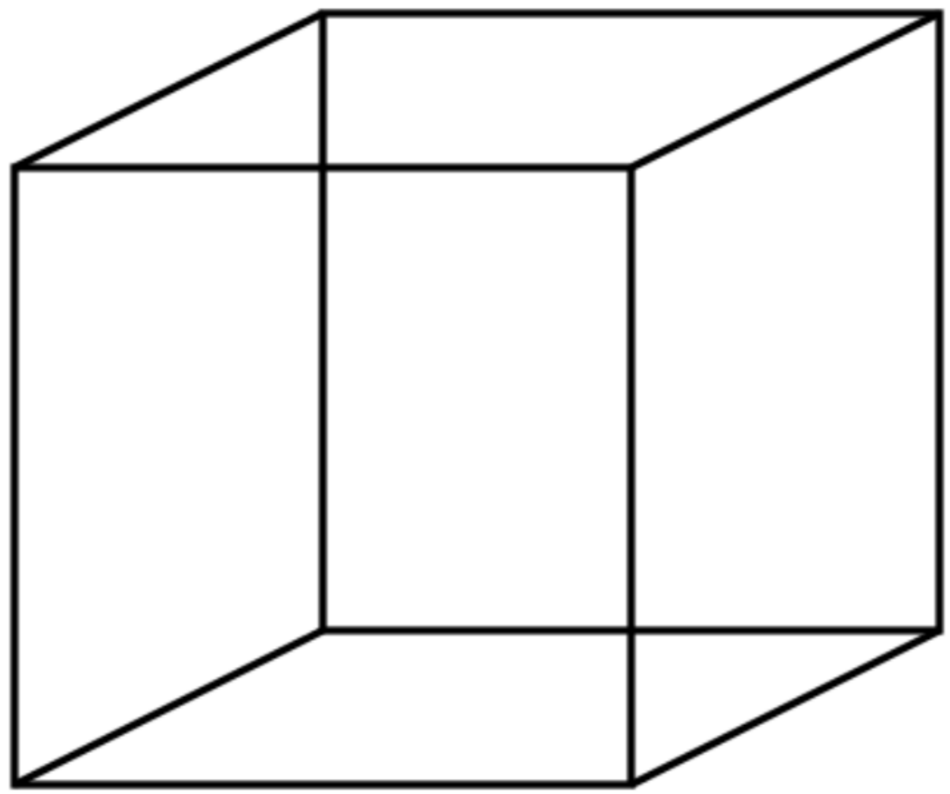
Bayesian reasoning in computer vision

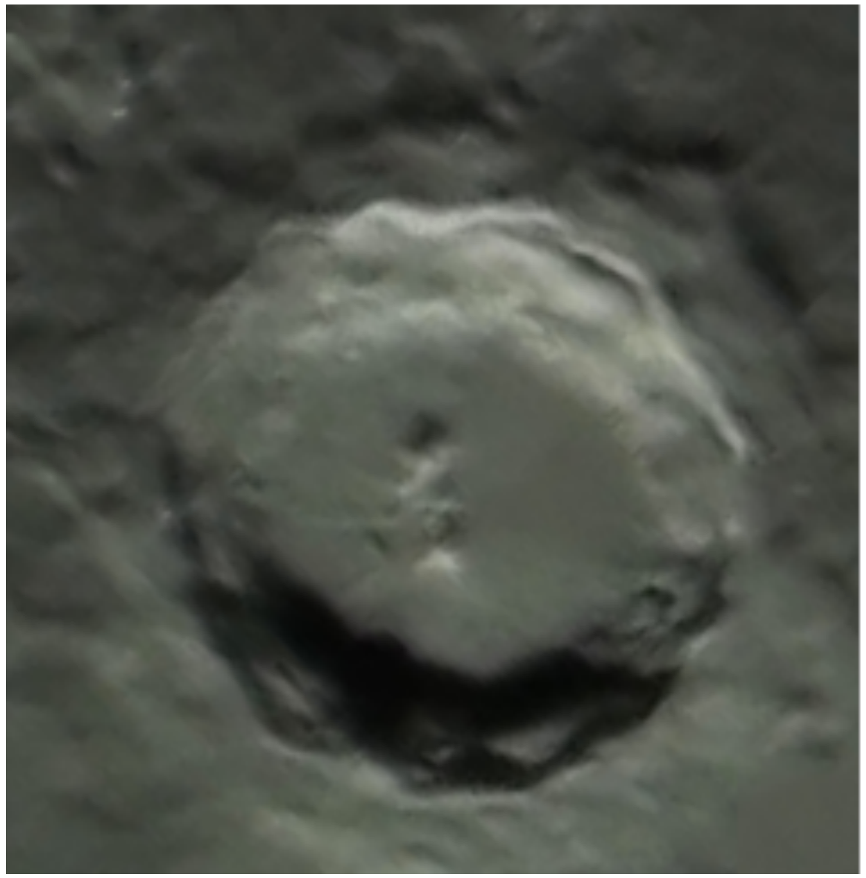
Bill Freeman, Antonio Torralba, Phillip Isola

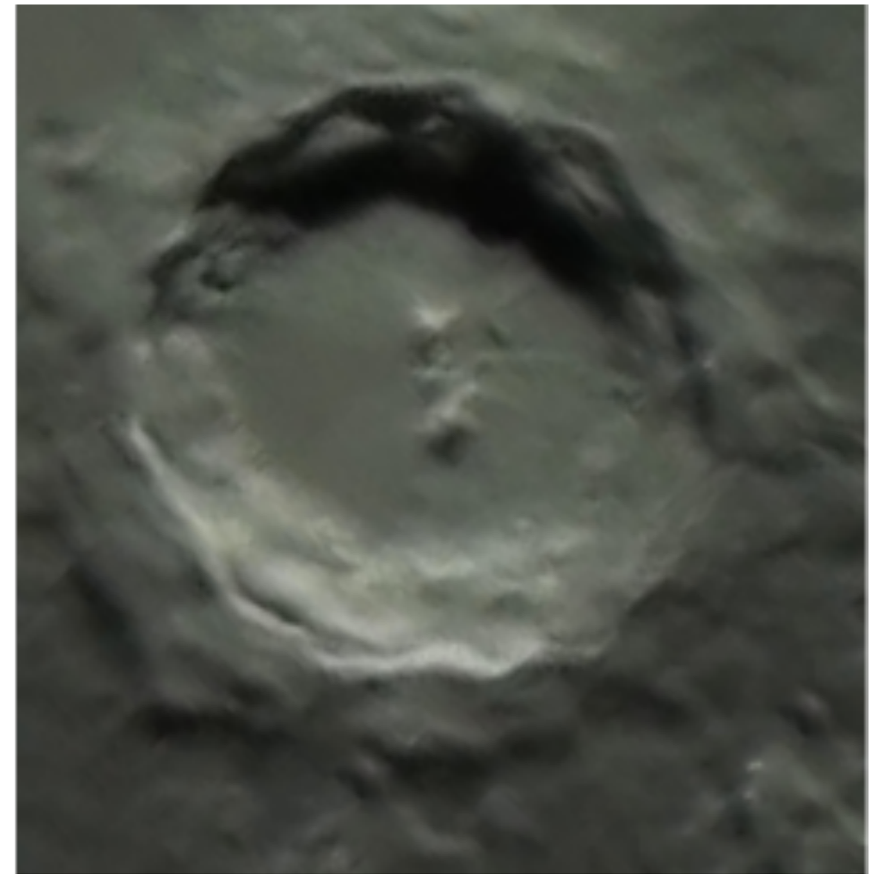
ambiguity in computer vision



https://www.michaelbach.de/ot/sze-Necker/index.html

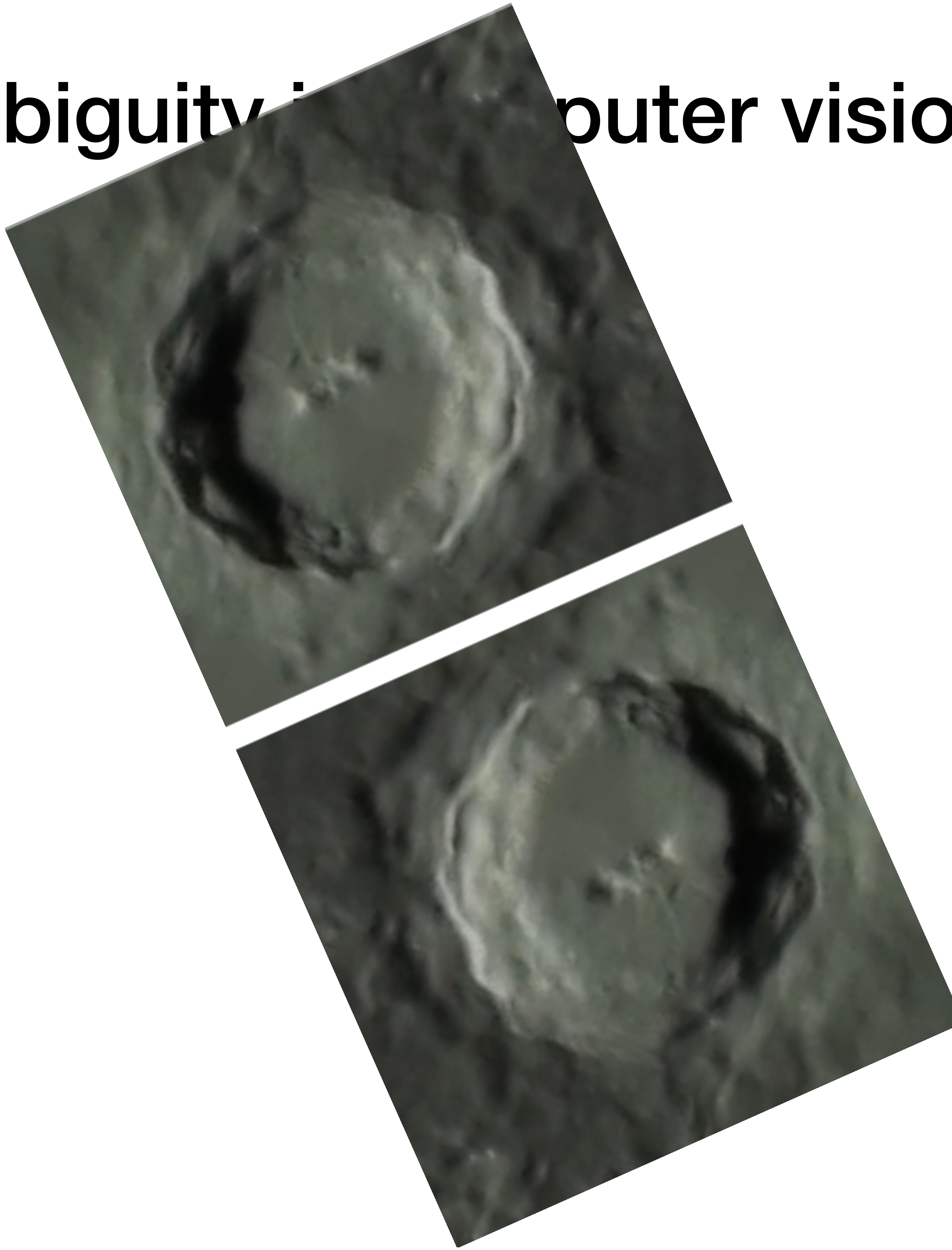
ambiguity in computer vision





http://lupuvictor.blogspot.com/2011/08/copernicus-crater-optical-illusion.html

ambiguity i[illegible]puter vision



size ambiguity

size ambiguity

Distribution of surface reflectances

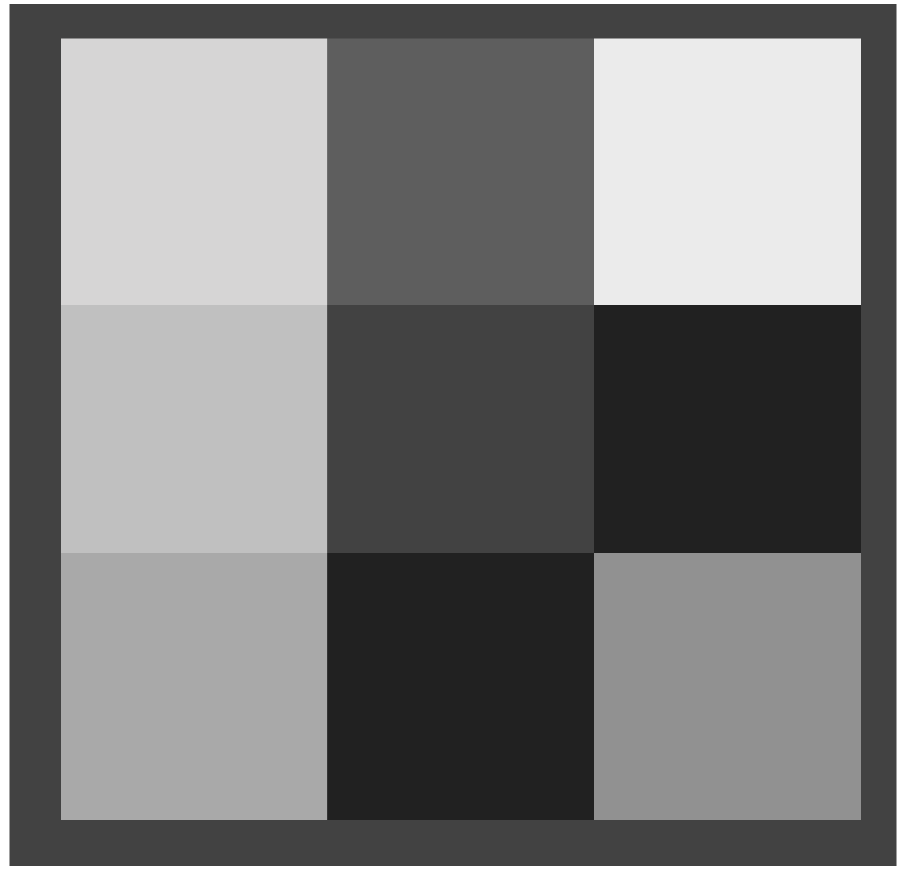
0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.10
0.11	0.12	0.13	0.14	0.15	0.16	0.17	0.18	0.19	0.20
0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29	0.30
0.31	0.32	0.33	0.34	0.35	0.36	0.37	0.38	0.39	0.40
0.41	0.42	0.43	0.44	0.45	0.46	0.47	0.48	0.49	0.50
0.51	0.52	0.53	0.54	0.55	0.56	0.57	0.58	0.59	0.60
0.61	0.62	0.63	0.64	0.65	0.66	0.67	0.68	0.69	0.70
0.71	0.72	0.73	0.74	0.75	0.76	0.77	0.78	0.79	0.80
0.81	0.82	0.83	0.84	0.85	0.86	0.87	0.88	0.89	0.90
0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.00

Distribution of illuminant intensities

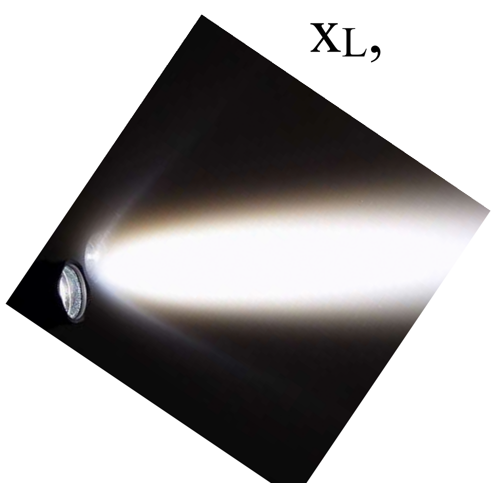
1	2	3	4	5	6	7	8	9	10
11	12	13	14	15	16	17	18	19	20
21	22	23	24	25	26	27	28	29	30
31	32	33	34	35	36	37	38	39	40
41	42	43	44	45	46	47	48	49	50
51	52	53	54	55	56	57	58	59	60
61	62	63	64	65	66	67	68	69	70
71	72	73	74	75	76	77	78	79	80
81	82	83	84	85	86	87	88	89	90
91	92	93	94	95	96	97	98	99	100

Surface brightness ambiguity

Observation, y

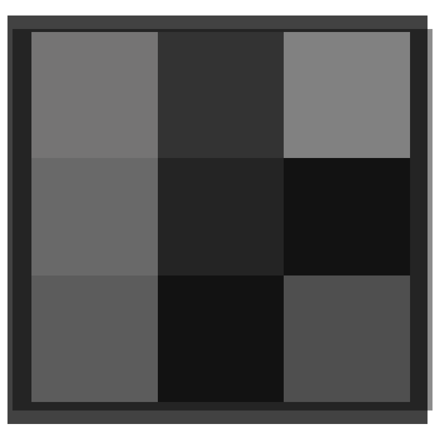


x_L,



Bright light

$x_1 \ldots x_N$

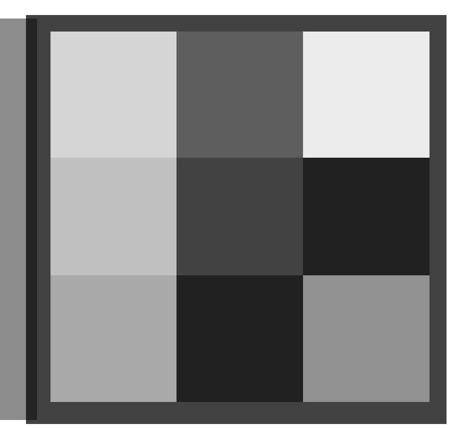


Dim squares

x_L,

Dim light

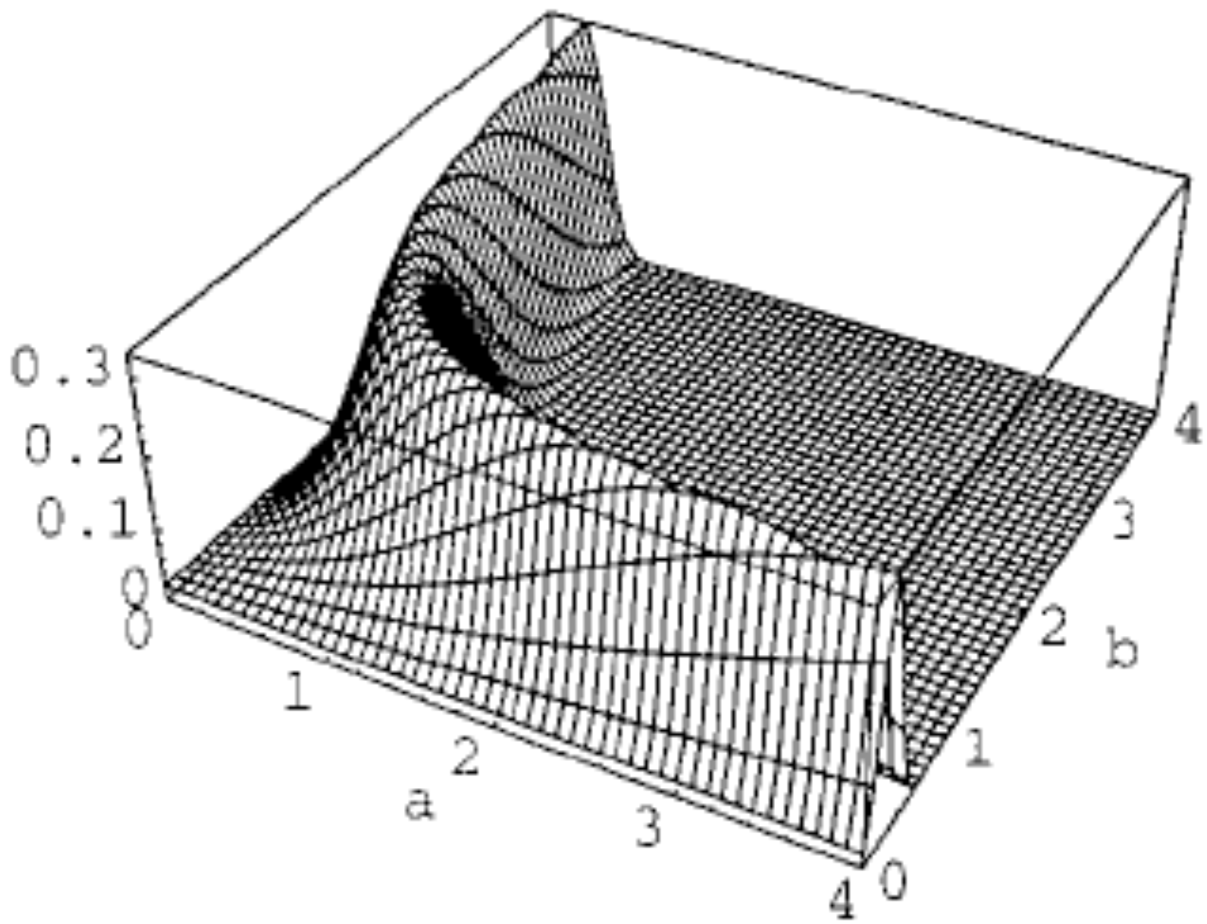
$x_1 \ldots x_N$



Bright squares

https://workingperson.com/surefire-flashlights-luma-max-pocket-flashlight-l4-ha-wh.html

Likelihood term for a b = 1 problem



Role of priors in computer vision

Sinha and Poggio, 1996

Role of priors in computer vision

https://www.michaelbach.de/ot/

Role of the loss function

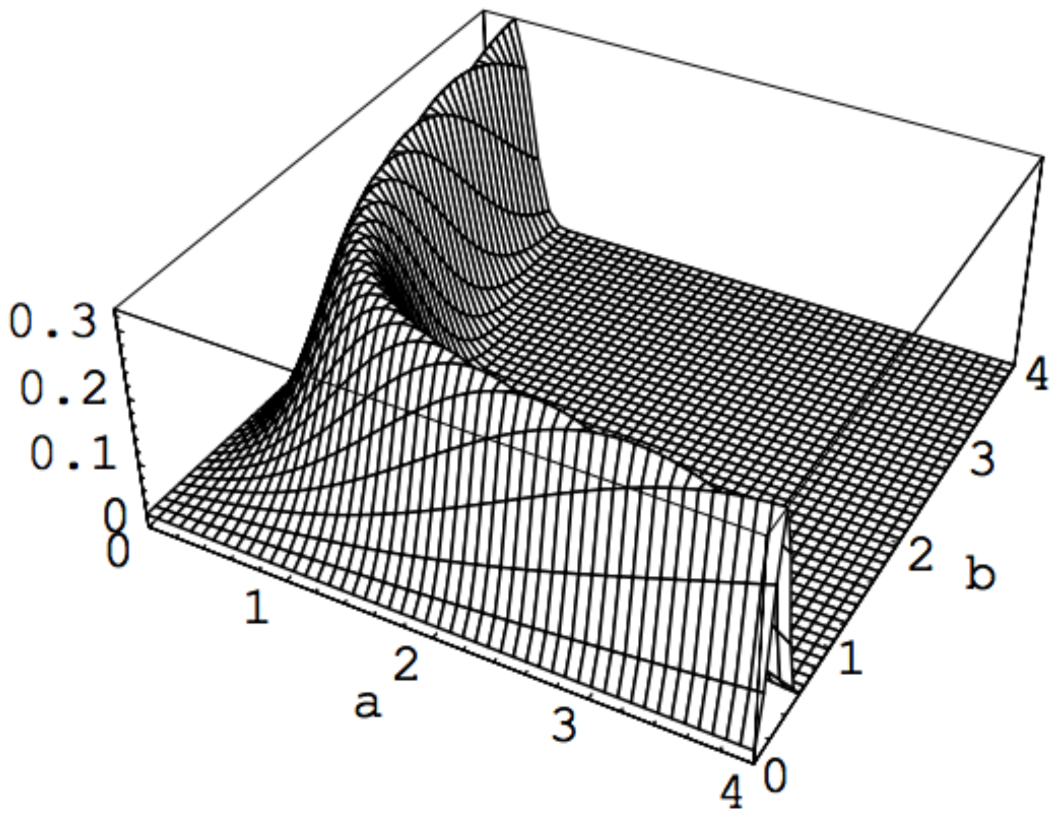
Picking a single best x

From the supplementary notes for this lecture:

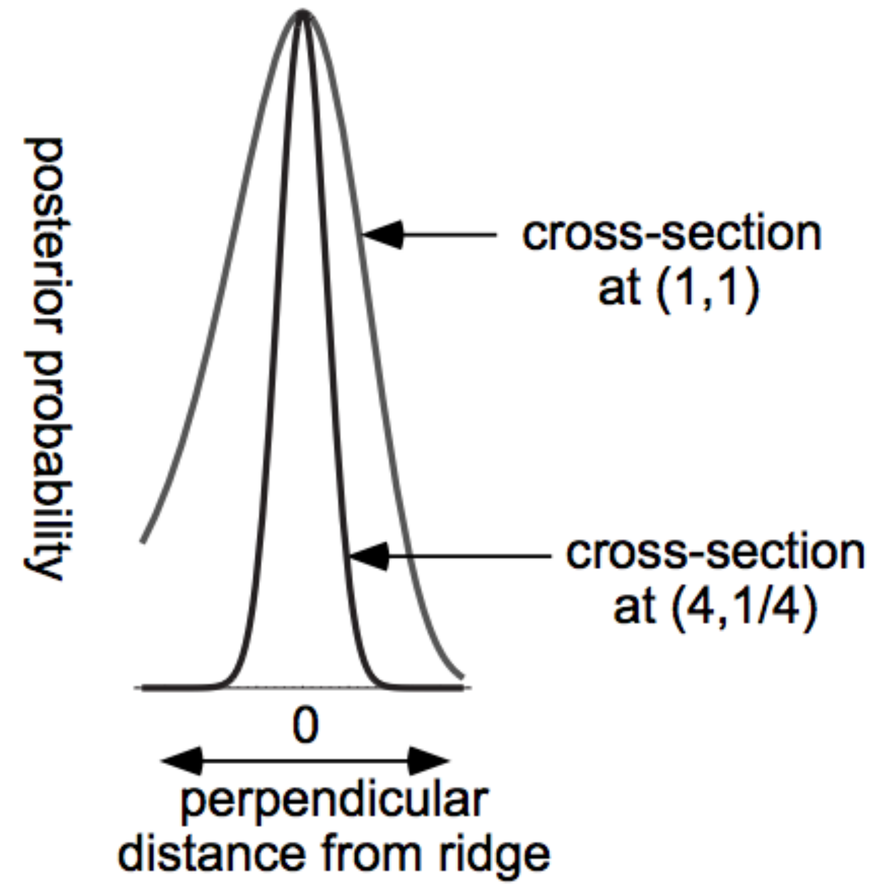
with the *loss function*, which specifies the penalty for guessing wrong. Let $\hat{\vec{x}}$ be your estimate of the parameters, $\vec{x}$. Then $L(\hat{\vec{x}}, \vec{x})$ is the loss incurred by guessing $\hat{\vec{x}}$ when the true value was $\vec{x}$. With the posterior probability, we can calculate the expected loss, $\bar{L}(\hat{\vec{x}}, \vec{x})$

$$\bar{L}(\hat{\vec{x}}, \vec{x}) = \int_{\vec{x}} L(\hat{\vec{x}}, \vec{x}) P(\vec{x}|\vec{y}) \tag{6.20}$$

We often use a loss function which is only a function of $\hat{\vec{x}} - \vec{x}$.



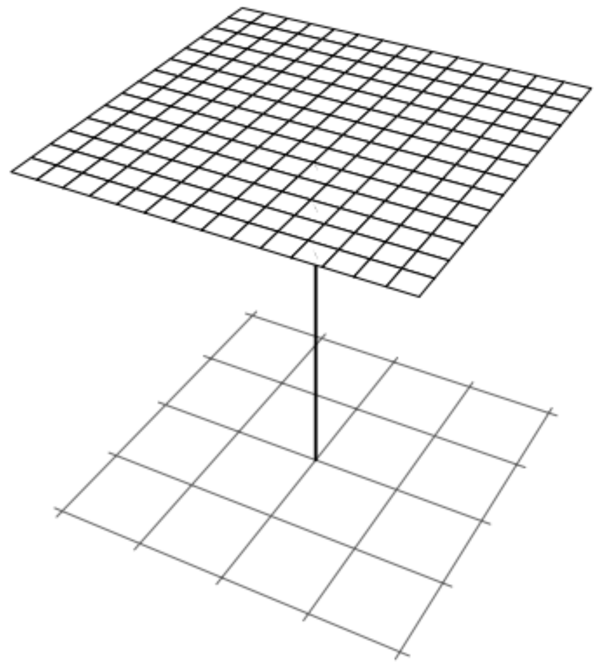
(a) Posterior Probability



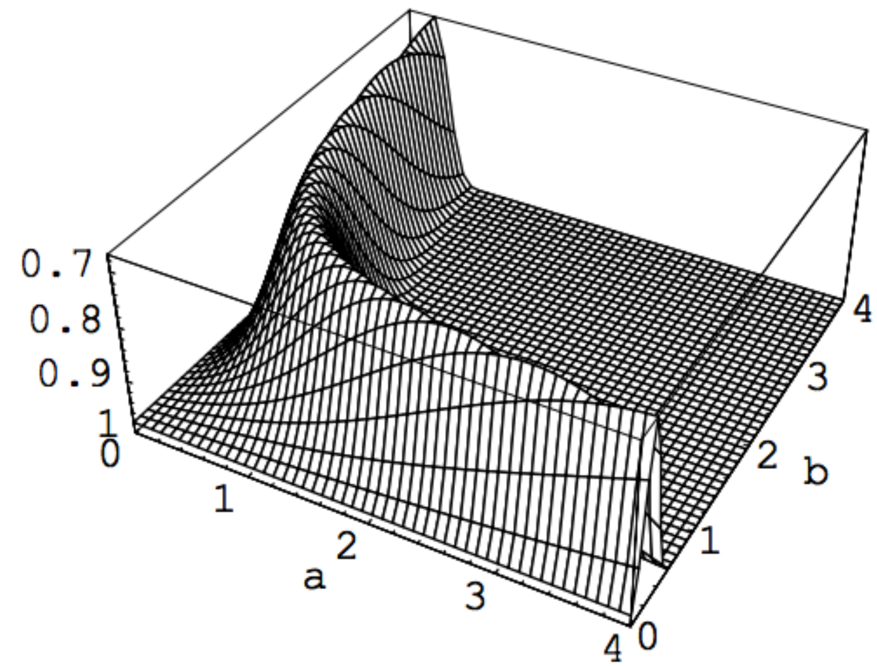
(b) Ridge Thickness Variations

http://www.merl.com/publications/docs/TR94-23.pdf

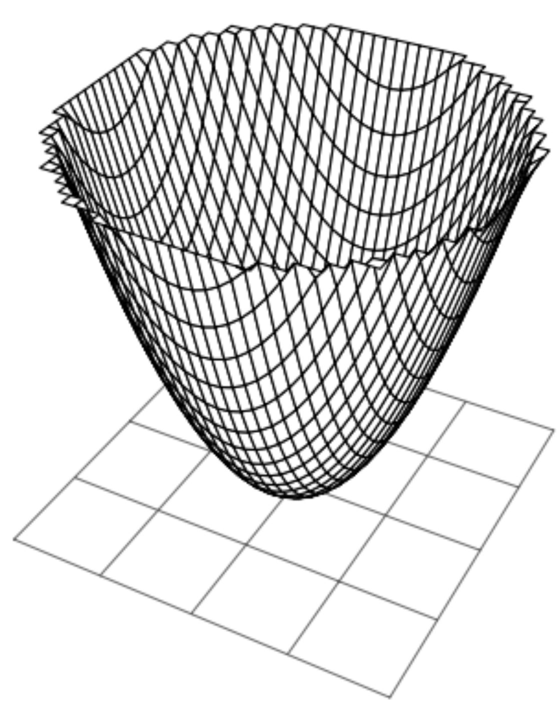
Two loss functions (left), and the (minus) expected losses for the 1=ab problem



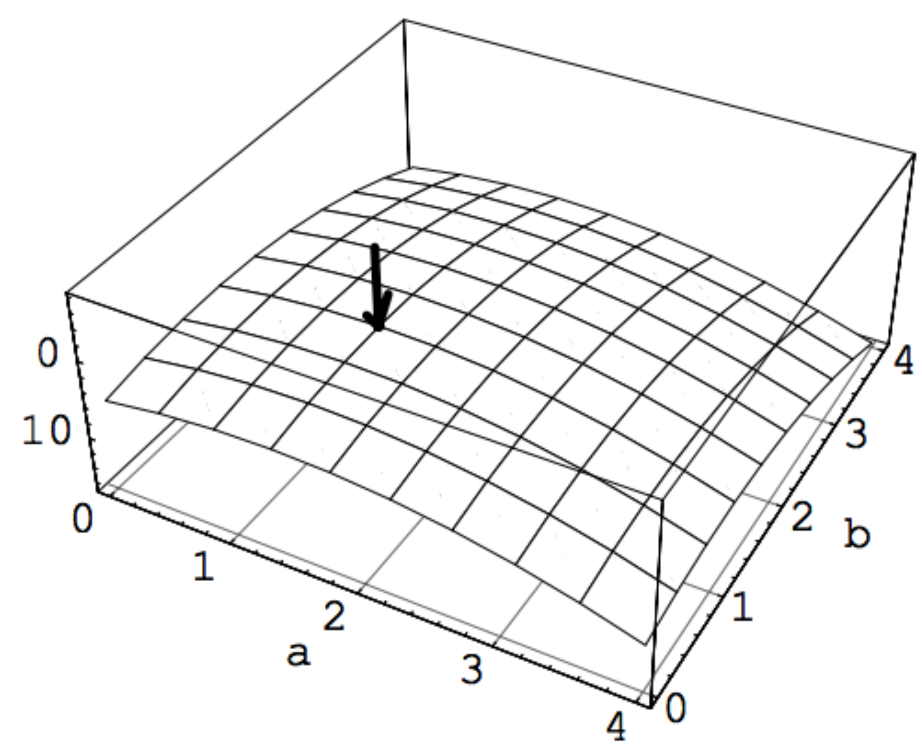
(a) MAP loss fn.



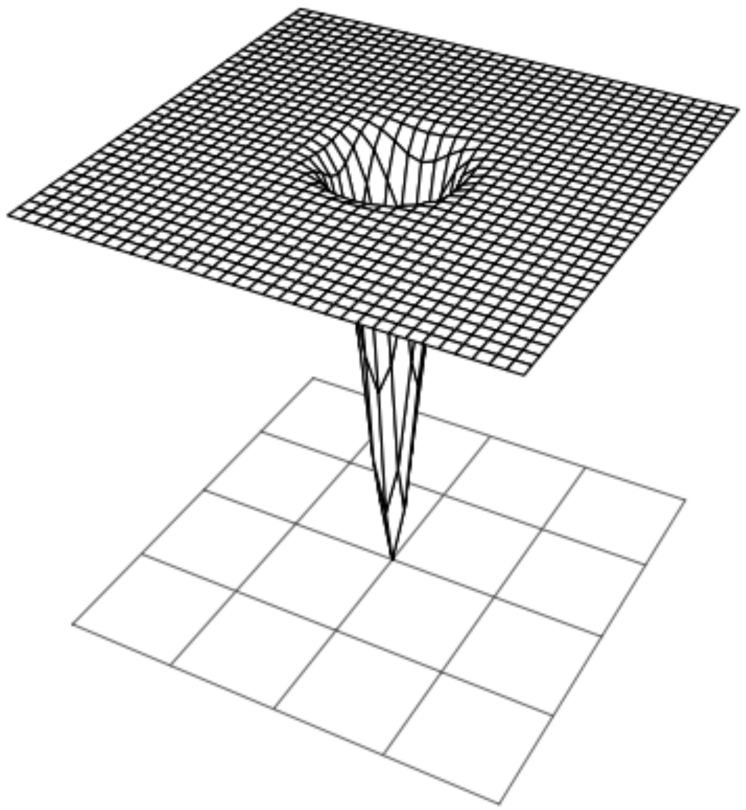
(d) (minus) MAP risk



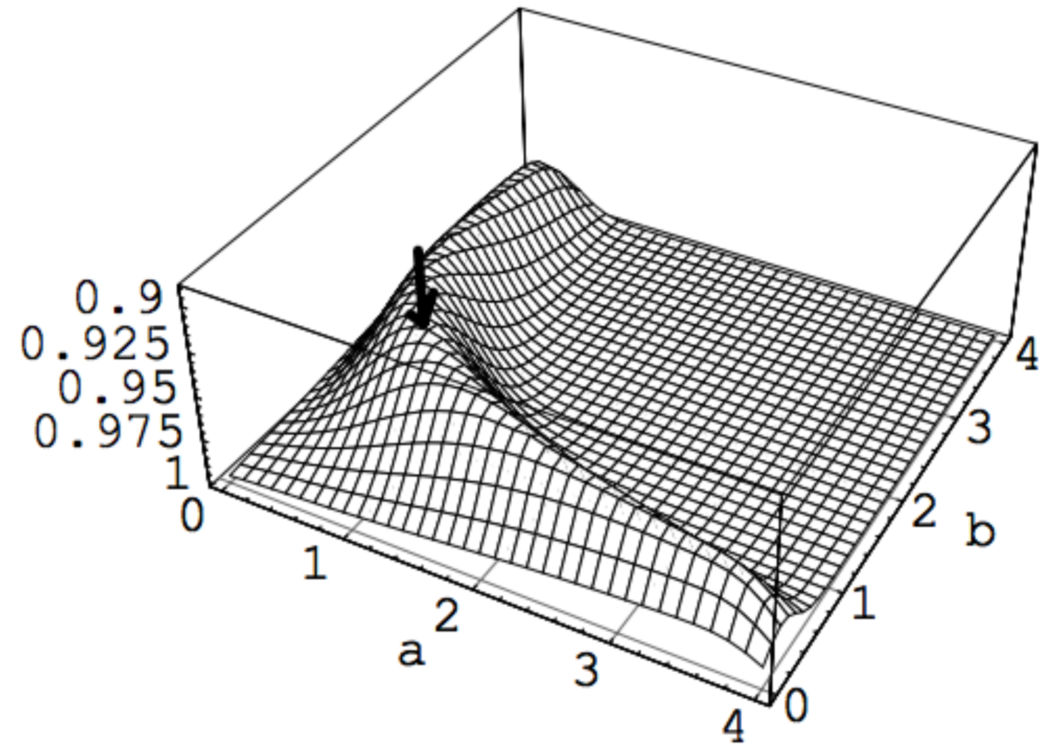
(b) MMSE loss fn.



(e) (minus) MMSE risk



(c) MLM loss fn.



(f) (minus) MLM risk