

② Gauss Curv. & 2nd Fundamental Form. (6)

- Curvature has something to do with (VII)
2nd derivatives: $\circ \circ$ define

$$\tilde{x}_{ij} = \frac{\partial}{\partial u^i} \tilde{x}_j(u^1, u^2)$$

Since $\tilde{x}_j = \frac{\partial}{\partial u^i} x(u^1, u^2)$ we have

$$\tilde{x}_{ij} = \frac{\partial}{\partial u^i} \frac{\partial}{\partial u^j} x(u^1, u^2)$$

$$= \frac{\partial}{\partial u^i} \frac{\partial}{\partial u^j} (x(u^1, u^2), y(u^1, u^2), z(u^1, u^2)).$$

is a vector in \mathbb{R}^3 .

- Since derivatives of vectors tangent to M have normal components, (like curves!), \tilde{x}_{ij} has a component in direction \vec{n} . (Assume \vec{n} is an orientation on M)

• Since $\vec{n}, \underline{x}_1, \underline{x}_2$ is a basis for \mathbb{R}^3 at each $P \in M \subseteq \mathbb{R}^3$, and since $\underline{x}_{ij} \in \mathbb{R}^3$, we can write \underline{x}_{ij} as a linear comb of $\vec{n}, \underline{x}_1, \underline{x}_2$

Define L_{ij} & Γ_{ij}^k at P by

$$\underline{x}_{ij} = L_{ij} \vec{n} + \Gamma_{ij}^k \underline{x}_k$$

L & Γ describe all 2nd deriv vector \underline{x}_{ij} @ $P \in M$

Defn: $L_{ij} \equiv$ 2nd Fundamental form @ P

$\Gamma_{ij}^k \equiv$ Christofel symbols \equiv Connection Coefficients

$$\underline{x}_{ij} = \underline{x}_{ji} \Rightarrow L_{ij} = L_{ji}, \quad \Gamma_{ij}^k = \Gamma_{ji}^k$$

Both are Symmetric in every coord system.

• Note: $\Gamma_{ij}^k x_m$ are the 2nd deriv's in the surface \Rightarrow the part that can be expressed by $\frac{\partial}{\partial u^1}, \frac{\partial}{\partial u^2}$ in \underline{x} -coords. (03)

Theorem ① L_{ij} transforms like a $\binom{0}{2}$ -tensor (like g_{ij} & η_{ij}) $\Rightarrow L_{ij}$ is a symmetric $\binom{0}{2}$ -tensor.

Theorem ② $\Gamma_{ij}^k = \frac{1}{2} g^{k\sigma} \{ g_{ij,\sigma} + g_{\sigma i,j} + g_{\sigma j,i} \}$ is not a tensor, but is intrinsic in that they can be measured in the world system via knowing the g 's.

Theorem (3): The geodesics on M are solutions of the ODE's:

$$\frac{d^2 u^k}{dt^2} + \Gamma_{ij}^k \frac{du^i}{dt} \frac{du^j}{dt} = 0$$

These are curves of shortest (critical) length (locally not globally), & have property that their normal ~~derivatives~~ vectors \vec{N} have no component tangent to M .

□ The second Fundamental form —

①

• Recall: g_{ij} , η_{ij} are $\binom{0}{2}$ -tensors i.e.,

$$\eta_{ij} \frac{\partial u^i}{\partial v^\alpha} \frac{\partial u^j}{\partial v^\beta} = \bar{\eta}_{\alpha\beta}$$

• As $\binom{0}{2}$ tensors they operate on pairs of vectors

$$\eta(\underline{X}, \underline{Y}) = \eta_{ij} du^i \otimes du^j (\underline{X}, \underline{Y}) = \eta_{ij} a^i b^j$$

||

$$\eta(\underline{X}, \underline{Y}) = \bar{\eta}_{\alpha\beta} dv^\alpha \otimes dv^\beta (\underline{X}, \underline{Y}) = \bar{\eta}_{\alpha\beta} \bar{a}^\alpha \bar{b}^\beta$$

$$\underset{\sim}{\chi}_{ij} = \frac{\partial}{\partial u^i} \underset{\sim}{\chi}_j(u^1, u^2) = \frac{\partial}{\partial u^i} \frac{\partial}{\partial u^j} \underset{\sim}{\chi}(u^1, u^2)$$

$$\underset{\sim}{\chi}_{\alpha\beta} = \frac{\partial}{\partial v^\alpha} \underset{\sim}{\chi}_\beta(u^1, v^2) = \frac{\partial}{\partial v^\alpha} \frac{\partial}{\partial v^\beta} \underset{\sim}{\chi}(u^\alpha, v^\beta)$$

$\underset{\sim}{\chi}_i$ are vectors: $\underset{\sim}{\chi}_\alpha = \underset{\sim}{\chi}_i \frac{\partial u^i}{\partial v^\alpha}$

$\underset{\sim}{\chi}_{ij}$ are not tensors.

• Let $\vec{n}(p)$ be a cont choice of unit normal (2)
 so $(\vec{n}, \underline{x}_1, \underline{x}_2)$ is a basis @ P . (orientation)

Thus we can write $\underline{x}_{ij}, \underline{y}_{ij}$ as linear combs
 of $(\vec{n}, \underline{x}_1, \underline{x}_2)$ @ each P :

$$\underline{x}_{ij} = L_{ij} \vec{n} + \Gamma_{ij}^k \underline{x}_k$$

$$\underline{y}_{\alpha\beta} = L_{\alpha\beta} \vec{n} + \Gamma_{\alpha\beta}^\sigma \underline{y}_\sigma$$

Claim: L_{ij} transforms like a $\begin{pmatrix} 0 \\ 2 \end{pmatrix}$ -tensor:

i.e.,
$$\bar{L}_{\alpha\beta} = L_{ij} \frac{\partial u^i}{\partial v^\alpha} \frac{\partial u^j}{\partial v^\beta}$$

P.f. First note: $L_{ij} = \underline{x}_{ij} \cdot \vec{n}$
 $\bar{L}_{\alpha\beta} = \underline{y}_{\alpha\beta} \cdot \vec{n}$

Then:

$$\bar{L}_{\alpha B} = y_{\alpha B} \cdot \vec{n} = \left(\frac{\partial y_{\alpha B}}{\partial v^{\alpha}} \right) \cdot \vec{n} \quad (3)$$

But $\frac{\partial}{\partial v^{\alpha}} = \frac{\partial u^i}{\partial v^{\alpha}} \frac{\partial}{\partial u^i}$, $y_{\alpha B} = \frac{\partial u^j}{\partial v^{\alpha}} \tilde{x}_{ij} \Rightarrow$

$$\bar{L}_{\alpha B} = \frac{\partial u^i}{\partial v^{\alpha}} \frac{\partial}{\partial u^i} \left(\frac{\partial u^j}{\partial v^{\alpha}} \tilde{x}_{ij} \right) \cdot \vec{n}$$

$$= \left\{ \frac{\partial u^i}{\partial v^{\alpha}} \frac{\partial}{\partial u^i} \left(\frac{\partial u^j}{\partial v^{\alpha}} \right) \tilde{x}_{ij} + \frac{\partial u^i}{\partial v^{\alpha}} \frac{\partial u^j}{\partial v^{\alpha}} \tilde{x}_{ij} \right\} \cdot \vec{n}$$

= 0!

$$= \frac{\partial u^i}{\partial v^{\alpha}} \frac{\partial u^j}{\partial v^{\alpha}} \underbrace{\tilde{x}_{ij}}_{L_{ij}} \cdot \vec{n}$$

$$= \frac{\partial u^i}{\partial v^{\alpha}} \frac{\partial u^j}{\partial v^{\beta}} L_{ij} \quad \text{as claimed } \square$$

Q We have: L_{ij} is a tensor

$$L_{ij} = L_{ji} \Rightarrow \text{symmetric.}$$

Now recall: $L^i_j = g^{io} L_{oj}$ is the (1)-tensor obtained by raising the index with the metric.

Said Differently, L^i_j is a transformation matrix symmetric wrt the inner product

$$g_{ij}: \quad \langle L\mathbb{X}, \mathbb{Y} \rangle \stackrel{?}{=} \langle \mathbb{X}, L\mathbb{Y} \rangle$$

$$\langle L^i_k a^k \frac{\partial}{\partial x^i}, b^j \frac{\partial}{\partial x^j} \rangle = \langle a^i \frac{\partial}{\partial x^i}, L^j_l b^l \frac{\partial}{\partial x^j} \rangle$$

$$\underbrace{g_{ij} L^i_k a^k b^j}_{L_{jk} a^k b^j} = g_{ij} a^i L^j_l b^l$$

$$L_{jk} a^k b^j = L_{jl} a^i b^l$$

Yes because $L_{ij} = L_{ji}$ ✓

- Symmetric Matrix Thm: if L^i_j is symmetric wrt a pos def. inner prod g , then L has real e-vals & an. basis of e-vectors. That is: $\exists N_1, N_2$

$$N_1 = a^i \tilde{x}_i, \quad N_2 = b^j \tilde{x}_j, \quad \langle N_1, N_2 \rangle = 0$$

$$\boxed{\begin{aligned} LN_1 &= k_1 N_1 \\ L^i_j a^j &= k_1 a^i \end{aligned}}$$

$$\boxed{\begin{aligned} LN_2 &= k_2 N_2 \\ L^i_j b^j &= k_2 b^i \end{aligned}}$$

$$k_1 \leq k_2$$

- Now recall: comp's L^i_j of a $\binom{1}{1}$ -tensor form a transformation matrix L which transforms by $\bar{L} = B^{-1} L B$

Evals satisfy: $|L - \lambda I| = 0 \Leftrightarrow \lambda^2 - (\text{tr} L)\lambda + \det L = 0$

$$|\bar{L} - \lambda I| = |B^{-1} L B - \lambda B^{-1} I B| = |B^{-1} (L - \lambda I) B| = |L - \lambda I| = 0$$

$$\Leftrightarrow \lambda^2 - (\text{tr} \bar{L})\lambda + \det L$$

Since both poly's are the same,

(6)

$$\text{tr } \bar{L} = \text{tr } L$$

$$\det \bar{L} = \det L$$

Conclude: the trace & determinant of a (1) - tensor are good indept numbers!

• Another Way - In basis N_1, N_2 we know

$$\bar{L} = \begin{bmatrix} K_1 & 0 \\ 0 & K_2 \end{bmatrix},$$

So $\text{trace } \bar{L} = K_1 + K_2 = \text{trace}(L)$

$$\det \bar{L} = K_1 K_2 = \det L$$

Defn: $\frac{1}{2}(K_1 + K_2) = \text{Mean Curvature (Extrinsic)}$

$K \equiv K_1 K_2 = \text{Gaussian Curvature (Intrinsic)}$

• Thm: A surface that has $K_1 + K_2 = 0$ everywhere \equiv zero mean curvature minimizes the surface area with given boundary \approx minimal surface \equiv soap bubble. ($K_1 + K_2$ does not just depend on g but also on how M is embedded in $\mathbb{R}^3 \Rightarrow$ not intrinsic)

• Interpretation of L & K

• Since $L \equiv L^i_j du^j \otimes \frac{\partial}{\partial u^i}$ is a $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$ -tensor it operates on vectors to give vectors:

$$\text{Eg } \Sigma = a^i \frac{\partial}{\partial u^i} \Rightarrow L(\Sigma) = \left(L^i_j du^j \otimes \frac{\partial}{\partial u^i} \right) (\Sigma)$$

Or in matrix form based on \underline{x} -comp's

$$\begin{array}{l} La = b \\ L^i_j a^j = b^i \end{array}$$

$$= L^i_j du^j(\Sigma) \frac{\partial}{\partial u^i}$$

$$= L^i_j a^j \frac{\partial}{\partial u^i} = \Sigma$$

Theorem: $L(\underline{X}) =$ minus the rate at which \vec{n} changes in the \underline{X} direction on M (The way the normal vector changes keeps track of curvature.) $L\underline{X} = -\underline{X}(\vec{n}) = L: T_p M \rightarrow T_p M$

• $\vec{n} = \underline{n}(u^1, u^2)$ is a coord system

(really: $\vec{n} = \vec{n}(p) = \vec{n}(x(u^1, u^2)) \equiv \underline{n}(u^1, u^2) \in S^2$)

$S^2 =$ unit sphere in \mathbb{R}^3 , $\vec{n} \in S^2$

• Thus $\underline{n}_1 = \frac{\partial}{\partial u^1} \underline{n}(u^1, u^2)$ & $\underline{n}_2 = \frac{\partial}{\partial u^2} \underline{n}(u^1, u^2)$

both make sense

• Since $\underline{n}_i = \frac{\partial}{\partial u^i} \underline{n}(u^1, u^2)$ holds (u^j fixed), $\|\underline{n}_i\| = 1$

← The other one!

we must have $\underline{n}_i \perp \vec{n}$

if $\|\gamma(t)\| = \text{const}$, then $\dot{\gamma}(t) \cdot \gamma(t) = 0$

Thus \underline{n}_i lie in span of $\underline{x}_1, \underline{x}_2 \Rightarrow$

$\exists \bar{L}_j^i$ such that $\underline{n}_i = \bar{L}_j^i \underline{x}_j$

• Now we can show $\bar{L}_{ij} = -L_{ij}$

P.F. $\langle \underline{n}, \underline{x}_i \rangle = 0$ (Key starting identity!)

$$\Rightarrow 0 = \frac{\partial}{\partial u_j} \langle \underline{n}, \underline{x}_i \rangle = \left\langle \frac{\partial}{\partial u_j} \underline{n}, \underline{x}_i \right\rangle + \left\langle \underline{n}, \frac{\partial}{\partial u_j} \underline{x}_i \right\rangle$$

$$= \langle \underline{n}_j, \underline{x}_i \rangle + \langle \underline{n}, \underline{x}_{ji} \rangle$$

$$= \langle \bar{L}_j^k \underline{x}_k, \underline{x}_i \rangle + L_{ji}$$

$$= \bar{L}_j^k \underbrace{\langle \underline{x}_k, \underline{x}_i \rangle}_{g_{ki}} + L_{ji}$$

$$=$$

$$= \bar{L}_{ij} + L_{ji}$$

$$\boxed{\bar{L}_{ij} = -L_{ij} !}$$

\Rightarrow

$$\boxed{\underline{n}_i = -L_i^k \underline{x}_k}$$

• Conclude: $\underline{\tilde{n}}_j = \frac{\partial}{\partial u^i} \underline{\tilde{n}} = -L^i_j \underline{\tilde{x}}_i$

If $\underline{\tilde{X}} = a^i \frac{\partial}{\partial u^i}$, then

$$\left(a^j \frac{\partial}{\partial u^i} \right) \underline{\tilde{n}} = - \left(L^i_j a^j \right) \underline{\tilde{x}}_i$$

$$\underline{\tilde{X}}(\underline{\tilde{n}}) = -L(\underline{\tilde{X}}) \quad \left(\underline{\tilde{x}}_i = \frac{\partial}{\partial u^i} !! \right)$$

$L(\underline{\tilde{X}}) = -\underline{\tilde{X}}(\underline{\tilde{n}})$

← Weingarten map L

output $L(\underline{\tilde{X}})$

rate at which $\underline{\tilde{n}}$ changes in $\underline{\tilde{X}}$ direction

In words: $L\underline{\tilde{X}}$ has geometrical meaning as the rate at which $\underline{\tilde{n}}$ changes in $\underline{\tilde{X}}$ direction — $\|\underline{\tilde{n}}\| = 1$, so $\underline{\tilde{X}}(\underline{\tilde{n}}) \in T_p \mathcal{M}$ ✓

• Corollary: Assume $\|\underline{\Sigma}\| = 1$. Then ("curvature") (10)

$\|L\underline{\Sigma}\| = \|\underline{\Sigma}(\vec{n})\|$ is maximized & minimized in directions N_1 & N_2 .

Proof: $\underline{\Sigma} = \alpha_1 N_1 + \alpha_2 N_2$

$$1 = \|\underline{\Sigma}\|^2 = \|\alpha_1 N_1\|^2 + \|\alpha_2 N_2\|^2 = \alpha_1^2 + \alpha_2^2 \quad (N_i \text{ or } N_j)$$

Thus

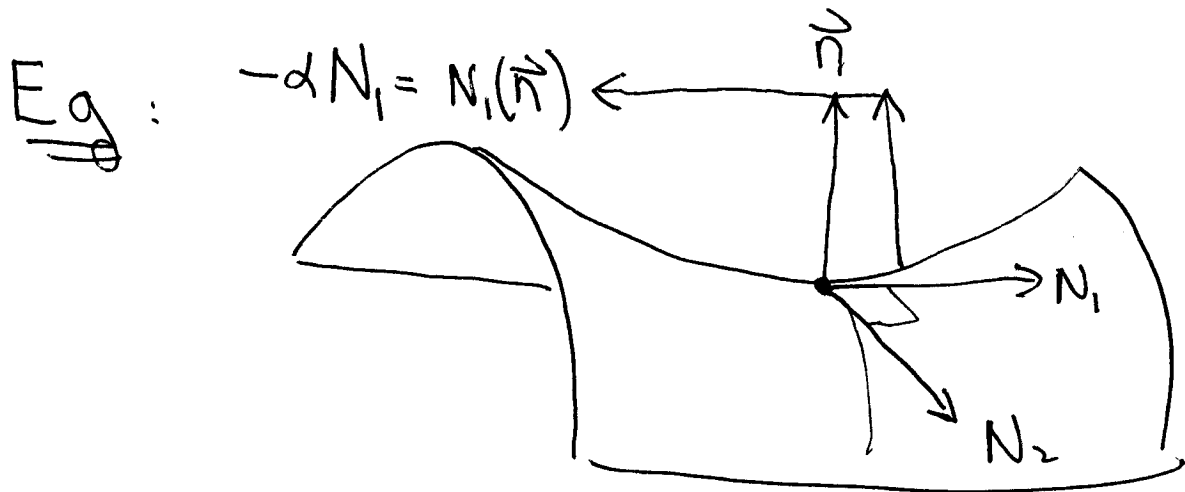
$$\begin{aligned} \|L\underline{\Sigma}\|^2 &= \|L(\alpha_1 N_1 + \alpha_2 N_2)\|^2 = \|\alpha_1 k_1 N_1\|^2 + \|\alpha_2 k_2 N_2\|^2 \\ &= \alpha_1^2 k_1^2 + \alpha_2^2 k_2^2 \end{aligned}$$

But $|k_1| \leq |k_2| \Rightarrow$

$$k_1^2 \leq \alpha_1^2 k_1^2 + \alpha_1^2 k_2^2 \leq \alpha_1^2 k_1^2 + \alpha_2^2 k_2^2 \leq \alpha_1^2 k_2^2 + \alpha_2^2 k_2^2 \leq k_2^2$$

$\Rightarrow \|L\underline{\Sigma}\| = \|\underline{\Sigma}(\vec{n})\|$ maximized/minimized at values $|k_2|$ & $|k_1|$. ✓

Picture : @ each pt \exists two or. directions N_1 & N_2 in which $L_i N_i = k_i N_i$.



$$N_1(\vec{n}) = \lim_{\epsilon \rightarrow 0} \frac{\vec{n}(P + \epsilon N_1) - \vec{n}(P)}{\epsilon} = -\alpha N_1$$

$$N_2(\vec{n}) = \lim_{\epsilon \rightarrow 0} \frac{\vec{n}(P + \epsilon N_2) - \vec{n}(P)}{\epsilon} = +\beta N_2 \quad \alpha, \beta \neq 0$$

$$-D(\vec{n}) = L D, \quad L \text{ has e-values } k_1, \beta, k_2 \Rightarrow$$

$$-N_1(\vec{n}) = L N_1 = k_1 N_1 \Rightarrow \alpha = k_1$$

$$-N_2(\vec{n}) = L N_2 = k_2 N_2 \Rightarrow \beta = -k_2$$

Idea : convex up (rel to \vec{n}) = $k_i > 0$
 convex down (rel to \vec{n}) = $k_i < 0$

• Result: $K = k_1 k_2 < 0 \Rightarrow$ saddle shape (12)
convex up in direction N_i
convex down in direction $N_{\bar{i}}$
(signs of k_1 & k_2 change with normal, but not
 $k_1 k_2$)

$K = k_1 k_2 > 0 \Rightarrow$ convexity the same in all
directions \approx sphere,

Geometrical Interpretation of Gauss Curvature K

We have:

$$\underline{x}(u^1, u^2) = (x(u^1, u^2), y(u^1, u^2), z(u^1, u^2))$$

$$\underline{x}_1 = \frac{\partial \underline{x}}{\partial u^1}, \quad \underline{x}_2 = \frac{\partial \underline{x}}{\partial u^2}, \quad g_{ij} = \langle \underline{x}_i, \underline{x}_j \rangle$$

$$\underline{n}(u^1, u^2) = \vec{n}(\underline{x}(u^1, u^2))$$

$$\underline{n}_1 = -L_1^k \underline{x}_k, \quad \underline{n}_2 = -L_2^l \underline{x}_l$$

$$\begin{aligned} \text{so } \hat{g}_{ij} &= \langle \underline{n}_i, \underline{n}_j \rangle = \langle -L_i^k \underline{x}_k, -L_j^l \underline{x}_l \rangle \\ &= L_i^k \langle \underline{x}_k, \underline{x}_l \rangle L_j^l = L_i^k g_{kl} L_j^l \end{aligned}$$

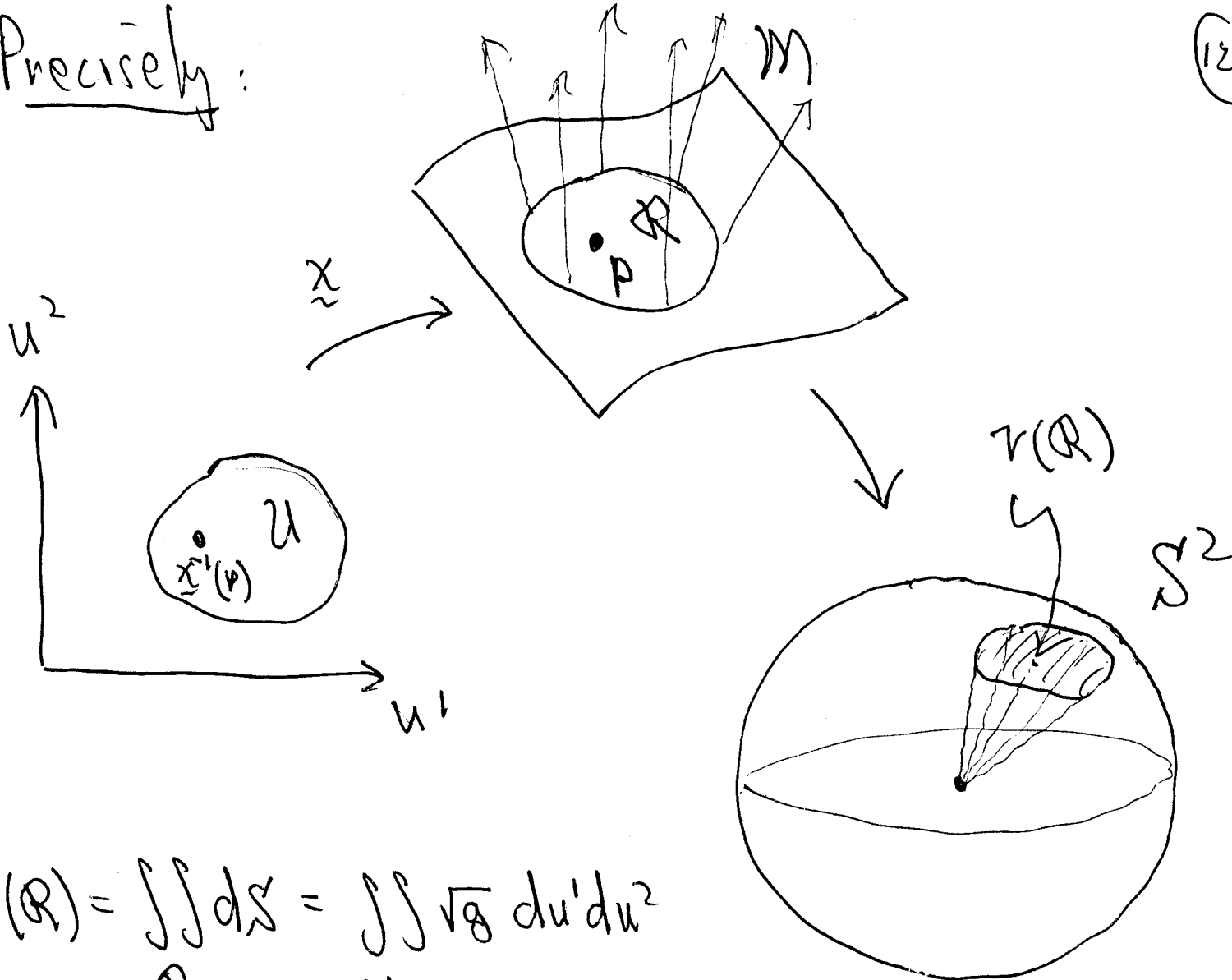
$$\begin{aligned} \underline{\underline{\text{Thus}}}: \quad \hat{g} &= \det |g_{ij}| = (\det L)^2 \det |g_{ij}| \\ &= K^2 g \end{aligned}$$

Conclude: The amplification factor for areas⁽¹²⁾
for \underline{x} -map is \sqrt{g} , & the amp. factor
for areas for \underline{n} -map is $\sqrt{g} K$ (K times larger)

Said Differently -

" K is the ratio of the area $A(V(\mathcal{R}))$ of
the region $V(\mathcal{R})$ swept out on S^2 by
normals \vec{n} on \mathcal{R} , to the area $A(\mathcal{R})$ on
 M , in the limit $A(\mathcal{R}) \rightarrow 0$ "

Precisely:



$$A(Q) = \iint_Q dS = \iint_U \sqrt{g} du^1 du^2$$

$$A(v(Q)) = \iint_{v(Q)} dS = \iint_U \sqrt{\hat{g}} du^1 du^2 = \iint_U \sqrt{g} K du^1 du^2$$

So

$$\lim_{A \rightarrow 0} \left\{ \frac{A(v(Q))}{A(Q)} = \frac{\iint_U \sqrt{g} K du^1 du^2}{\iint_U \sqrt{g} du^1 du^2} \right\} = \frac{A(U) \sqrt{g(P)} K(P)}{A(U) \sqrt{g(P)}} = K(P)$$

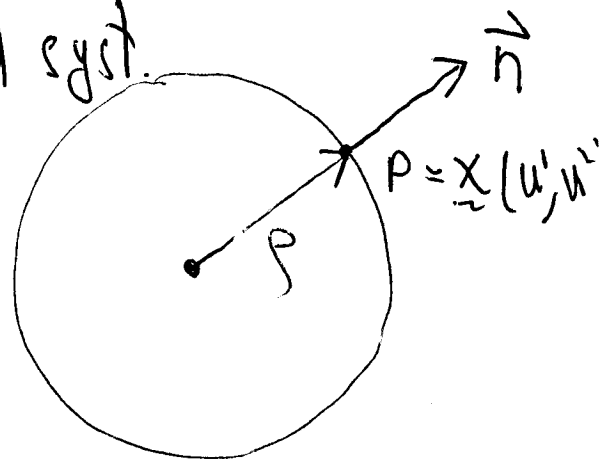
- Result: $K = k_1 k_2 < 0 \Rightarrow$ Saddle shape! (13)
 convex up in direction N_i
 convex down in other direction N_{i-1}
- $K = k_1 k_2 > 0 \Rightarrow$ convexity the same in all directions \in sphere

Ex Let $M = S_p^2 \equiv$ sphere of radius p ,
 center $(0,0,0) \in \mathbb{R}^3$, \underline{x} a coord syst.

• $\underline{x}(u^1, u^2) = (x(u^1, u^2), y(u^1, u^2), z(u^1, u^2))$

$\underline{n}(u^1, u^2) = \frac{1}{p} \underline{x}(u^1, u^2)$

$\Rightarrow \underline{x}_1 = p \underline{n}_1, \underline{x}_2 = p \underline{n}_2$



• Choose $\Sigma_p \in T_p M$ $\Sigma_p = a^i \frac{\partial}{\partial u^i} \equiv a^i \underline{x}_i$

$\Sigma_p(\underline{n}) = a^i \frac{\partial}{\partial u^i} \underline{n}(u^1, u^2) = \frac{1}{p} a^i \frac{\partial}{\partial u^i} \underline{x}(u^1, u^2) = \frac{1}{p} a^i \underline{x}_i$

$= \frac{1}{p} \Sigma_p = -L \Sigma_p \Rightarrow L = -\frac{1}{p} \text{Id} = K = |L| = \frac{1}{p}$

• Conclude: $K_1 = K_2 = -\frac{1}{\rho}$ ($K_1 = K_2 \Rightarrow P$ called umbilic point)

$$\underline{K} = \left(-\frac{1}{\rho}\right)\left(-\frac{1}{\rho}\right) = \frac{1}{\rho^2} > 0 \quad \checkmark$$

Thm: S^2_ρ has constant Gaussian curvature

$K > 0$. (It's the only space of const $\underline{K} = \underline{K}_0 > 0$)

• Note: $L \rightarrow -L$, $k_i \rightarrow -k_i$ if we switch $\vec{n} \rightarrow -\vec{n}$.

• The hyperbolic plane = space of constant negative curvature

$$ds^2 = \frac{du^2 + dv^2}{(1-u^2-v^2)^2}$$

$$0 \leq u^2, v^2 < 1$$

$$g_{ij} = \begin{bmatrix} \frac{1}{(1-u^2-v^2)^2} & 0 \\ 0 & \frac{1}{(1-u^2-v^2)^2} \end{bmatrix}$$

Problem - cannot be embedded in $\mathbb{R}^3 \Rightarrow$

can't get L from $\underline{X}(\vec{n}) = -L\underline{X} \Rightarrow$ need

an intrinsic formula for K to compute it! (This metric meets Euclid 1-4 but not 5) (14)

• Theorem: (Gauss's Thm Egregium)

① Gaussian Curvature is intrinsic —

$$K = R_{1221}$$

$$R^i_{jkl} = \frac{\partial \Gamma^i_{jl}}{\partial u^k} - \frac{\partial \Gamma^i_{jk}}{\partial u^l} + \Gamma^{\sigma}_{jl} \Gamma^i_{\sigma k} - \Gamma^{\sigma}_{jk} \Gamma^i_{\sigma l}$$

(curl)

+ (commutator)

$$\Gamma^i_{jk} = \frac{1}{2} g^{i\sigma} \left\{ -g_{\sigma j, k} + g_{\sigma k, j} + \underbrace{g_{ki, j}} \right\}$$

K can be computed from

$g_{ij}(u^1, u^2)$ alone (intrinsic)

$\frac{\partial}{\partial u^i} g_{kl}(u^1, u^2)$
etc

(2) If two surfaces are locally isometric, their Gaussian curvatures are equal.

(15)

Defn: An isometry $f: M \rightarrow N$

is a 1, onto, differentiable map such that the lengths of all curves are the

same; i.e. $\gamma: [a, b] \rightarrow M \Rightarrow f \circ \gamma$ has

same length as γ .

$$\int_a^b \|\dot{\gamma}(t)\|_M dt = \int_a^b \|\dot{f \circ \gamma}(t)\|_N dt$$

\forall curve.

(16)
③ Not every smooth positive definite metric determines a surface in \mathbb{R}^3 : (Hyperbolic plane is one.) However, if:

① g_{ij} pos def & $L_{ij} = L_{ji}$ given fn's of (u^1, u^2) st.

② $R_{iik}^l = L_{ik} L_j^l - L_{ij} L_k^l$ (Gauss Eqn)

$$\frac{\partial L_{ij}}{\partial u^k} - \frac{\partial L_{ik}}{\partial u^j} = \Gamma_{ik}^l L_{lj} - \Gamma_{ij}^l L_{lk}$$

(Codazzi-Mainardi)

Then \exists surface with given g_{ij}, L_{ij} & all such surfaces are isometric & in fact \exists rigid motion that takes one to other.

Pf (omitted) Rather than go thru pf, time better spent learning about Riemann Curvature Tensor $R_{ijkl} \dots$