



fisheye lenses

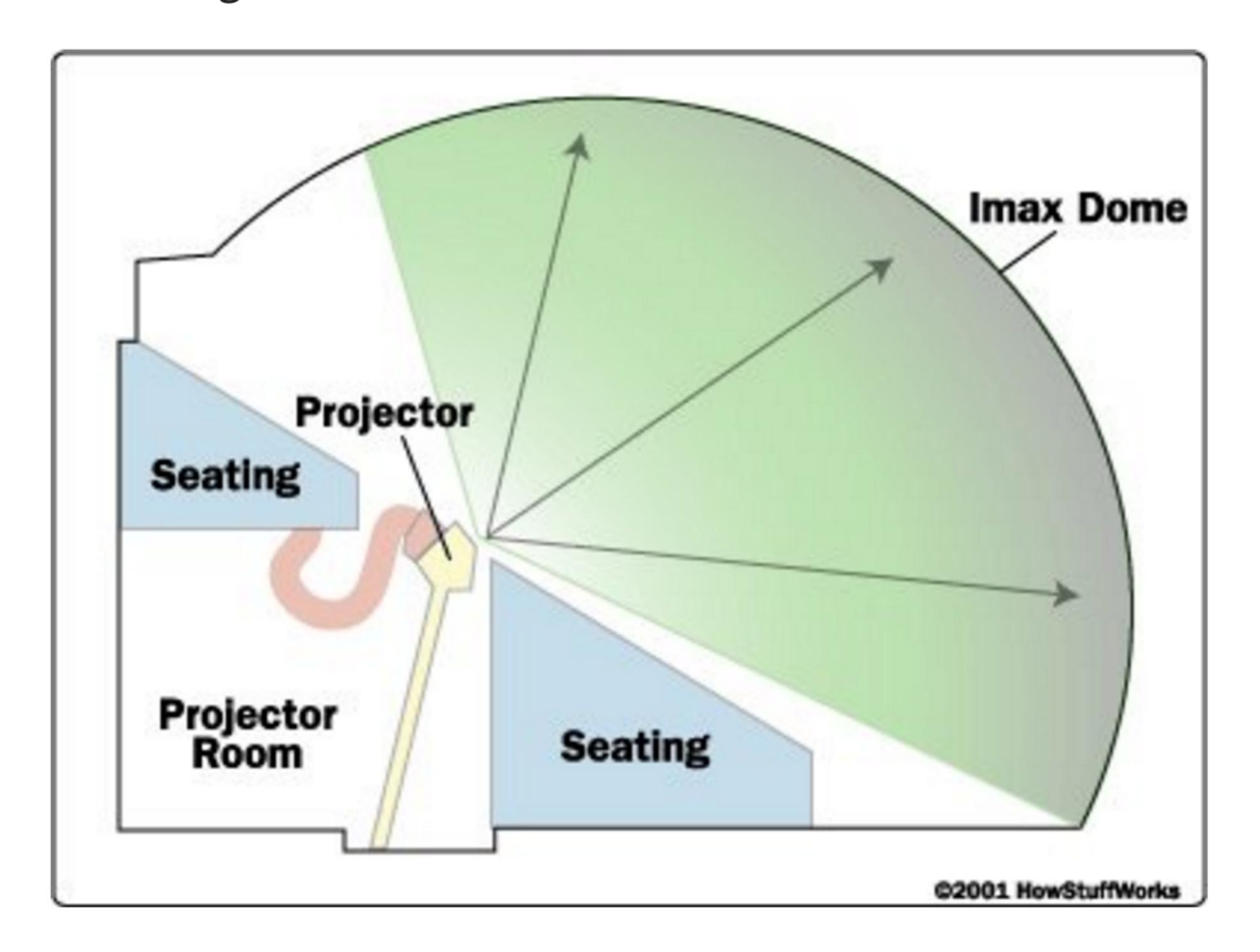




panoramic cameras



rendering for the imax dome



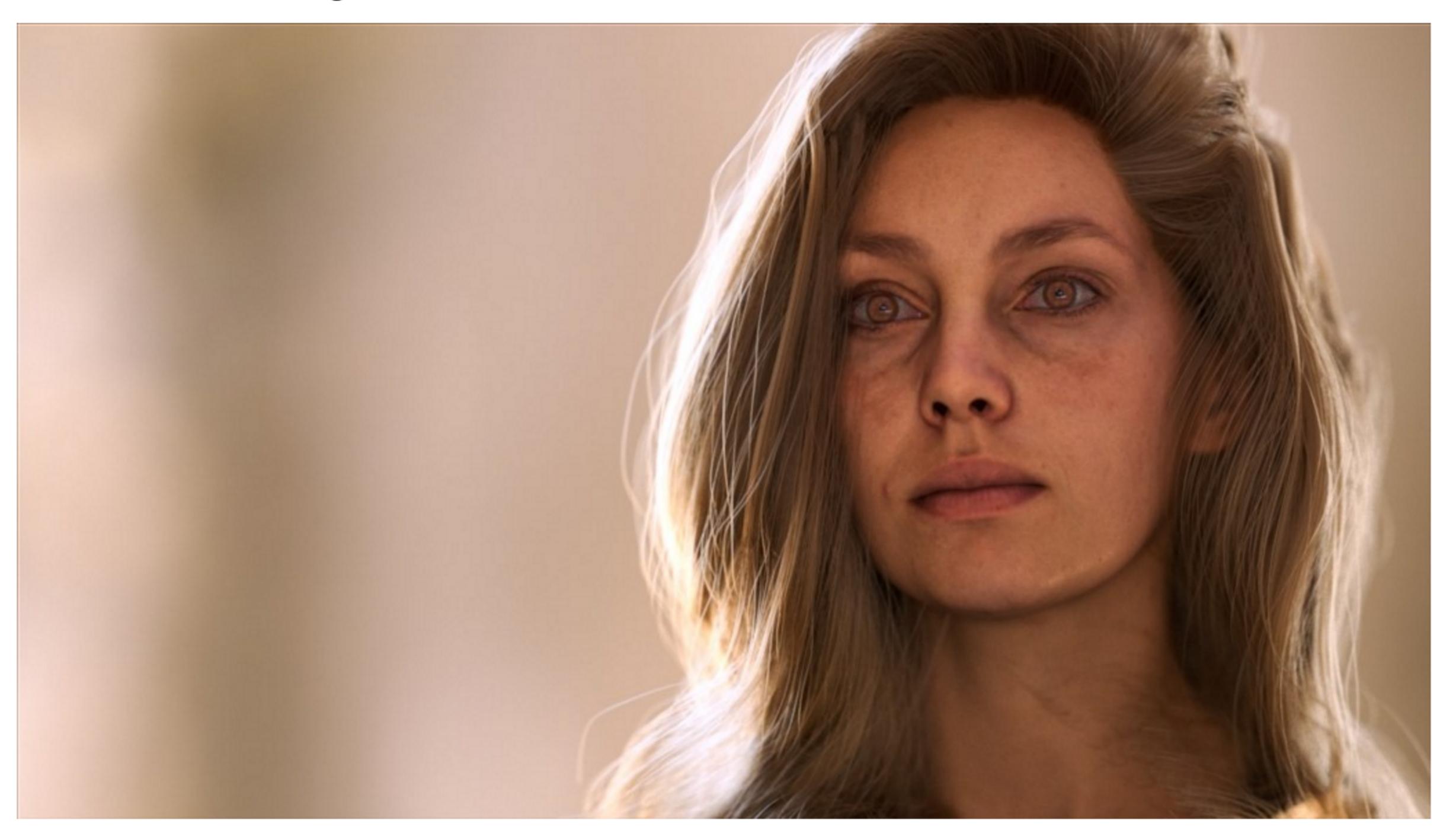
rendering for virtual reality





photorealistic rendering

flat and boring bokeh





photorealistic rendering

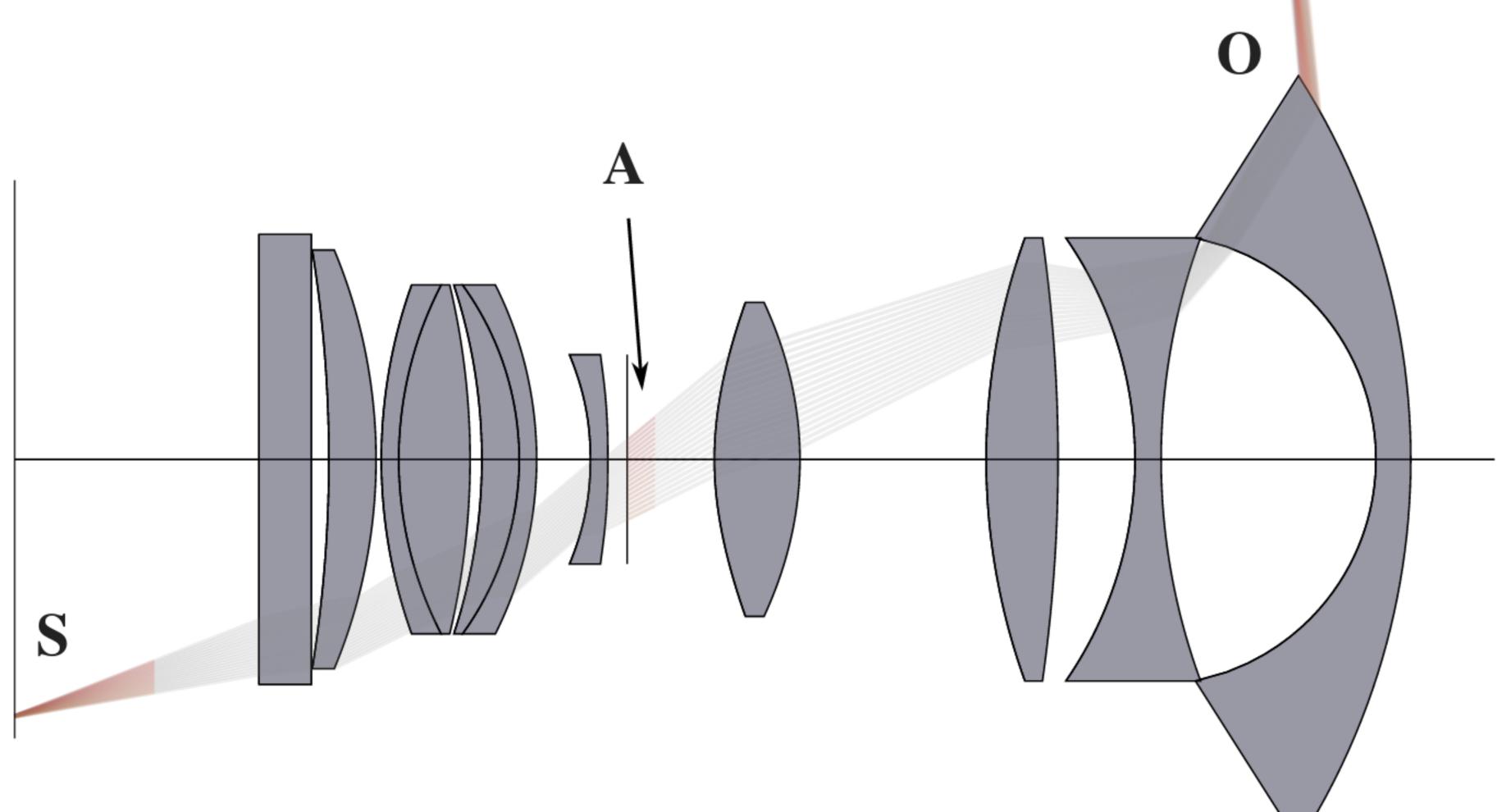
interesting bokeh, distortion, and vignetting to match plate





approximate lens systems with simple polynomial

- collapse complicated ray tracing
- ightharpoonup simple function evaluations $\mathbf{A} = P_a(\mathbf{S})$ and $\mathbf{O} = P_o(\mathbf{S})$



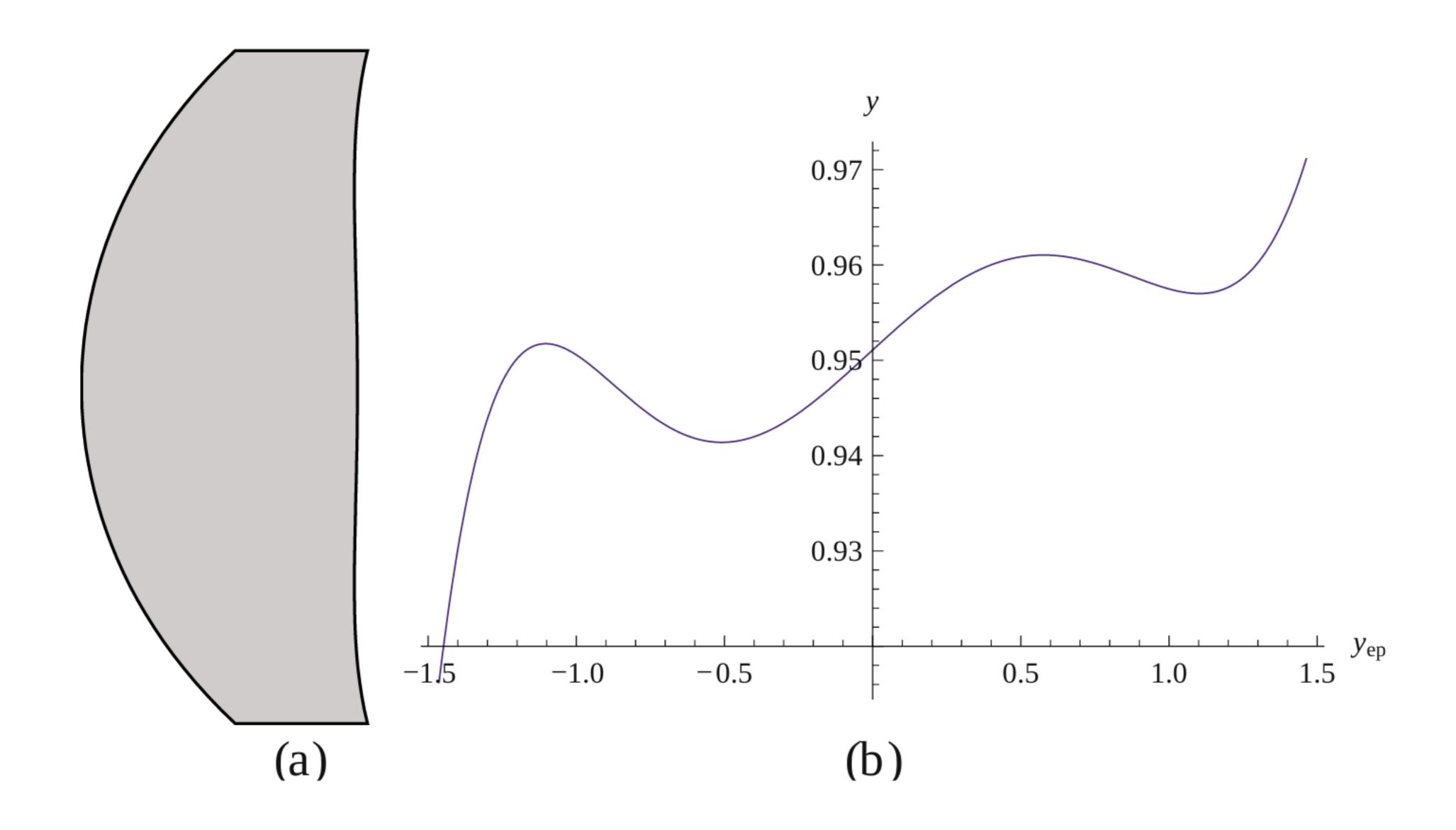
 $P_a(\mathbf{S}): (x_s, y_s, dx_s, dy_s, \lambda) \mapsto (x_a, y_a, dx_a, dy_a, \tau_a)$

 $P_o(\mathbf{S}): (x_s, y_s, dx_s, dy_s, \lambda) \mapsto (x_o, y_o, dx_o, dy_o, \tau_o)$



optics use polynomials to ray trace

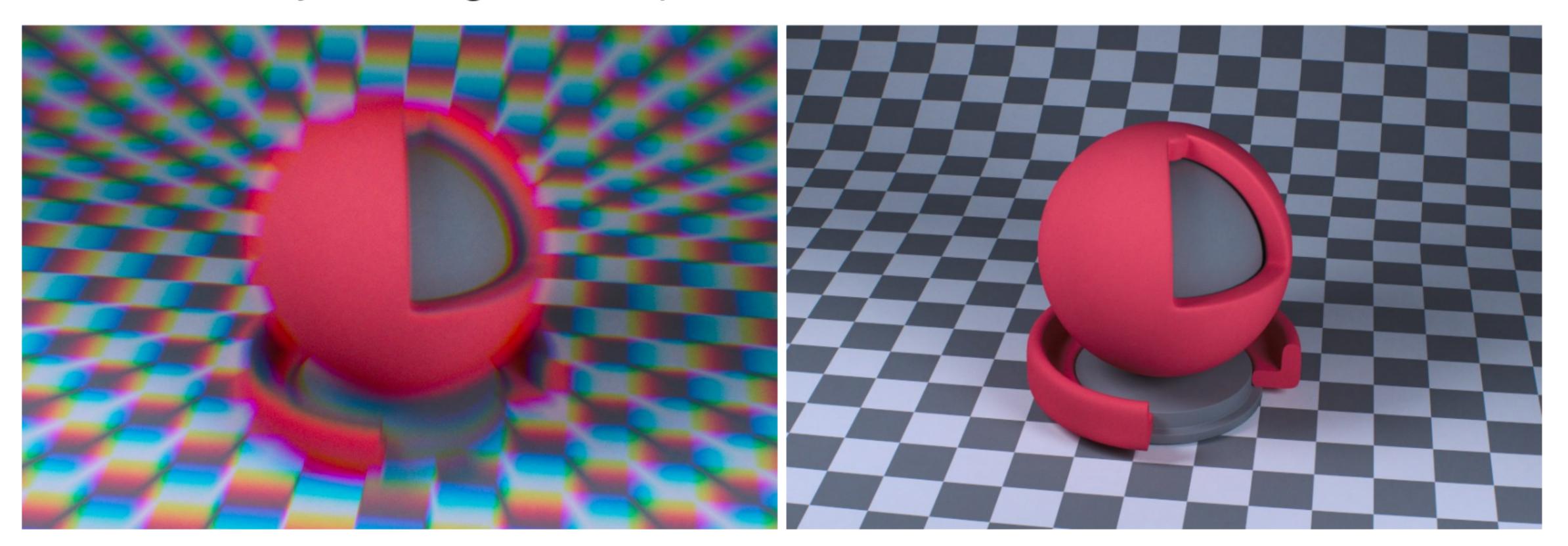
- approximate ray tracing using polynomials for lens designers [ZHB10]
- and analyse error in that domain directly





all based on Taylor expansion

- scary formulas for analytic differentiation required!
- not precise in outer rims [HD14]
 - use Taylor configuration, optimise coefficients





Taylor polynomials

- don't like cumbersome analytic Taylor expansions
 - needs pen and paper or computer algebra software
 - expand every lens element, insert, re-truncate polynomials
- want polynomial with only few coefficients (fast evaluation!)
- > and more precision (analytic Taylor expansion hardly tractable for high degree)
 - idea: select from higher-degree terms

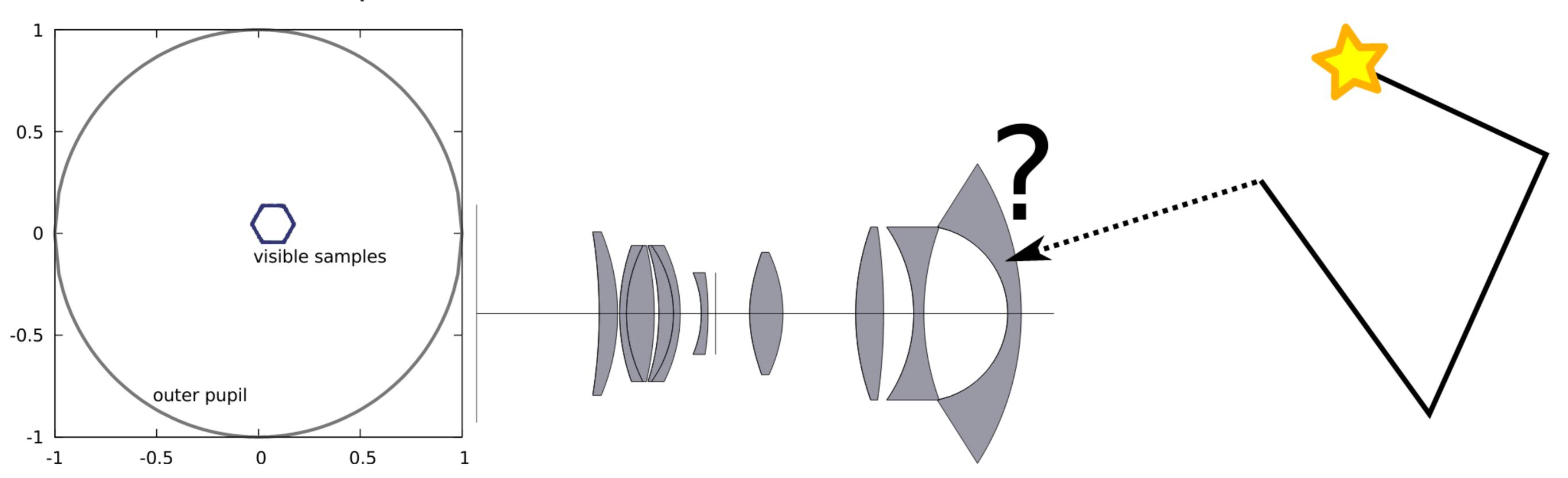
$$\cos x = \sum_{n=0}^{\infty} \frac{f^{(n)}(0)}{n!} x^n$$

$$= f(0) + f'(0)x + \frac{f''(0)}{2!}x^2 + \frac{f'''(0)}{3!}x^3 + \frac{f'''(0)}{4!}x^4 + \frac{f''(0)}{5!}x^5 + \cdots$$



fisheye lenses

- precision in periphery is important!
- current lens connections (for light tracing)
 - sample outer pupil uniformly
 - have terrible performance

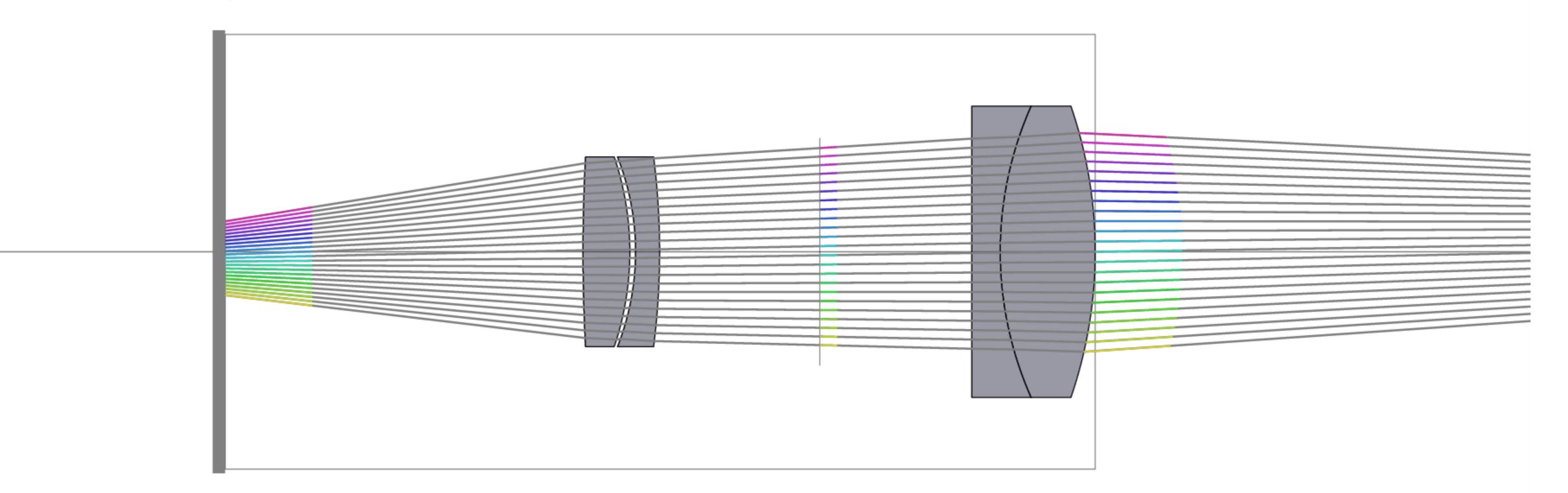




sampling the outer pupil

- why didn't we bother earlier?
 - not such a bad strategy for long lenses

petzval kodak

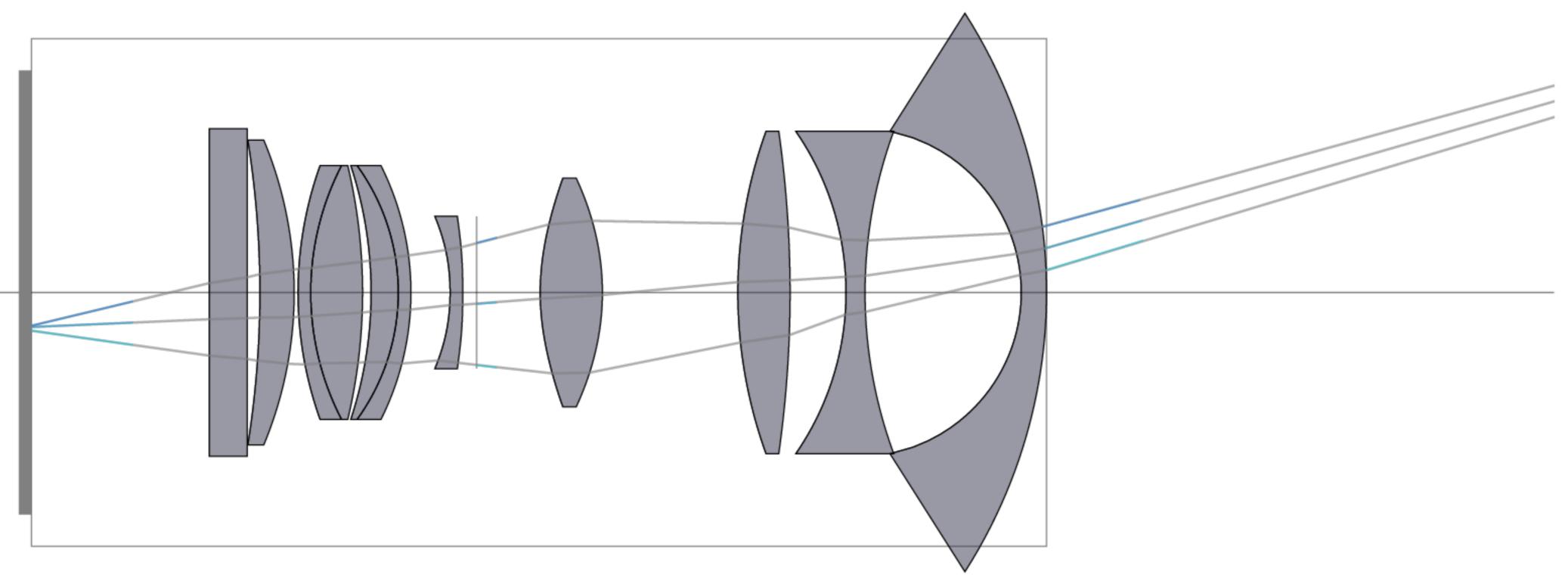




sampling the outer pupil

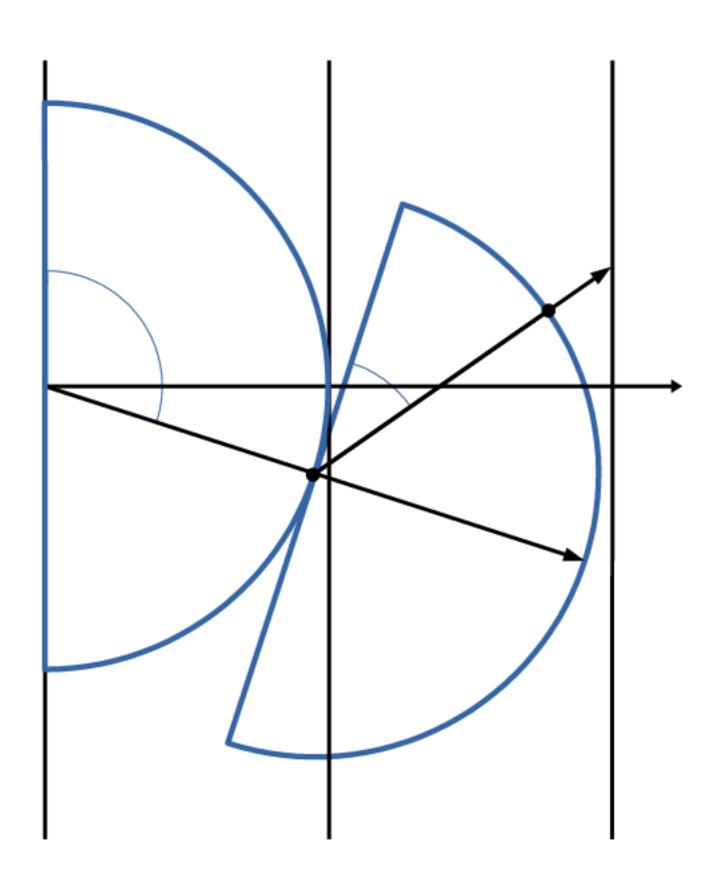
- why didn't we bother earlier?
 - but terrible for fisheyes

fisheye aspherical





- parametrise the light fields for fisheyes
 - no plane/plane 180-degree limit

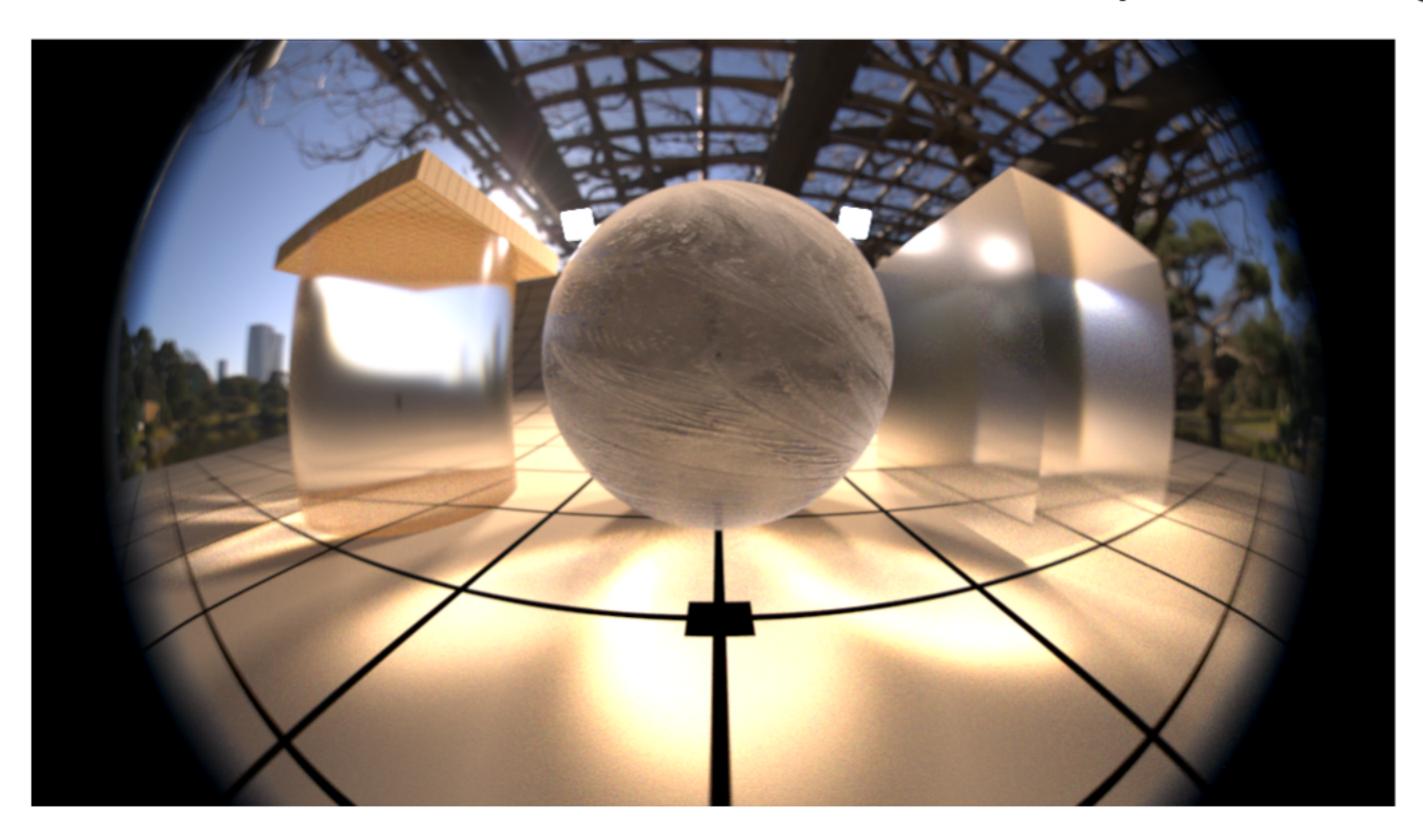




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 - no plane/plane 180-degree limit
- sparse fitting of high-degree polynomials
 - use orthogonal matching pursuit (OMP)
 - enables trade-off between approximation error and evaluation speed



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 - enable the use in bidirectional path tracing etc.

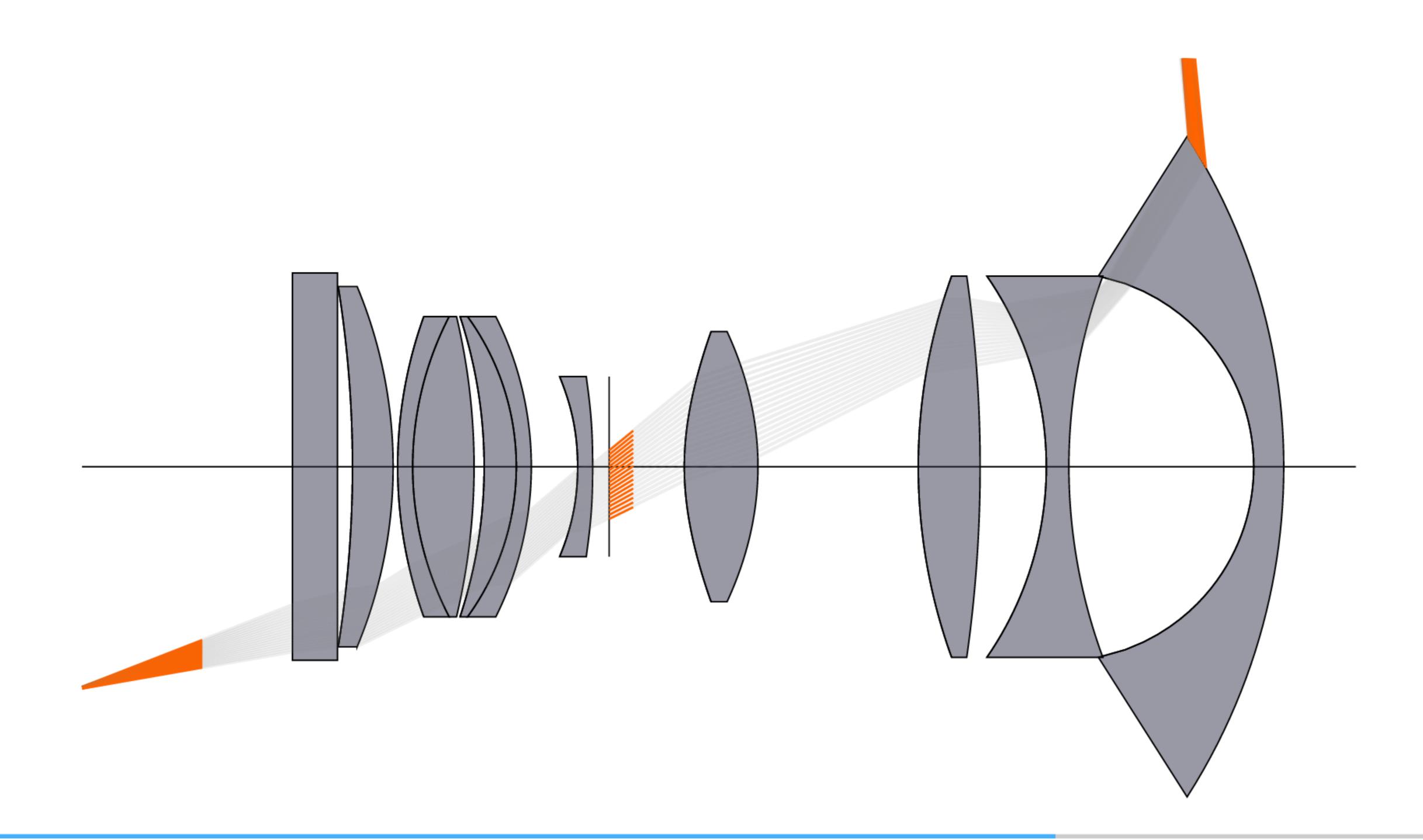




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- fast GPU preview rendering implementation

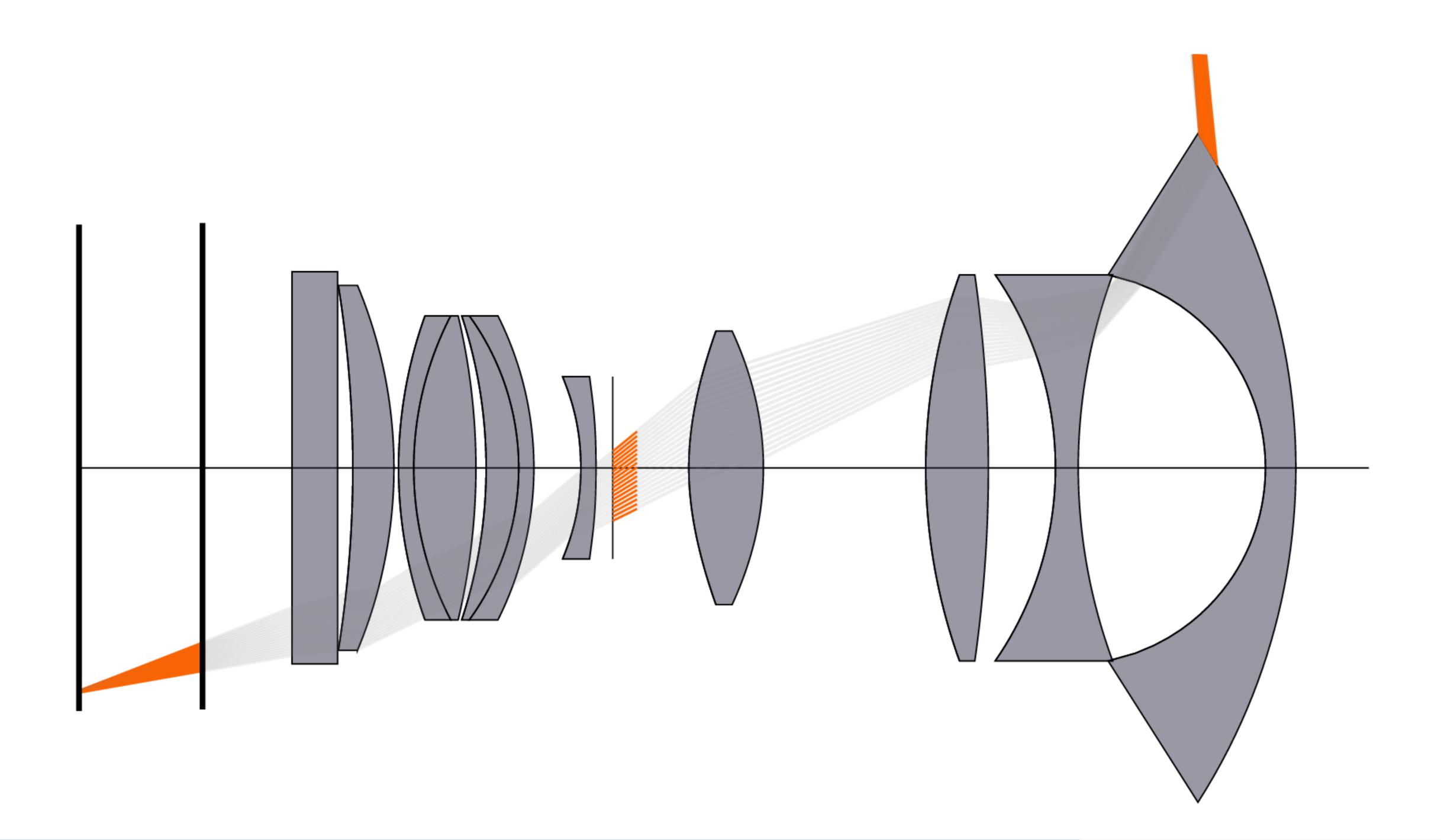






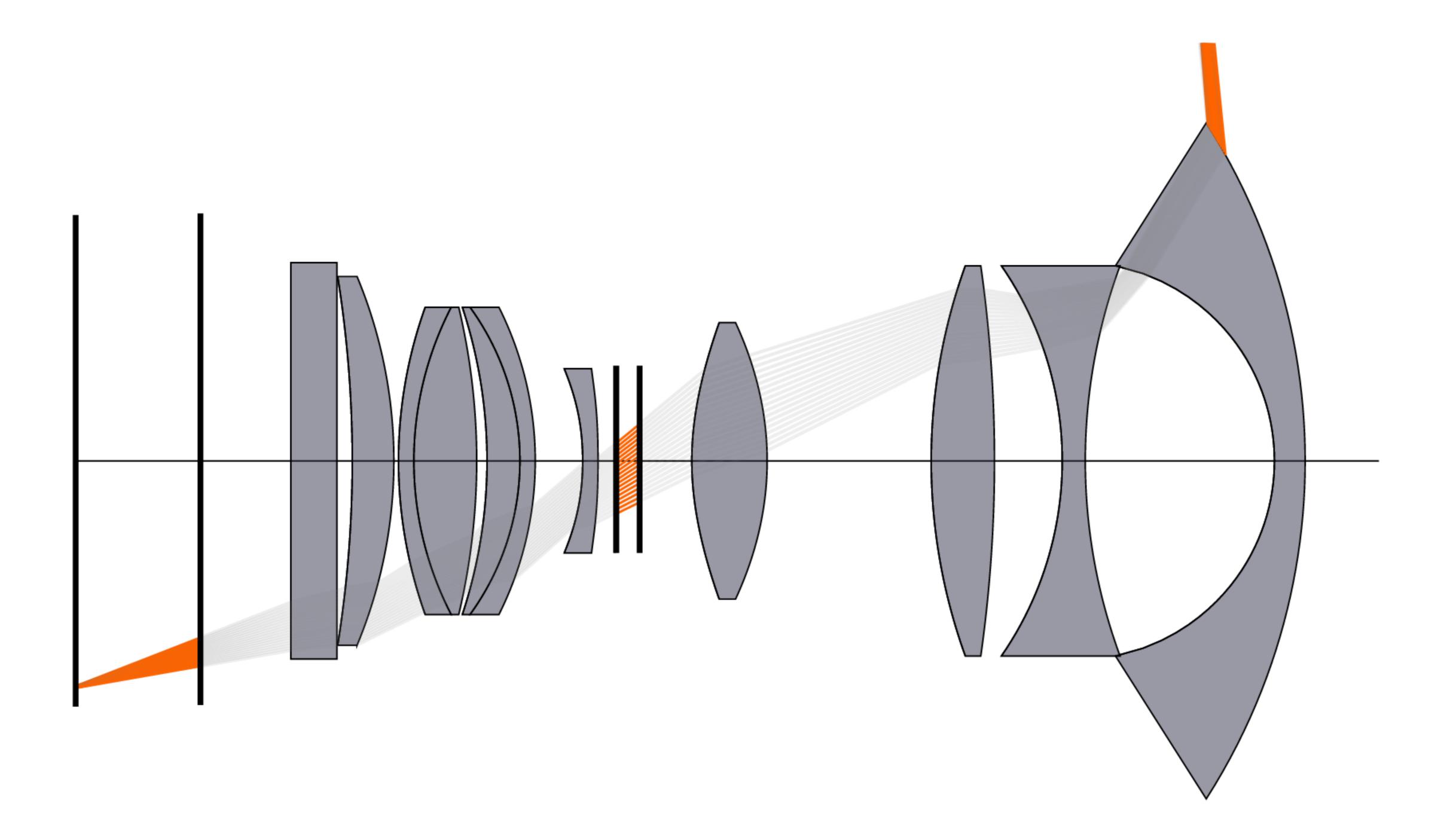


plane/plane on sensor



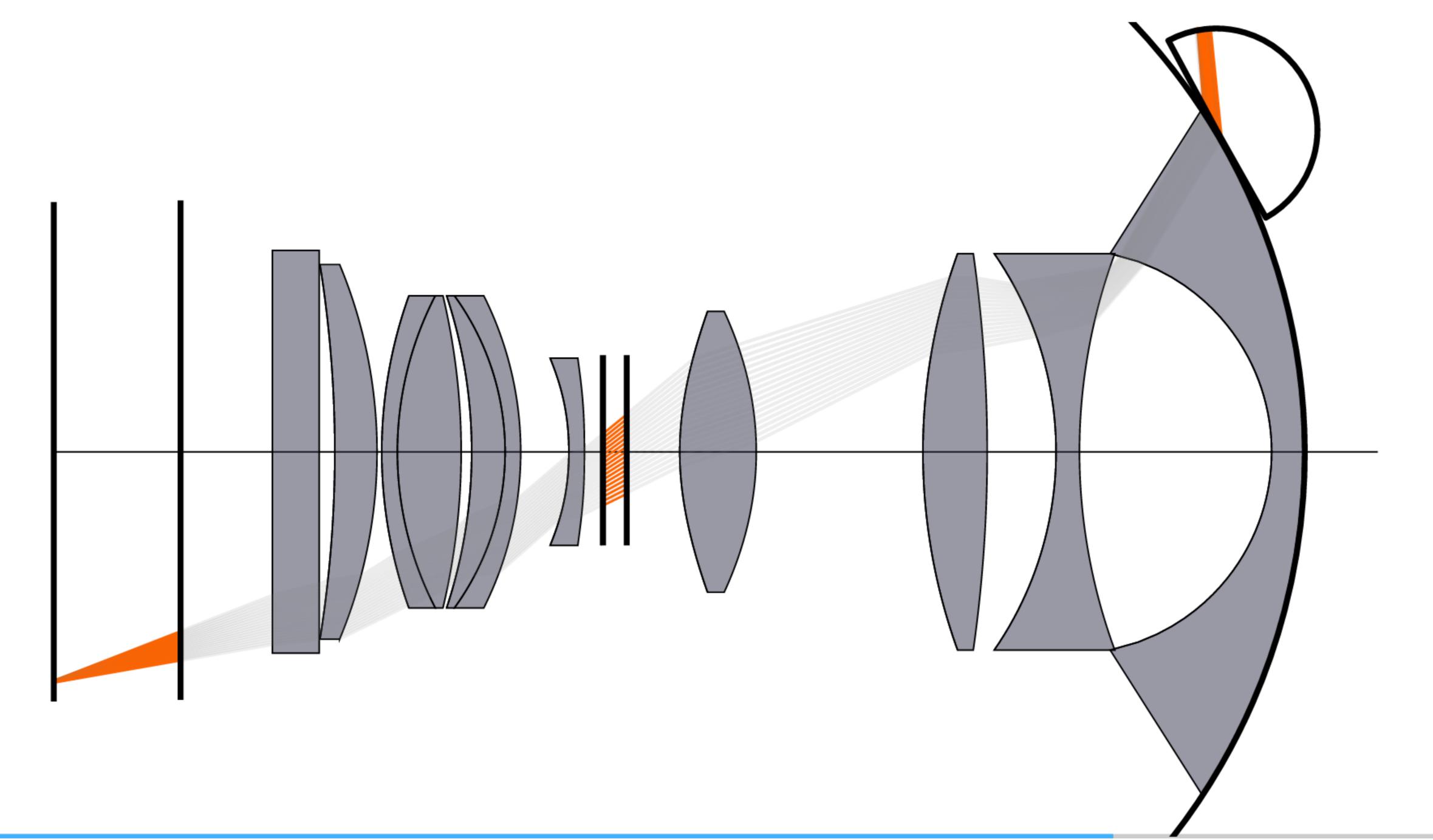


- plane/plane on sensor
- plane/plane on aperture

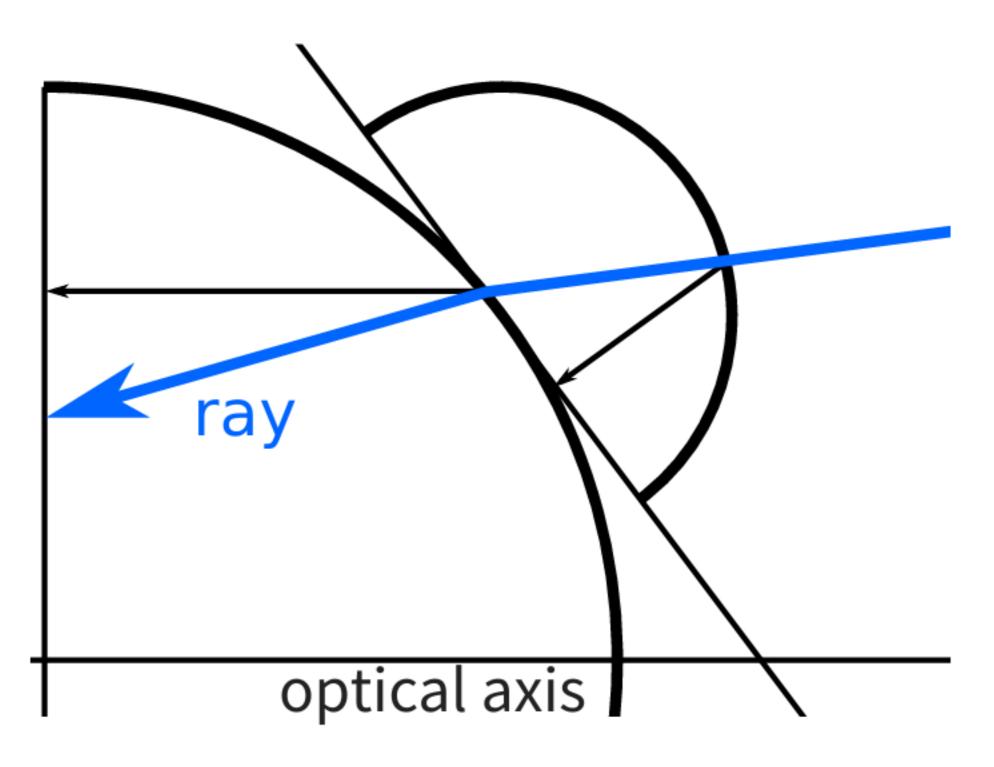




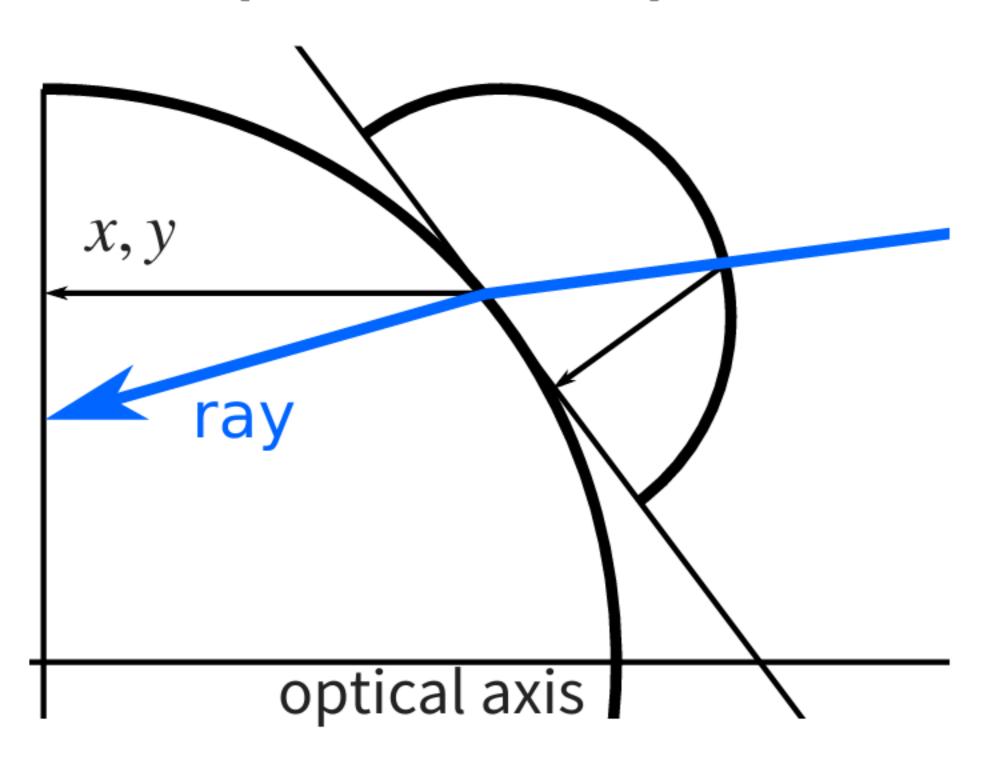
- plane/plane on sensor
- plane/plane on aperture
- hemi-sphere/hemi-sphere on outer pupil



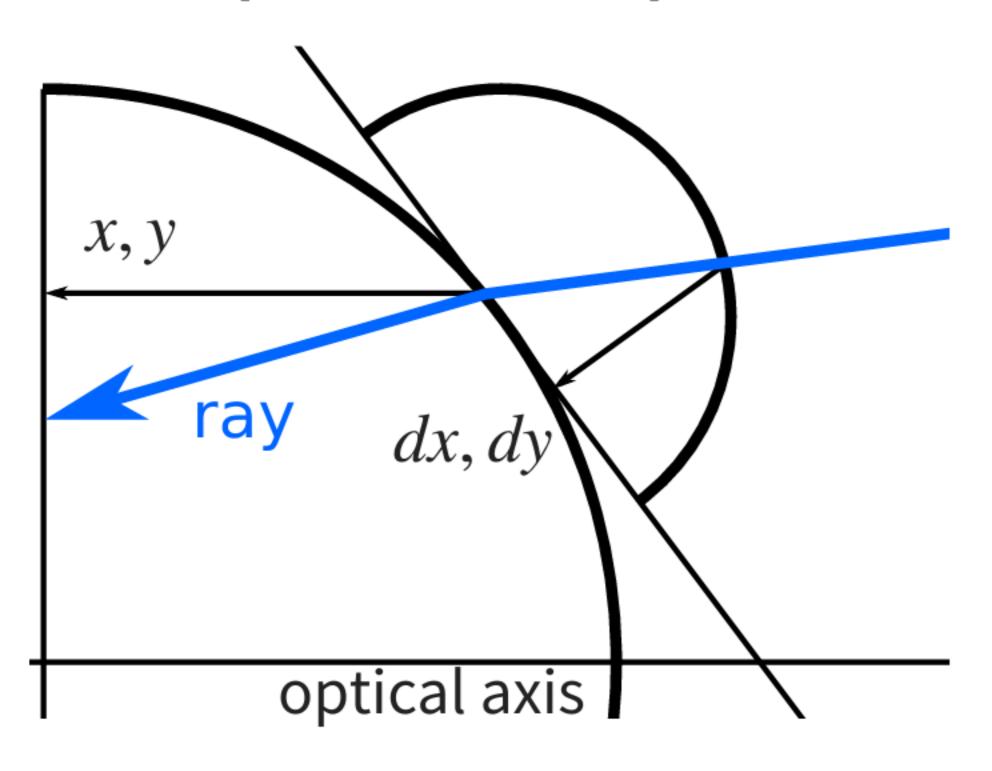




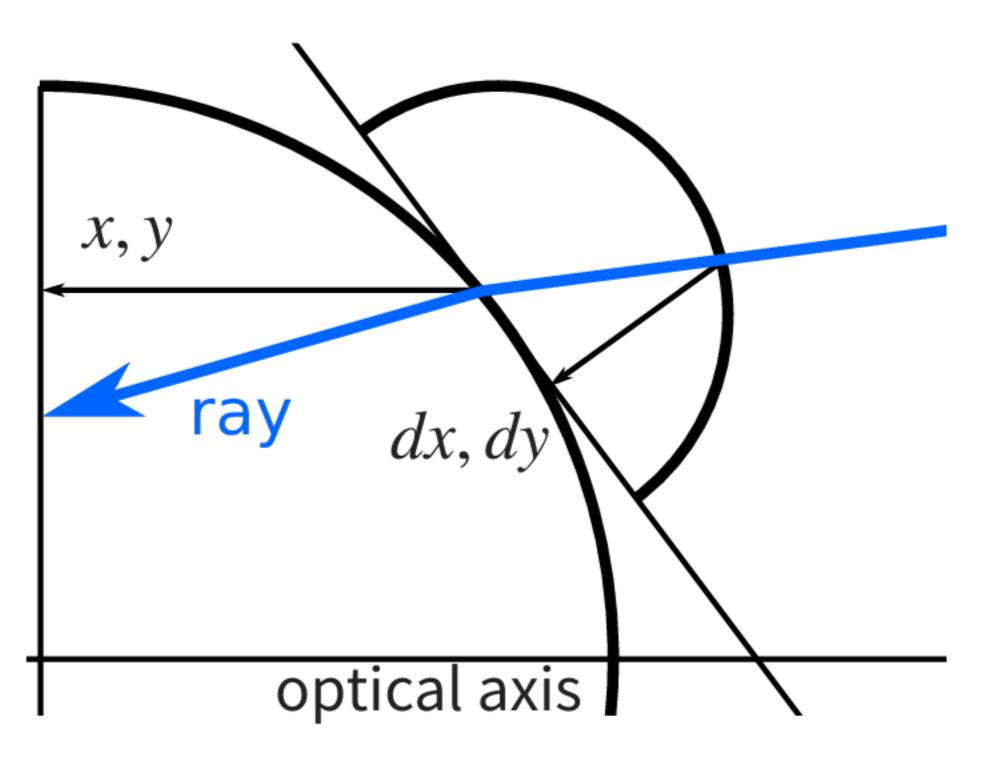




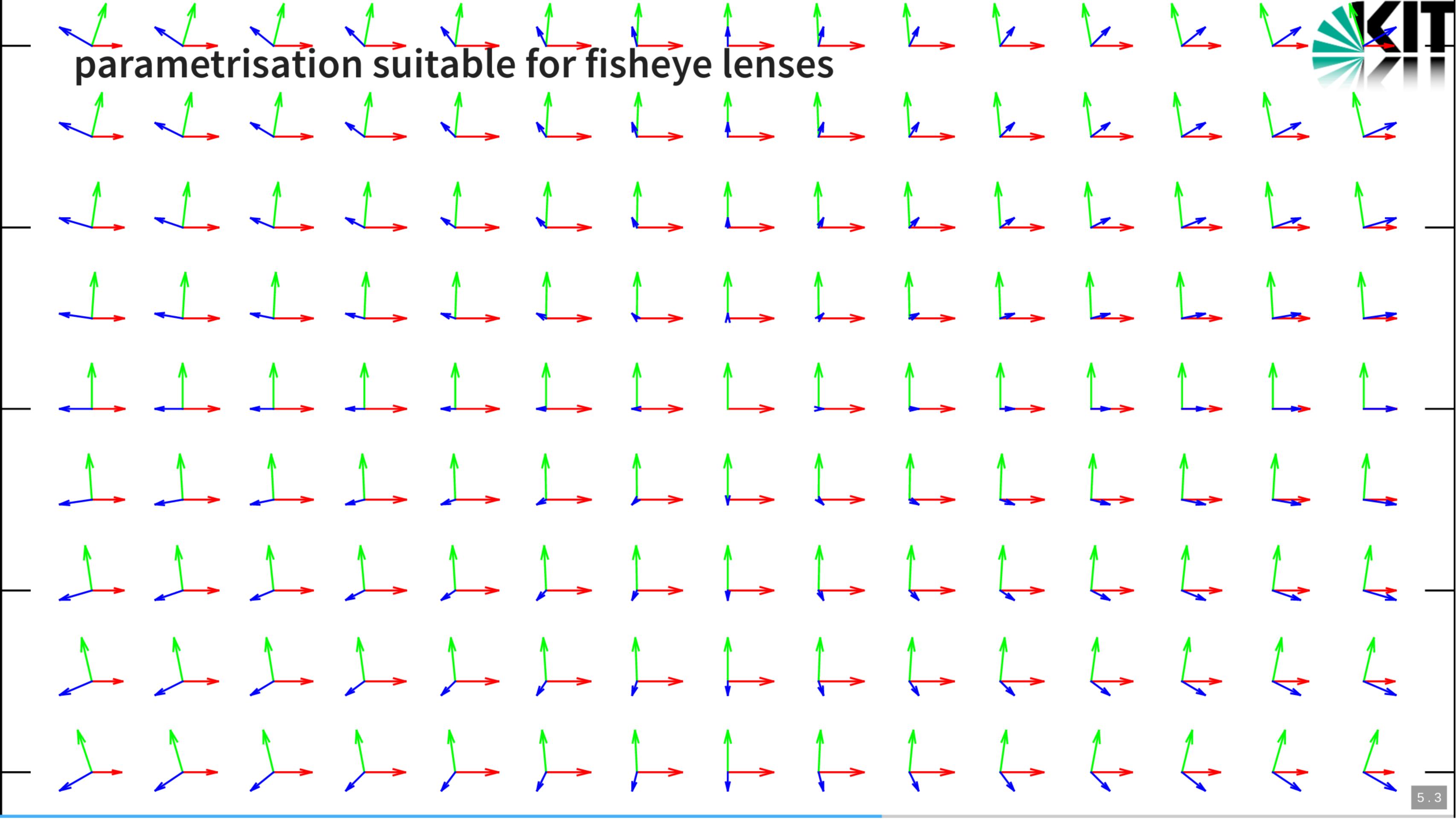








- \triangleright need to specify tangent frame for dx, dy
- avoid the singularity in interesting regions on the outer pupil





polynomial consists of these terms:

$$c \cdot \underbrace{\chi_s^{d_0} y_s^{d_1} d\chi_s^{d_2} dy_s^{d_3} \lambda_s^{d_4}}_{=:T_t} \text{ with degree } \sum_{i=0}^4 d_i \le d$$



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- find most closely matching polynomial for given set of ray traced reference samples
 - linear problem, Galerkin projection of function $\mathbf{O} = P_o(\mathbf{S})$ to

$$\mathbf{O} \approx \hat{\mathbf{\Phi}} \cdot \mathbf{c}$$

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- standard procedure (linear least squares), but the matrix is too large for our taste!



finding a sparse polynomial

- use orthogonal matching pursuit [TG07]
- $hinkspace iteratively select most important columns in <math>\hat{\Phi}$

$$\hat{\Phi} \cdot \mathbf{c} = \begin{pmatrix} T_1 & T_2 & T_3 & \cdots & T_{N-1} & T_N \\ T_1 & T_2 & T_3 & \cdots & T_{N-1} & T_N \\ \cdots & & & & & \\ T_1 & T_2 & T_3 & \cdots & T_{N-1} & T_N \end{pmatrix} \cdot \begin{pmatrix} c_1 \\ c_2 \\ c_3 \\ \vdots \\ c_{N-1} \\ c_N \end{pmatrix} \approx \mathbf{O}$$



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- original just looks for largest impact on residual (fast)
- we got better results by re-fitting all coefficents c of all previously selected columns in the inner loop (somewhat slower)
- details see the paper



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we use up to 40 coefficients per equation (out of 4368 for degree 11)



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 - in particular no analytic Taylor expansion required!



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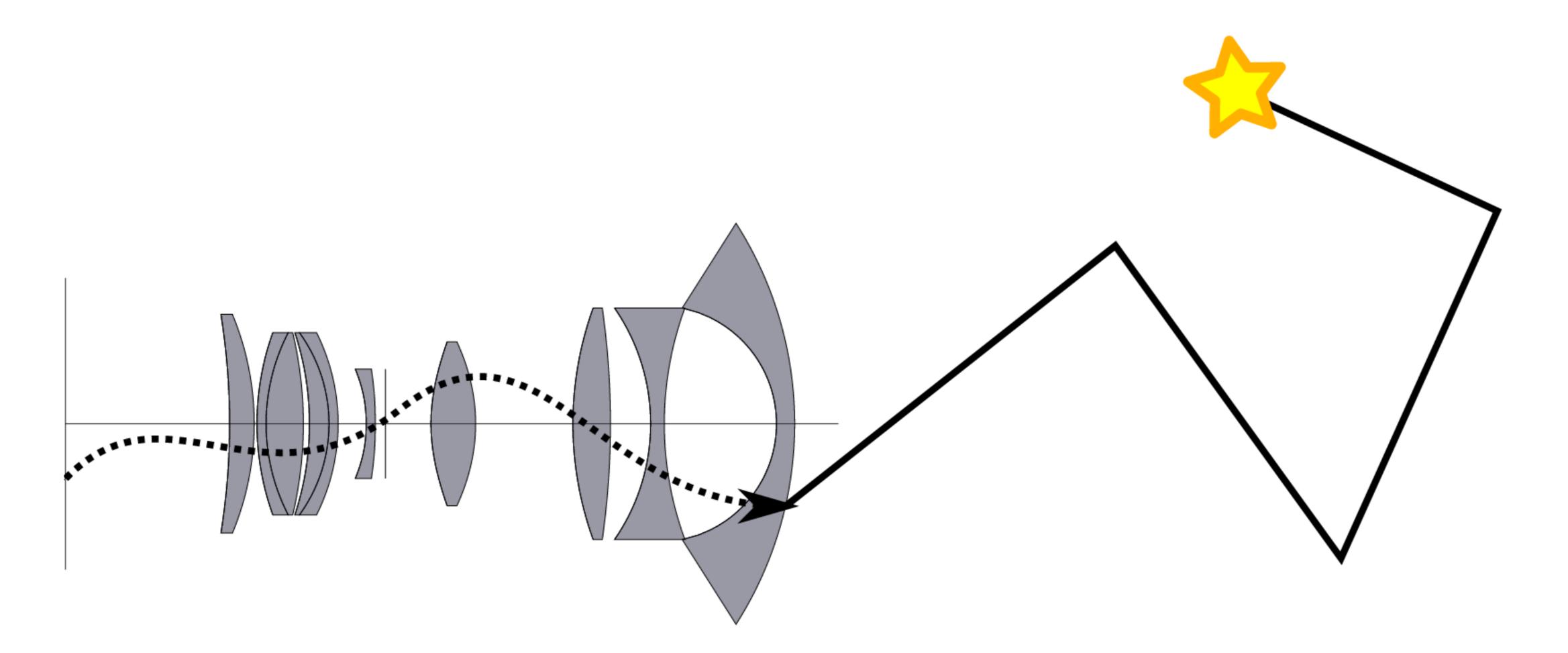
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- we use up to 40 coefficients per equation (out of 4368 for degree 11)
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- \triangleright we also fit Fresnel transmittance τ to support coatings



use polynomials for path tracing

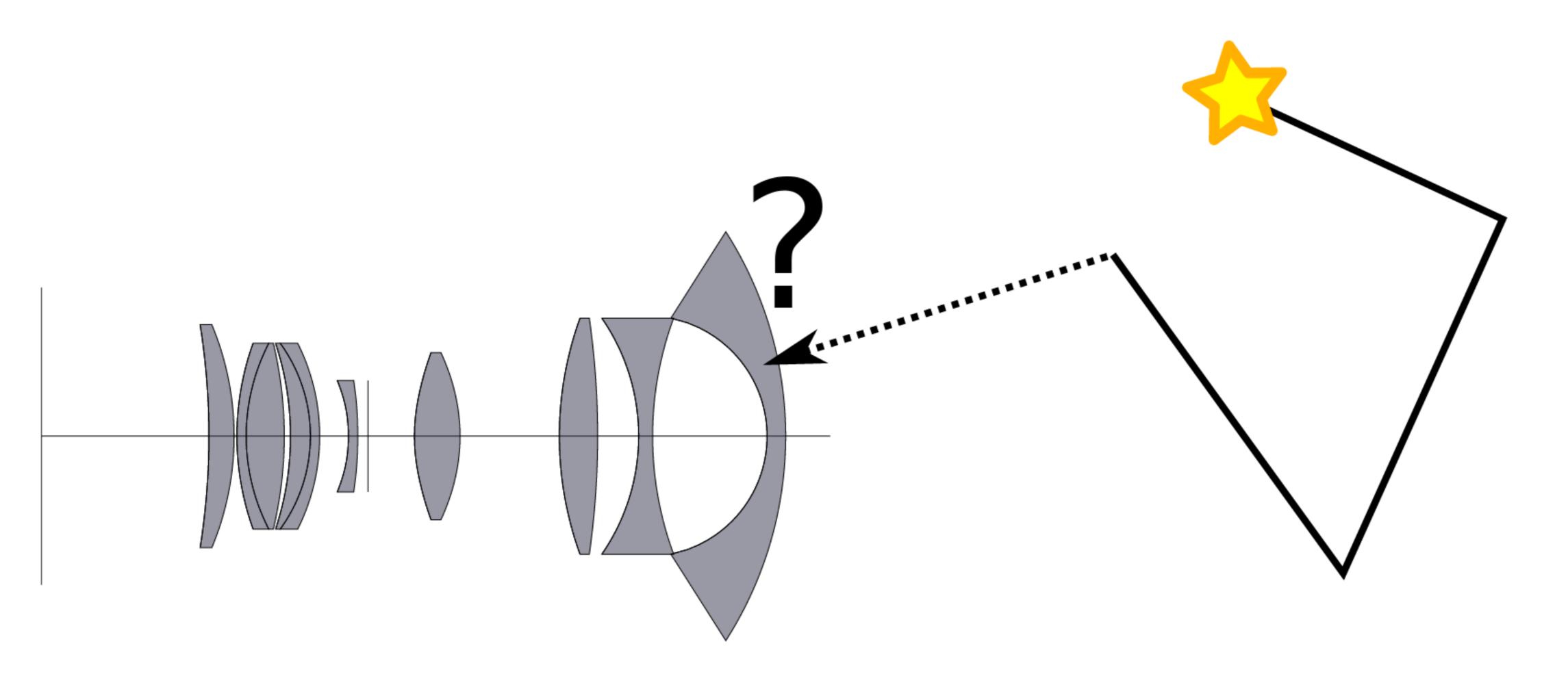
- we know how do do this for path tracing from the camera
- efficiently by sampling the aperture [HD14]:
 - sample point on aperture
 - iteratively find position and direction on sensor
- require derivatives of polynomial
 - Newton's method





use polynomials for light tracing

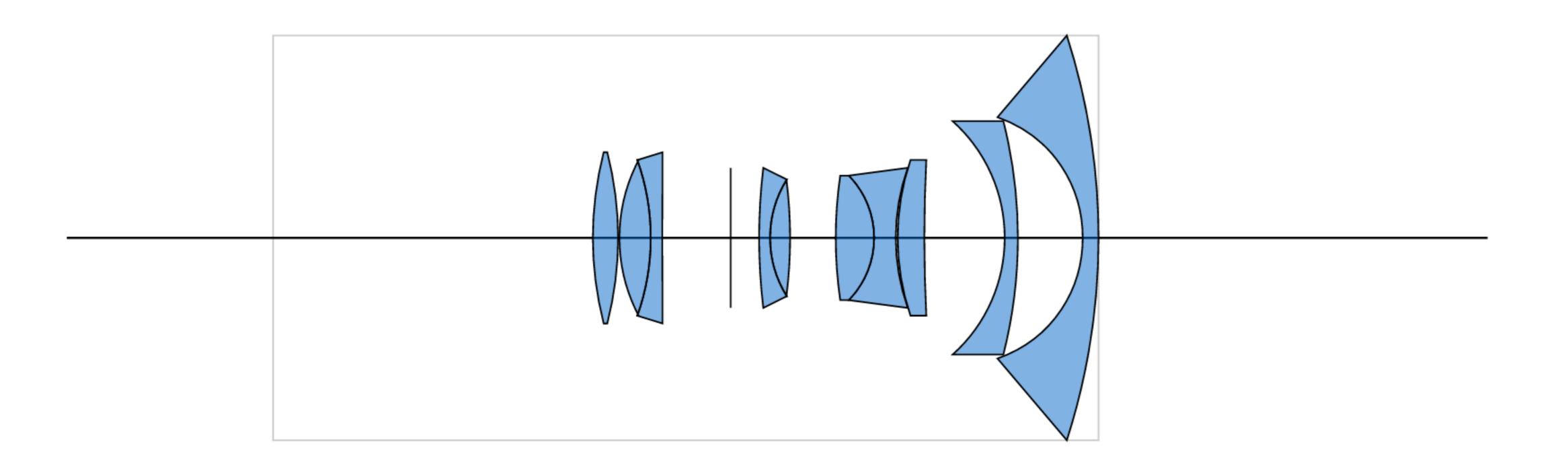
- light tracing/deterministic camera connection?
 - sample point on aperture
 - keep point in scene fixed
 - iteratively find position and direction on sensor
- transform probability densities for multiple importance sampling
 - details see the paper





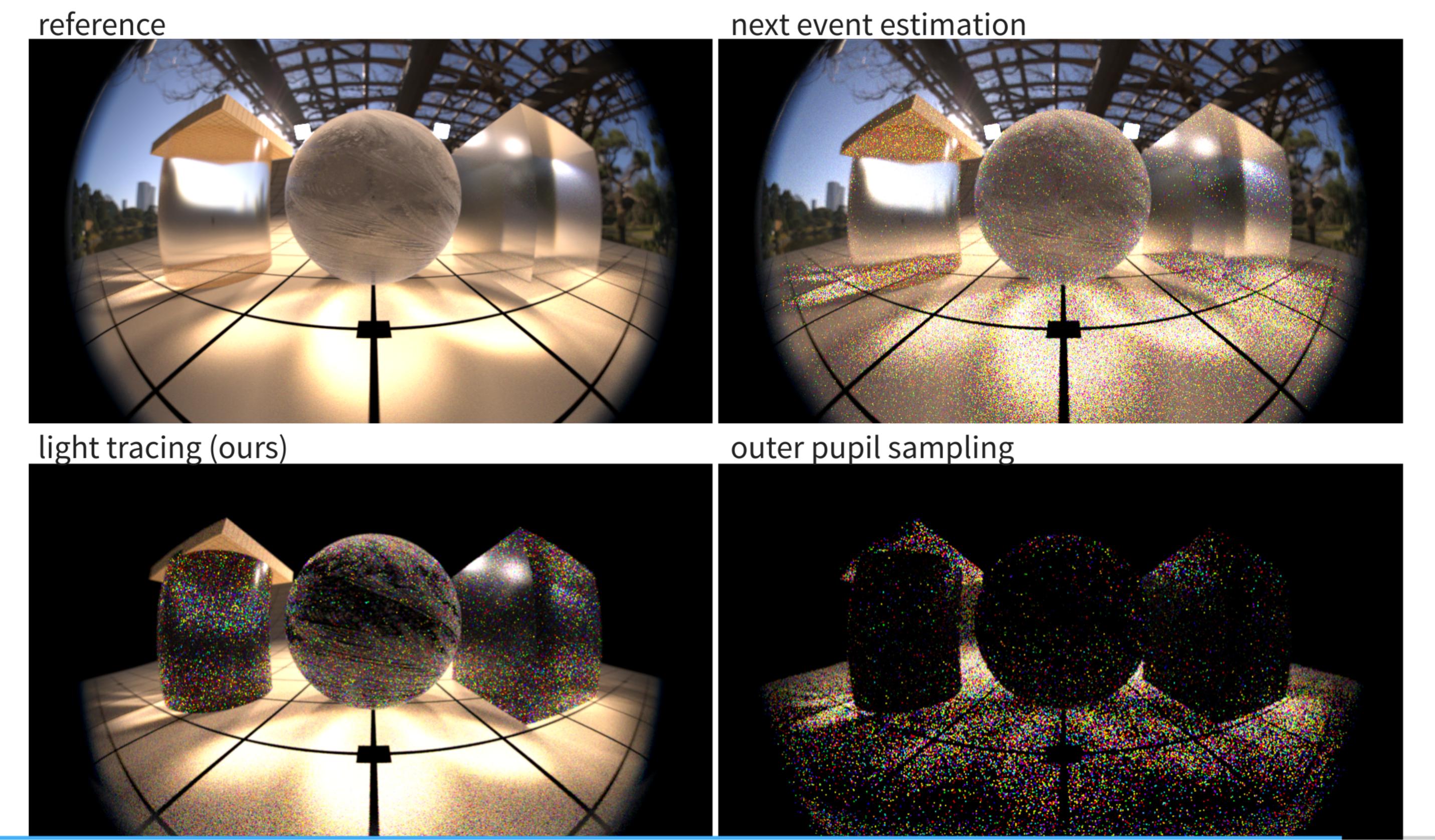
aperture sampling via 2-step Newton iteration

- initial guess: straight on optical axis
- ▶ aperture error ⇒ update sensor direction
- ▶ error in outgoing direction ⇒ update sensor position



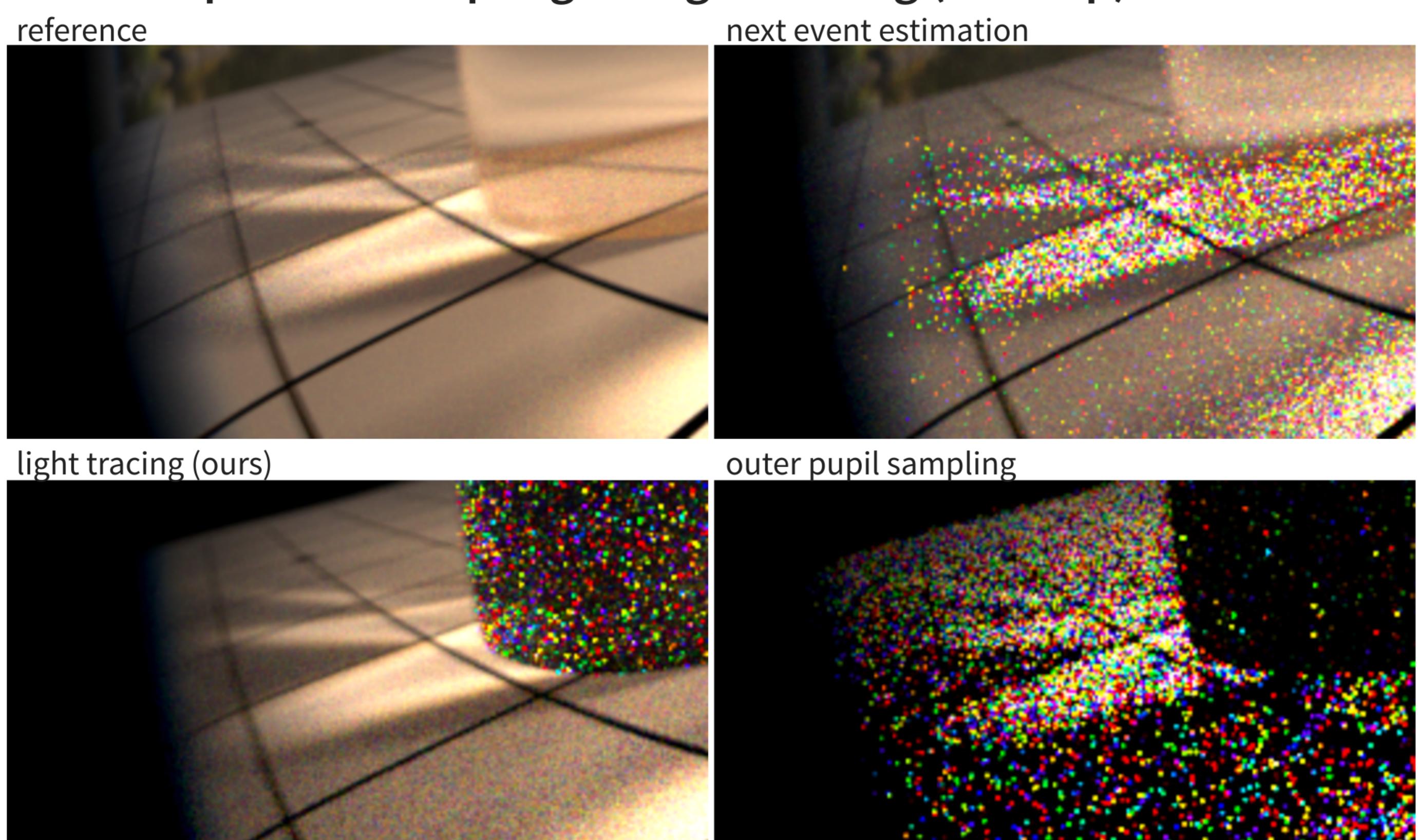


results: aperture sampling for light tracing (512spp)



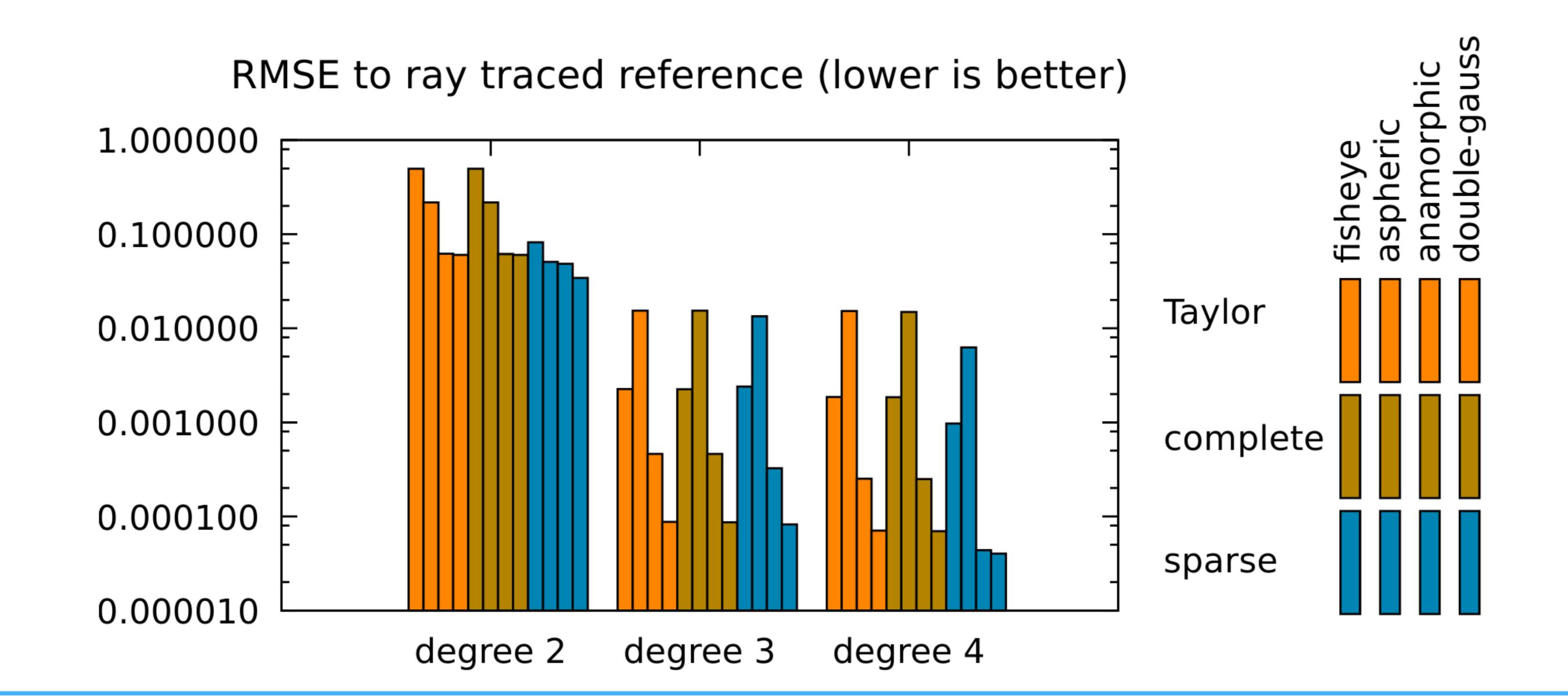


results: aperture sampling for light tracing (closeup)



results: accuracy of sparse polynomials

- almost always better than Taylor or full polynomials (use higher degree terms!)
 - Taylor and complete: same degree (2, 3, 4)
 - Taylor and sparse: same number of coefficients
 - analytic Taylor expansion past degree 4 becomes very hard





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	coeffs	fisheye	aspheric	anamorphic	double-gauss
Taylor 2	4	4.97 · 10 -1	$2.17 \cdot 10 - 1$	6.18 · 10 -2	6.03 · 10 -2
Complete 2	21	4.97 · 10 -1	2.17 · 10 -1	6.17 · 10 -2	6.02 · 10 -2
Sparse	4	8.21 · 10 -2	5.07 · 10 -2	4.85 · 10 −2	3.43 ⋅ 10 −2
Taylor 3	16	2.26 · 10 -3	1.54 · 10 -2	4.63 · 10 -4	8.76 · 10 -5
Complete 3	56	2.25 · 10 -3	1.54 · 10 -2	4.62 · 10 -4	8.69 · 10 -5
Sparse	16	2.40 · 10 -3	1.34 · 10 -2	3.25 ⋅ 10 −4	8.22 · 10 -5
Taylor 4	28	1.86 · 10 -3	1.52 · 10 -2	2.52 · 10 -4	7.07 · 10 -5
Complete 4	126	1.85 · 10 -3	1.49 · 10 -2	2.50 · 10 -4	6.98 · 10 -5
Sparse	28	9.72 · 10 -4	6.26 · 10 -3	4.40 · 10 -5	4.02 · 10 -5



real time implementation

- works on deep image buffer data (here from [ZKP13])
- evaluate generated polynomial code in GLSL shader
- proof-of-concept implementation
 - 137 ms, 1080x720 px, 144 spp, AMD Radeon R9 390
 - limited by texture fetches more than by lens evaluation
- performance can probably be improved a lot by doing something smarter
 - e.g. Deferred Image-based Ray Tracing/HPG talk on Tuesday...
 - or with rasterisation (Comparison of Projection Methods for Rendering Virtual Reality)







conclusion

- more precise polynomials
 - higher degree terms, still sparse (fast)
- simpler construction
 - no Taylor expansion (which becomes untractable for higher degrees)
- now also practical for bidirectional/Metropolis
 - aperture sampling for light tracing
- proof of concept GPU implementation
- source code available

