Linear algebra formulas and algorithms

$A_{\theta} = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix}$ **Rotation Matrix:**

Linear systems

Consistency of $A\mathbf{x} = \mathbf{b}$: **b** is in the column space $LU: U = E_k \cdots E_1 A: L = E_1^{-1} \cdots E_k^{-1}$ Back and forth substitution: $L\mathbf{y} = \mathbf{b}; U\mathbf{x} = \mathbf{y}; LU\mathbf{x} = \mathbf{b}$ Cramer: $x_i = \det(B_i) / \det(A)$.

Matrix algebra

$$(AB)^{-1} = B^{-1}A^{-1} \qquad (P^{-1}DP)^n = P^{-1}D^nP \qquad \det(AB) = \det(A)\det(B)$$

Inversion Algorithm:
$$[A \quad I] \to [I \quad A^{-1}]$$

Invertibility: det $A \neq 0$

Basis algorithms

- 1. Row space: nonzero rows of row reduced form. Dimension: rank.
- 2. Column space: pivot columns of original matrix. Dimension: rank.

3. Null space: one basis vector per free variable: set one free variable equal to 1, set the

others equal to 0, and solve for the basic variables. Dimension: nullity.

4. Eigenspace: Null space of $A - \lambda I$.

- 5. Orthogonal complement of column space: Null space of transpose.
- 6. Orthogonal basis: Gram-Schmidt applied to any known basis.

Eigenvalues

Roots of the characteristic polynomial

Sum: trace. Product: determinant.

Diagonalization and Power algorithms; exponential

 $P^{-1}AP = D$: P is the matrix of eigenvectors, D is the matrix of eigenvalues.

Symmetric case: $P^T P = 1$ (use an orthogonal basis consisting of unit vectors).

 $A^n = PD^nP^{-1}; e^A = Pe^DP^{-1}; \det(e^A) = e^{\operatorname{tr}}(A)$

Conic sections: diagonalize the matrix of the quadratic form and look at the conic section corresponding to the diagonal matrix.

Dot products and Projections

 $||\mathbf{u}|| = \sqrt{\mathbf{u} \cdot \mathbf{u}}$

 $A\mathbf{u} \cdot \mathbf{v} = \mathbf{u} \cdot A^T \mathbf{v}$ (adjoint property)

Projection of \mathbf{v} in the direction of \mathbf{u} : $\frac{\mathbf{v} \cdot \mathbf{u}}{\mathbf{u} \cdot \mathbf{u}} \mathbf{u}$ The projection matrix in this case is $\mathbf{v}\mathbf{v}^T/\mathbf{v}^T\mathbf{v}$ (a matrix divided by a number).

Projection onto a subspace V: if you have an orthogonal basis for V, use the sum of the projections onto each basis vector; otherwise, use $P = A(A^T A)^{-1} A^T$ where the columns of A are a basis for V (laborious).

Gram-Schmidt: remove from each vector its projection onto the span of the previous vectors; use the *new* basis vectors to do this.

Least squares $(A\mathbf{x} = \mathbf{b})$: project **b** into the column space of A and solve; in practice, multiply on the left by A^T and solve.