NLA: **Golub** for $k=1:m,n$: $u_k=(sgn(b_{k,k})\|b_{k:m,k}\|e_1+b_{k:m,k})$; $u_k:=\hat{u}_k$; $U_k:=I-2u_ku_k^T$; $B_{k:m,k:n}:=U_kB_{k:m,k:n}$; $U=[I_{k-1,k-1},0;0,U_k]$;for $j=1:m,n-1$: $v_k^T:=sgn(b_{k,k+1})\|b_{k,k+1:n}\|e_1+b_{k:m,k}$;$V_k:=I-2v_kv_k^T$;$B_{1:m,k+1:n}=B_{1:m,k+1:n}V_k$; $V=[I_{k,k},0;0,V_k]$endfor endfor; $2\cdot(2mn^2-2n^3/3)$ **Householder** for $k=[1,n]$: $x=A_{k:m,k}$; $v_k=sgn(x)\|x\|e_k+x$; $v_k=\frac{v_k}{\|v_k\|}$ for $j=[k,n]$ $A_{k:m,j}=A_{k:m,j}-2v_k\left[v_k^*A_{k:m,j}\right]$ endfor endfor. $2mn^2-\frac{2n^3}{3}$. **MG-S** $V=A$;for $i=[1,n]$: $r_{ii}=\|v_i\|$; $q_i=\frac{v_i}{r_{ii}}$;for $j=[i+1,n]$ $v_j=v_j-(q_i^Tv_j)q_i$; $r_{ij}=q_i^Tv_j$ endfor endfor. $2mn^2$. **Arnoldi:** $q_1:=\hat{b}$; $q_{k+1}h_{k+1,k}=Aq_k-\sum_{i=1}^{k}q_ih_{ik}$; $h_{ik}=q_i^T(Aq_k)$; $h_{k+1,k}:=\|v\|\rightarrow AQ_k:=Q_kH_k+q_{k+1}[0\ldots h_{k+1,k}]$. **Givens** $3mn^2$ **SVD:** $=\sum_i^{r:=\min m,n}u_i\sigma_iv_i^T$. **QR Algo:** $A_{k+1}=Q_k^TA_kQ_k\rightarrow A_{k+1}=\left(Q^{(k)}\right)^TAQ^{(k)}\&A^k=(Q_1\ldots Q_k)(R_k\ldots R_1):=Q^{(k)}R^{(k)}$, via induction **GMRES:** $\min\|AQ_ky-b\|\rightarrow\min\|H_ky-\|b\|e_1\|$ **CG Bound:** With $c=x-x_0, c_k=x_k-x_0$ s.t. $r_k=A(c-c_k)$ we have $r_k^Tv=0\;\forall\;v\in\mathcal{K}_k$ so $v^tA(c-c_k)=0$, s.t. $y=c_k=\arg\min\|c-y\|_A$. WTS $e_k=e_0p_k(A)$ with $p(0)=1$, and write $e_0:=\sum\gamma_iv_i$ with $Av_i=\lambda_iv_i\rightarrow\|e_k\|_A=\min_{p_k,p(0)=1}\max|p(\lambda_i|\|e_0\|_A$ **CG Convergence:** $\|e_k\|=\min_{p(0)=1}\|p_k(A)e_0\|=\min_{p_k(A)}\max|p_k(\lambda)|\|e_0\|\rightarrow\leq2\left((\sqrt{k_2}-1)/(\sqrt{k_2}+1)\right)^k$; need $\alpha:=2(\lambda_1+\lambda_2)$ **Cheb:** $T_k(x)=\frac{1}{2}(z^k+z^{-k})$; $2xT_k=T_{k+1}+T_{k-1}$ **CG Conditions:** To show $r_{k+1}^Tr_k=0$ first show $p_k^TAp_k=p_k^TAr_k$ via β then show $p_k^Tr_k=r_k^Tr_k$ via $p_{k-1}^Tr_k=0$. **MP:** $\sigma(G)\in[\sqrt{m}-\sqrt{n},\sqrt{m}+\sqrt{n}]\rightarrow k_2=O(1)$ **Sketch:** with $GA\hat{x}=Gb$, and via $C-F$ $\left\|G[A,b][v,-1]^T\right\|\leq(s+\sqrt{n+1})\left\|R[v,-1]^T\right\|$, similar for lower bound via MP $\rightarrow\|A\hat{x}-b\|\leq(\sqrt{s}+\sqrt{n+1})/(\sqrt{s}-\sqrt{n+1})\|Ax-b\|$ **Blend:** solve $\left\|(A\hat{R}^{-1})y-b\right\|=0$ via CG;$k_2(A\hat{R}^{-1})=O(1)$ with $GA=\hat{Q}\hat{R}$ PROOF: $A=QR$; $GA=GQR=\hat{G}R$. Let $\hat{G}=\hat{Q}\hat{R}$ so $GA=\hat{Q}\hat{R}R\rightarrow\tilde{R}^{-1}=R^{-1}\hat{R}^{-1}\rightarrow k_2(A\tilde{R}^{-1})=k_2(\hat{R}^{-1})=O(1)$ by MP. $O(mn)$ to solve via normal **Bounds:** $\left\|ABB^{-1}\right\|\geq\|AB\|\left\|B^{-1}\right\|\rightarrow\|A\|/\left\|B^{-1}\right\|\geq\|AB\|$. **Weyls:** $\sigma_i(A+B)=\sigma_i(A)+[-\|B\|,\|B\|]$ **Rev Δ Ineq:** $\|A-B\|\geq|\|A\|-\|B\||$ **Courant Application:** $\sigma_i\left([A_1;A_2]\right)\geq\max\left(\sigma_i(A_1),\sigma_i(A_2)\right)$ **Schur:** Take $Av_1=\lambda_1v_1$; construct $U_1=[v_1,V_\perp]\rightarrow AU_1=U_1[e_1,X]$. Repeat. **Conditioning** $\kappa_2(A)=\sigma_1/\sigma_n=\|A\|\left\|A^{-1}\right\|$ **Similarity:** $A\rightarrow P^{-1}AP$, same λ.

CO: **G-N:** $\vec{\boldsymbol{x}}_{k+1}=\vec{\boldsymbol{x}}_k-\frac{\boldsymbol{\nabla}f_k}{J^TJ}$, with $J:=$ Jacobian of $r(x)$ **SD:** $\|x_{k+1}-x_*\|\leq\left(k_2(H)-1\right)/\left(k_2(H)+1\right)\|x_k-x_*\|$ with H hessian **bArm:** w/ $\phi(\alpha)=f(x_k+\alpha_ks_k)$, $\psi(\alpha)=\phi(\alpha)-\phi(0)-\beta\alpha\phi'(0)\leq0$, show $\psi'(0)=(1-\beta)\phi'(0)\leq0\rightarrow\psi(\alpha)\downarrow$ with α. **BFGS:** To show $H_{k+1}\geq0$ nec. $\gamma^T\delta>0$. Suff via γ,δ LI $\rightarrow$ use $\|\cdot\|_H\rightarrow\gamma^T\delta>0$. **Quad Penalty Meth** With $y=-c/\sigma,\|\boldsymbol{\nabla}_\sigma\Phi\|\leq\epsilon^k,\sigma^k\rightarrow0,x\rightarrow x_*,\boldsymbol{\nabla}c(x_*)$ LI, then $y\rightarrow y_*$, $x\rightarrow KKT$. PROOF: If $y_*:=J_*^\dagger\boldsymbol{\nabla}f_*\rightarrow\|y_k-y_*\|=\left\|J_k^\dagger\boldsymbol{\nabla}f_k-Iy_*\right\|\leq\left\|J_k^\dagger\right\|\|\boldsymbol{\nabla}_\sigma\Phi\|\rightarrow0$. Also, $\boldsymbol{\nabla}f_*-J_*^Ty_*=0$, and $c_{k\rightarrow*}=-\sigma^{k\rightarrow*}y_{k\rightarrow*}=0$ so $x_*\rightarrow KKT$ **Quad Pen. Meth Newt** Have $w=(J\Delta x+c)/\sigma$ so $[\boldsymbol{\nabla}^2f,J^T;J,-\sigma I][\Delta x,w]^T=-[\boldsymbol{\nabla}f,c]$ **Trust Region Radius:** $\rho_k:=(f(x_k)-f(x_k+s_k))/(f(x_k)-m_k(s_k))$ **TR-Method:** If $\rho\approx1$ then double radius, update step $x_{k+1}=x_k+s_k$. If $\rho\geq0.1$ then same radius, update step. If ρ small shrink radius, don't update step. **Cauchy:** Is the point on gradient which minimises the quadratic model within TR. Want $m_k(s_k)\leq m_k(s_{kc})$, where $s_{kc}:=-\alpha_{kc}\boldsymbol{\nabla}f(x_k)$, and $\alpha_{kc}:=\arg\min m_k\left(\alpha\boldsymbol{\nabla}f(x_k)\right)$ subject to $\|\alpha\boldsymbol{\nabla}f\|\leq\Delta$, i.e. $\alpha_{max}:=\Delta/\|\boldsymbol{\nabla}f\|$. **Calculation of Cauchy:** We want to prove cauchy model decrease i.e. $f(x_k)-m_k(s_k)\geq f(x_k)-m_k(s_{kc})\geq0.5\|\boldsymbol{\nabla}f_k\|\min\left\{\Delta_k,\frac{\|\boldsymbol{\nabla}f_k\|}{\|\boldsymbol{\nabla}^2f_k\|}\right\}$. First define $\Psi(\alpha):=m_k(-\alpha\boldsymbol{\nabla}f)$ s.t. $\Psi:=f_k-\alpha\|f_k\|^2-0.5\alpha^2H_k$, with $H_k:=\left[\boldsymbol{\nabla}f_k\right]^T\left[\boldsymbol{\nabla}^2f_k\right]\left[\boldsymbol{\nabla}f_k\right]$. N.B. that $\alpha_{min}:=\frac{\|\boldsymbol{\nabla}f_k\|^2}{H_k}$ if $H_k>0$, from $\Psi'(0)<0$. Now A: If $H_k\leq0$ then we have $\Psi(\alpha)\leq f_k-\alpha\|\boldsymbol{\nabla}f_k\|^2\rightarrow\alpha_{kc}=\alpha_{max}$. So, we have $f_k-m_{s_k}\geq f_k-m_{s_{kc}}\geq\|\boldsymbol{\nabla}f_k\|\Delta_k\geq0.5\|\boldsymbol{\nabla}f_k\|\min\left\{\Delta_k\right\}$. Now B.i: If $H_k>0\rightarrow\alpha_{kc}=\alpha_{min}$. Here $f_k-m_{s_{kc}}=\alpha_{kc}\|\boldsymbol{\nabla}f\|^2-0.5\alpha_{kc}^2H_k=\frac{\|\boldsymbol{\nabla}f\|^4}{2H_k}\geq\frac{\|\boldsymbol{\nabla}f\|}{2}\min\left\{\frac{\|\boldsymbol{\nabla}f\|}{\|\boldsymbol{\nabla}^2f\|}\right\}$ via C-S. Now B.ii: If $H_k>0\rightarrow\alpha_{kc}=\alpha_{max}$. Here $\Delta/\|\boldsymbol{\nabla}f\|\leq\|\boldsymbol{\nabla}f\|^2/H_k\rightarrow\alpha_{kc}H_k\leq\|\boldsymbol{\nabla}f\|^2$. So $f_k-m_{kc}=-\alpha_{kc}\|\boldsymbol{\nabla}f\|^2+\frac{\alpha_{kc}^2}{2}H_k\geq\frac{\|\boldsymbol{\nabla}f\|^2}{2}\alpha_{kc}\geq0.5\|\boldsymbol{\nabla}f\|\min\left\{\Delta_k\right\}$ **TR-Global Convergence:** If $m_k(s_k)\leq m_k(s_{kc})$ then either $\exists k\geq0$ s.t. $\boldsymbol{\nabla}f_k=0$ or $\lim\|\boldsymbol{\nabla}f\|\rightarrow0$. Further, require $f\in C^2$, bounded below and also $\boldsymbol{\nabla}f$ L-cont. PROOF: Using def of ρ, $f_k-f_{k+1}\geq\frac{0.1}{2}\|\boldsymbol{\nabla}f_k\|\min\{\ldots\}$ from above. Let $\left\|\boldsymbol{\nabla}^2f\right\|:=L$, and assuming $\|\boldsymbol{\nabla}f\|\geq\epsilon$ we have $f_k-f_{k+1}\geq0.05\frac{c}{L}\epsilon^2$ assuming TR has a lower bound $c\epsilon/L$. Then sum over all successful jumps s.t. $f_0-f_{lower}\geq\sum_{i\in\mathbb{S}}f_i-f_{i+1}\geq|\mathbb{S}|\frac{0.05c\epsilon^2}{L}$ **KKT Feasibility:** Need $s^TJ\geq0$, $J_E^Ts=0$, and $s^T\boldsymbol{\nabla}f<0$. **KKT Conditions:** REMEMBER $c\geq0,\ \lambda\geq0$! **First Order KKT (Equality):** If we have x_* local min, then let $x=x_*+\alpha s$. Then we have $c_i(x(\alpha))\rightarrow0=c_i(x_*)+\alpha s^TJ\rightarrow s^TJ=0$. Further, we have $f(x)=f(x_*)+\alpha s^T\boldsymbol{\nabla}f\rightarrow\alpha s^T\boldsymbol{\nabla}f\geq0$. Repeat for negative α s.t. $s^T\boldsymbol{\nabla}f=0$. By Rank-Nullity (assuming $J_E(x_*)$ full rank), we have $\boldsymbol{\nabla}f_*=J_*^Ty+s_*$ for some y_*, which then implies (after s^T from LHS) that $\|s_*\|=0$, so $\boldsymbol{\nabla}f_*=J_*^Ty_*$. **KKT 2nd Order** If we have $\min f$ with $c(x)\geq0$, 2^{nd} order conditions are that $s^T\boldsymbol{\nabla}^2\mathcal{L}s\geq0$ for all $s\in\mathcal{A}$, with $\mathcal{A}$ defined s.t: EITHER $s^TJ_i=0\;\forall\;i$ s.t. $\lambda_i>0,c_i=0$, OR $s^T J_i \geq 0 \; \forall \; i$ s.t. $\lambda_i = 0, c_i = 0$, for J, c, λ evaluated at x_* For EQUALITY constraints instead need positive definite $\forall \; s$ s.t. $J^T s = 0$ **Convex Problems** $\hat{x} = KKT \Rightarrow \hat{x} = \arg\min f(x)$. Proof via $f \geq f(\hat{x}) + \nabla f^T(x - \hat{x})$ so $f \geq f(\hat{x}) + \hat{y}^T A(x - \hat{x}) + \sum_{i \in I} \lambda_i J_i^T (x - \hat{x})$. Choose $Ax = b$, and note that c_i concave s.t. $\lambda_i J_i^T(\hat{x})(x - \hat{x}) \geq \lambda_i (c_i(x) - c_i(\hat{x})) = \lambda_i c_i(x) \geq 0 \to f(x) \geq f(\hat{x})$. **Log-Barrier Global Convergence:** With $f \in C^1, \lambda_{ik} = \frac{\mu_k}{c_{ik}}, \|\nabla f_u(x_k)\| \leq \epsilon_k, \mu_k \to 0, x_k \to x_*$. Also, $\nabla c(x_*) LI \; \forall \; i \in \mathcal{A}$ (active constraints). Then x_* KKT and $\lambda \to \lambda_*$. PROOF: Have $J_A^\dagger(x_*) = (J_A(x_*) J_A(x_*)^T)^{-1} J_A(x_*)$. Also, $c_A = 0, c_I > 0$. So $\lambda = \mu / c \to 0$ so $\lambda_I = 0$ as $c_I > 0$. Next $\|\nabla f_k - J_{Ak} \lambda_{Ak}\| \leq \left\|\nabla f_k - J_k^T \lambda_k\right\| + \|\lambda_I\| \|\ldots\| = \|\nabla f_{\mu k}\| \to 0$. Now $\left\|J_A^\dagger \nabla f_k - \lambda_{kA}\right\| \leq \left\|J_A^\dagger\right\| \|\nabla f_k - J_{Ak}^T \lambda_{Ak}\| \to 0$. So with triangle ineq $\left\|\lambda_{kA} - J_{Ak}^\dagger \nabla f_k + J_{Ak}^\dagger \nabla f_k - \lambda_{A*}\right\| \to 0$, via cont. of ∇f and $J^\dagger$. Thus $\lambda_{Ak} \to \lambda_{A*} \geq 0$. Combine s.t. $\nabla f_k - J_{Ak}^T \lambda_{AK}$ with $k \to *$ so get KKT. **Primal-Dual Newton:** Have $\nabla f = J^T \lambda, C(x)\lambda = \mu e$ so $[\nabla^2 \mathcal{L}, -J^T; \Lambda J, C][dx, d\lambda]^T = -[\nabla f - J^T \lambda, C\lambda - \mu e]^T$