle = \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \right\}$$

$(\varepsilon_1, \varepsilon_2) \leftarrow (1, 2)$ *d-Tran matrix*

$(1, 2) \leftarrow (\varepsilon_1, \varepsilon_2)$ **INVERSE** *d-Tran matrix*

$$\begin{pmatrix} \langle\varepsilon_1|x\rangle & \langle\varepsilon_1|y\rangle \\ \langle\varepsilon_2|x\rangle & \langle\varepsilon_2|y\rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{pmatrix}, \quad \begin{pmatrix} \langle x|\varepsilon_1\rangle & \langle x|\varepsilon_2\rangle \\ \langle y|\varepsilon_1\rangle & \langle y|\varepsilon_2\rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{pmatrix}$$

Diagonalizing Transformations (D-Tran) from projectors

Given our eigenvectors and their Projectors.

$$\mathbf{P}_1 = \frac{(\mathbf{M} - 5 \cdot \mathbf{1})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_1 \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}}{k_1} = |\varepsilon_1\rangle\langle\varepsilon_1|$$

$$\mathbf{P}_2 = \frac{(\mathbf{M} - 1 \cdot \mathbf{1})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_2 \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix}}{k_2} = |\varepsilon_2\rangle\langle\varepsilon_2|$$

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**.

$$\left\{ \langle\varepsilon_1| = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}, \langle\varepsilon_2| = \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix} \right\}, \quad \left\{ |\varepsilon_1\rangle = \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix}, |\varepsilon_2\rangle = \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \right\}$$

$(\varepsilon_1, \varepsilon_2) \leftarrow (1, 2)$ *d-Tran matrix*

$(1, 2) \leftarrow (\varepsilon_1, \varepsilon_2)$ **INVERSE** *d-Tran matrix*

$$\begin{pmatrix} \langle\varepsilon_1|x\rangle & \langle\varepsilon_1|y\rangle \\ \langle\varepsilon_2|x\rangle & \langle\varepsilon_2|y\rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{pmatrix}, \quad \begin{pmatrix} \langle x|\varepsilon_1\rangle & \langle x|\varepsilon_2\rangle \\ \langle y|\varepsilon_1\rangle & \langle y|\varepsilon_2\rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{pmatrix}$$

Use *Dirac labeling for all components* so transformation is OK

$$\begin{pmatrix} \langle\varepsilon_1|x\rangle & \langle\varepsilon_1|y\rangle \\ \langle\varepsilon_2|x\rangle & \langle\varepsilon_2|y\rangle \end{pmatrix} \cdot \begin{pmatrix} \langle x|\mathbf{K}|x\rangle & \langle x|\mathbf{K}|y\rangle \\ \langle y|\mathbf{K}|x\rangle & \langle y|\mathbf{K}|y\rangle \end{pmatrix} \cdot \begin{pmatrix} \langle x|\varepsilon_1\rangle & \langle x|\varepsilon_2\rangle \\ \langle y|\varepsilon_1\rangle & \langle y|\varepsilon_2\rangle \end{pmatrix} = \begin{pmatrix} \langle\varepsilon_1|\mathbf{K}|\varepsilon_1\rangle & \langle\varepsilon_1|\mathbf{K}|\varepsilon_2\rangle \\ \langle\varepsilon_2|\mathbf{K}|\varepsilon_1\rangle & \langle\varepsilon_2|\mathbf{K}|\varepsilon_2\rangle \end{pmatrix}$$

$$\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{pmatrix} \cdot \begin{pmatrix} 4 & 1 \\ 3 & 2 \end{pmatrix} \cdot \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 5 \end{pmatrix}$$

Diagonalizing Transformations (D-Tran) from projectors

Given our eigenvectors and their Projectors.

$$\mathbf{P}_1 = \frac{(\mathbf{M} - 5 \cdot \mathbf{1})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_1 \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}}{k_1} = |\varepsilon_1\rangle\langle\varepsilon_1|$$

$$\mathbf{P}_2 = \frac{(\mathbf{M} - 1 \cdot \mathbf{1})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_2 \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix}}{k_2} = |\varepsilon_2\rangle\langle\varepsilon_2|$$

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**.

$$\left\{ \langle\varepsilon_1| = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}, \langle\varepsilon_2| = \begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix} \right\}, \quad \left\{ |\varepsilon_1\rangle = \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix}, |\varepsilon_2\rangle = \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \right\}$$

$(\varepsilon_1, \varepsilon_2) \leftarrow (1, 2)$ d-Tran matrix

$(1, 2) \leftarrow (\varepsilon_1, \varepsilon_2)$ INVERSE d-Tran matrix

$$\begin{pmatrix} \langle\varepsilon_1|x\rangle & \langle\varepsilon_1|y\rangle \\ \langle\varepsilon_2|x\rangle & \langle\varepsilon_2|y\rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{pmatrix}, \quad \begin{pmatrix} \langle x|\varepsilon_1\rangle & \langle x|\varepsilon_2\rangle \\ \langle y|\varepsilon_1\rangle & \langle y|\varepsilon_2\rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{pmatrix}$$

Use Dirac labeling for all components so transformation is OK

$$\begin{pmatrix} \langle\varepsilon_1|x\rangle & \langle\varepsilon_1|y\rangle \\ \langle\varepsilon_2|x\rangle & \langle\varepsilon_2|y\rangle \end{pmatrix} \cdot \begin{pmatrix} \langle x|\mathbf{K}|x\rangle & \langle x|\mathbf{K}|y\rangle \\ \langle y|\mathbf{K}|x\rangle & \langle y|\mathbf{K}|y\rangle \end{pmatrix} \cdot \begin{pmatrix} \langle x|\varepsilon_1\rangle & \langle x|\varepsilon_2\rangle \\ \langle y|\varepsilon_1\rangle & \langle y|\varepsilon_2\rangle \end{pmatrix} = \begin{pmatrix} \langle\varepsilon_1|\mathbf{K}|\varepsilon_1\rangle & \langle\varepsilon_1|\mathbf{K}|\varepsilon_2\rangle \\ \langle\varepsilon_2|\mathbf{K}|\varepsilon_1\rangle & \langle\varepsilon_2|\mathbf{K}|\varepsilon_2\rangle \end{pmatrix}$$

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Check inverse-d-tran is really inverse of *your* d-tran.

$$\begin{pmatrix} \langle\varepsilon_1|1\rangle & \langle\varepsilon_1|2\rangle \\ \langle\varepsilon_2|1\rangle & \langle\varepsilon_2|2\rangle \end{pmatrix} \cdot \begin{pmatrix} \langle 1|\varepsilon_1\rangle & \langle 1|\varepsilon_2\rangle \\ \langle 2|\varepsilon_1\rangle & \langle 2|\varepsilon_2\rangle \end{pmatrix} = \begin{pmatrix} \langle\varepsilon_1|1|\varepsilon_1\rangle & \langle\varepsilon_1|1|\varepsilon_2\rangle \\ \langle\varepsilon_2|1|\varepsilon_1\rangle & \langle\varepsilon_2|1|\varepsilon_2\rangle \end{pmatrix}$$

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

Diagonalizing Transformations (D-Tran) from projectors

Given our eigenvectors and their Projectors.

$$\mathbf{P}_1 = \frac{(\mathbf{M} - 5 \cdot \mathbf{1})}{(1 - 5)} = \frac{1}{4} \begin{pmatrix} 1 & -1 \\ -3 & 3 \end{pmatrix} = k_1 \begin{pmatrix} \frac{1}{2} \\ -\frac{3}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \end{pmatrix}}{k_1} = |\varepsilon_1\rangle\langle\varepsilon_1|$$

$$\mathbf{P}_2 = \frac{(\mathbf{M} - 1 \cdot \mathbf{1})}{(5 - 1)} = \frac{1}{4} \begin{pmatrix} 3 & 1 \\ 3 & 1 \end{pmatrix} = k_2 \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix} \otimes \frac{\begin{pmatrix} \frac{3}{2} & \frac{1}{2} \end{pmatrix}}{k_2} = |\varepsilon_2\rangle\langle\varepsilon_2|$$

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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$(\varepsilon_1, \varepsilon_2) \leftarrow (1, 2)$ *d-Tran matrix*

$(1, 2) \leftarrow (\varepsilon_1, \varepsilon_2)$ **INVERSE** *d-Tran matrix*

$$\begin{pmatrix} \langle\varepsilon_1|x\rangle & \langle\varepsilon_1|y\rangle \\ \langle\varepsilon_2|x\rangle & \langle\varepsilon_2|y\rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ \frac{3}{2} & \frac{1}{2} \end{pmatrix}, \quad \begin{pmatrix} \langle x|\varepsilon_1\rangle & \langle x|\varepsilon_2\rangle \\ \langle y|\varepsilon_1\rangle & \langle y|\varepsilon_2\rangle \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ -\frac{3}{2} & \frac{1}{2} \end{pmatrix}$$

Use *Dirac labeling for all components* so transformation is OK

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Check inverse-d-tran is really inverse of *your* d-tran. In standard quantum matrices inverses are “easy”

$$\begin{pmatrix} \langle\varepsilon_1|x\rangle & \langle\varepsilon_1|y\rangle \\ \langle\varepsilon_2|x\rangle & \langle\varepsilon_2|y\rangle \end{pmatrix} \cdot \begin{pmatrix} \langle x|\varepsilon_1\rangle & \langle x|\varepsilon_2\rangle \\ \langle y|\varepsilon_1\rangle & \langle y|\varepsilon_2\rangle \end{pmatrix} = \begin{pmatrix} \langle\varepsilon_1|\mathbf{1}|\varepsilon_1\rangle & \langle\varepsilon_1|\mathbf{1}|\varepsilon_2\rangle \\ \langle\varepsilon_2|\mathbf{1}|\varepsilon_1\rangle & \langle\varepsilon_2|\mathbf{1}|\varepsilon_2\rangle \end{pmatrix} \begin{pmatrix} \langle\varepsilon_1|x\rangle & \langle\varepsilon_1|y\rangle \\ \langle\varepsilon_2|x\rangle & \langle\varepsilon_2|y\rangle \end{pmatrix} = \begin{pmatrix} \langle x|\varepsilon_1\rangle & \langle x|\varepsilon_2\rangle \\ \langle y|\varepsilon_1\rangle & \langle y|\varepsilon_2\rangle \end{pmatrix}^\dagger = \begin{pmatrix} \langle x|\varepsilon_1\rangle^* & \langle y|\varepsilon_1\rangle^* \\ \langle x|\varepsilon_2\rangle^* & \langle y|\varepsilon_2\rangle^* \end{pmatrix} = \begin{pmatrix} \langle x|\varepsilon_1\rangle & \langle x|\varepsilon_2\rangle \\ \langle y|\varepsilon_1\rangle & \langle y|\varepsilon_2\rangle \end{pmatrix}^{-1}$$

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

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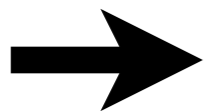
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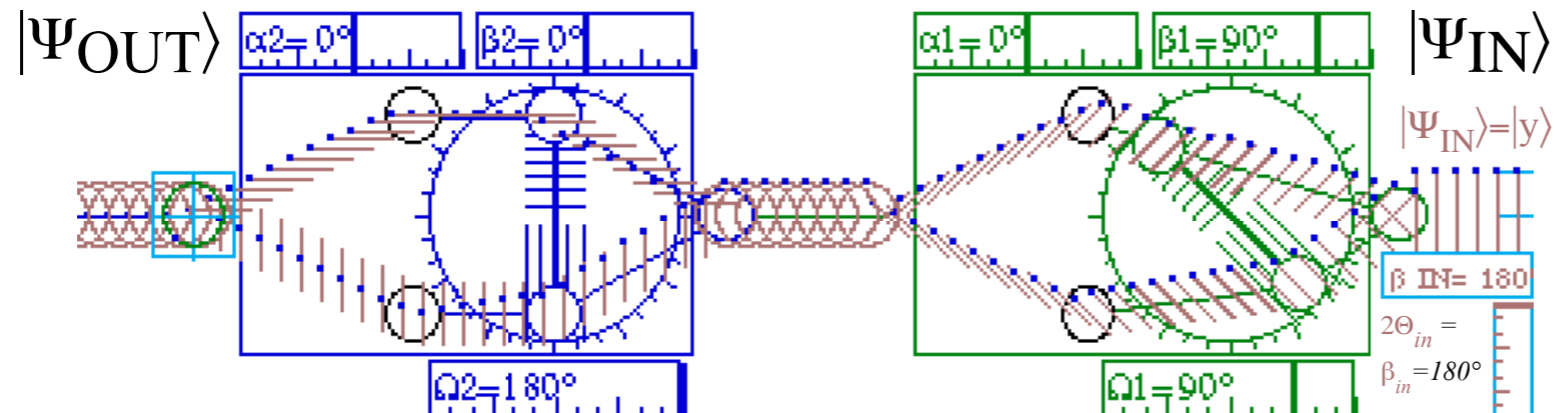


Matrix products and eigensolutions for active analyzers

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.

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

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

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

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

$$P_{+1} = \frac{\begin{pmatrix} \frac{-1}{\sqrt{2}} + 1 & \frac{i}{\sqrt{2}} \\ \frac{-i}{\sqrt{2}} & \frac{1}{\sqrt{2}} + 1 \end{pmatrix}}{1 - (-1)} = \frac{\begin{pmatrix} -1 + \sqrt{2} & i \\ -i & 1 + \sqrt{2} \end{pmatrix}}{2\sqrt{2}}, \quad P_{-1} = \frac{\begin{pmatrix} 1 + \sqrt{2} & -i \\ i & -1 + \sqrt{2} \end{pmatrix}}{2\sqrt{2}}$$

