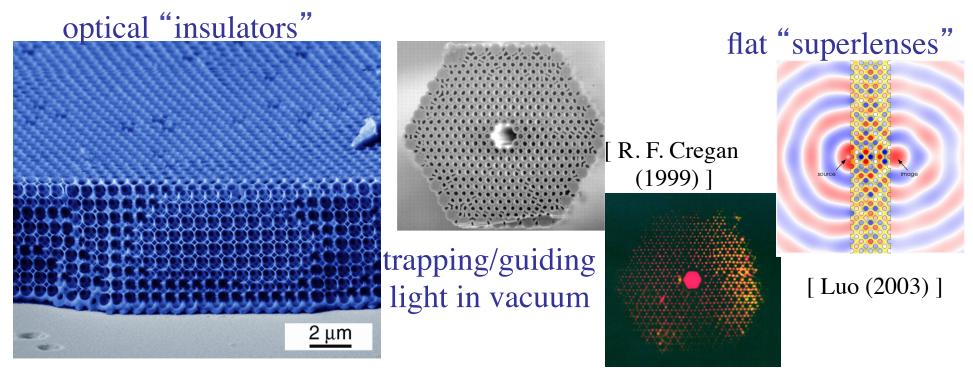
Computational Nanophotonics: Band diagrams and Eigenproblems

> Steven G. Johnson MIT Applied Mathematics

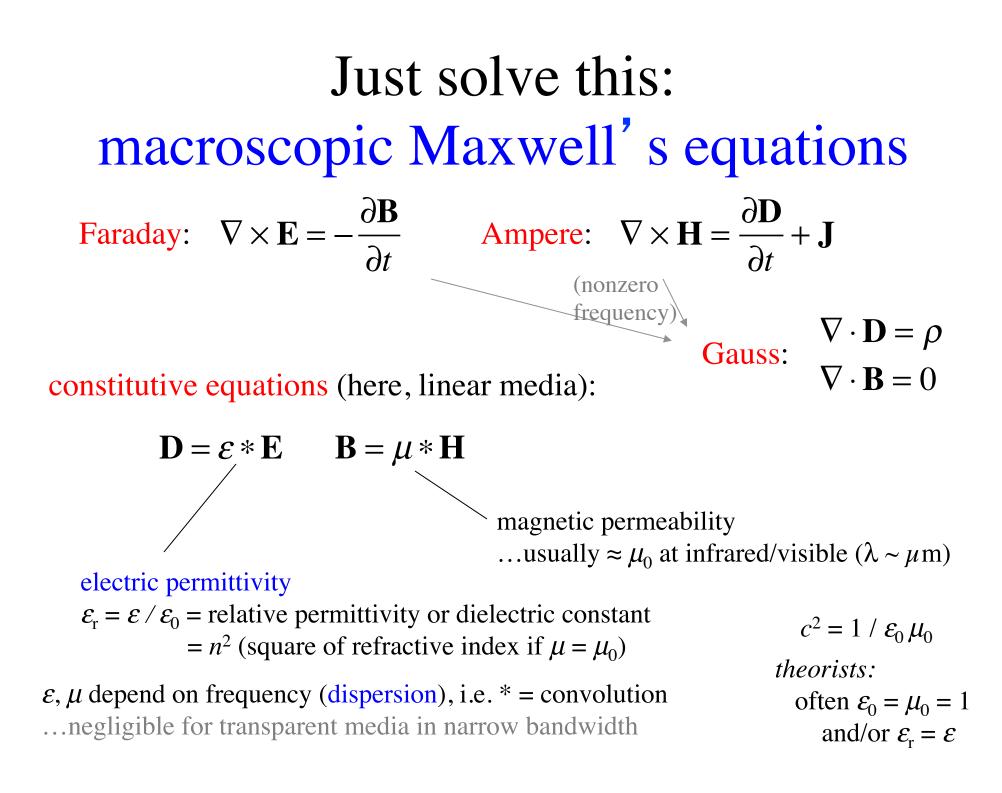
#### Nanophotonics:

classical electromagnetic effects can be greatly altered by  $\lambda$ -scale structures especially with *many* interacting scatterers



[ D. Norris, UMN (2001) ]

easy to study numerically (methods are "practically exact"), well-developed scalable 3d methods for arbitrary materials



# Limits of validity at the nanoscale?

- Continuum material models (*ɛ* etc.) have generally proved very successful down to ~ few nm feature sizes
   [For metal features at < 20nm scale, some predictions of
   small nonlocal effects (ballistic transport), but this is mostly neglected ]</li>
- Phenomena from resonant ~ nm features <<  $\lambda$  (e.g. spontaneous emission) usually can be incorporated perturbatively / semiclassically

(e.g. spontaneous emission ~ stochastic dipole source, spontaneous emission rate ~ local density of states ~ power radiated by dipole)

#### first, some perspective...

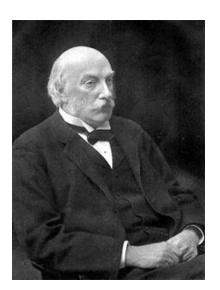
#### Development of Classical EM Computations

#### 1 Analytical solutions

vacuum, single/double interfaces various electrostatic problems, ...



James Clerk Maxwell,



scattering from small particles, periodic multilayers (Bragg mirrors), ...

> ... & other problems with very high symmetry and/or separability and/or small parameters

Lord Rayleigh

Development of Classical EM Computations

 Analytical solutions

2 Semi-analytical solutions: series expansions



Gustav Mie (1908)

e.g. Mie scattering of light by a sphere

#### Also called *spectral methods*:

Expand solution in rapidly converging Fourier-like basis

• spectral integral-equation methods:

exactly solve homogeneous regions (Green's func.),
& match boundary conditions via spectral basis
(e.g. Fourier series, spherical harmonics)

• spectral PDE methods:

spectral basis for unknowns in inhomogeous space(e.g. Fourier series, Chebyshev polynomials, ...)& plug into PDE and solve for coefficients

Development of Classical EM Computations

 Analytical solutions

#### 2 Semi-analytical solutions & spectral methods



Expand solution in *rapidly converging Fourier-like basis* e.g. Mie scattering of light by a sphere

Strength: can converge *exponentially fast* 

- fast enough for hand calculation
- analytical insights, asymptotics, ...

Gustav Mie (1908) Limitation: fast ("spectral") convergence requires basis to be redesigned for each geometry (to account for any discontinuities/singularities ... complicated for complex geometries!)

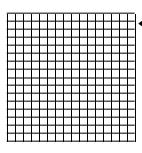
(Or: brute-force Fourier series, polynomial convergence)

Development of Classical EM Computations

 Analytical solutions

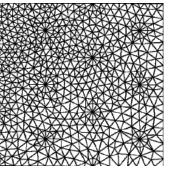
- 2) Semi-analytical solutions & spectral methods
- 3 Brute force: generic grid/mesh (or generic spectral)

PDEs: discretize space into grid/mesh
— simple (low-degree polynomial) approximations in each pixel/element



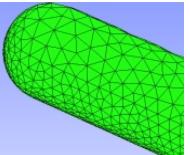
-finite differences
(or Fourier series)

& finite elements  $\rightarrow$ 



integral equations:

 boundary elements mesh surface unknowns coupled by Green's functions



lose orders of magnitude in performance … *but* re-usable code € computer time << €€€ programmer time

# Computational EM: Three Axes of Comparison

- What *problem* is solved?
- eigenproblems: harmonic modes ~  $e^{-i\omega t}$  (**J** = 0)
- frequency-domain response: **E**, **H** from  $J(\mathbf{x})e^{-i\omega t}$
- time-domain response: **E**, **H** from  $J(\mathbf{x}, t)$
- PDE or integral equation?

- What *discretization*? infinitely many unknowns
  - $\Rightarrow$  finitely many unknowns
- What *solution method*?

- finite differences (FD)
- finite elements (FEM) / boundary elements (BEM)
- spectral / Fourier

— ...

- dense linear solvers (LAPACK)
- sparse-direct methods
- iterative methods

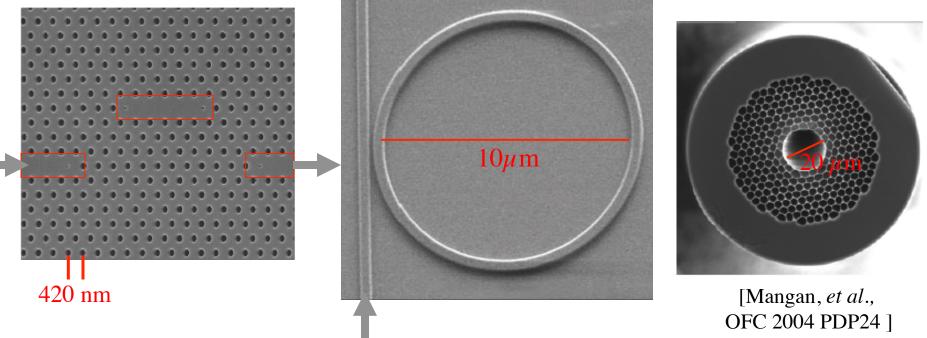
#### A few lessons of history

- All approaches still in widespread use
  - brute force methods in 90%+ of papers, typically the first resort to see what happens in a new geometry
  - geometry-specific spectral methods still popular, especially when particular geometry of special interest
  - analytical techniques used less to solve new geometries than to prove theorems, treat small perturbations, etc.
- No single numerical method has "won" in general
  - each has strengths and weaknesses, e.g. tradeoff between simplicity/ generalizability and performance/scalability
  - very mature/standardized problems (e.g. capacitance extraction) use increasingly sophisticated methods (e.g. BEM), research fields (e.g. nanophotonics) tend to use simpler methods that are easier to modify (e.g. FDTD)

#### Understanding Photonic Devices

[ Xu & Lipson, 2005 ]

[Notomi et al. (2005).]



Model the whole thing at once? Too hard to understand & design.

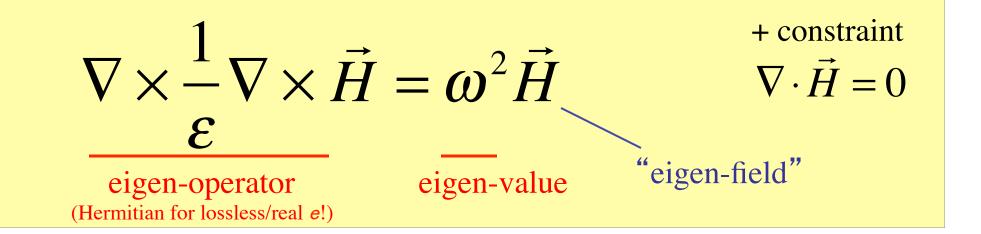
Break it up into pieces first: periodic regions, waveguides, cavities

# Building Blocks: "Eigenfunctions"

• Want to know what solutions exist in different regions and how they can interact: look for time-harmonic modes ~  $e^{-i\omega t}$ 

$$\vec{\nabla} \times \vec{E} = -\mu \frac{\partial}{\partial t} \vec{H} \rightarrow i\omega \vec{H}$$
$$\vec{\nabla} \times \vec{H} = \varepsilon \frac{\partial}{\partial t} \vec{E} + \vec{J} \rightarrow -i\omega \varepsilon \vec{E}$$

First task: get rid of this mess



#### Electronic & Photonic Eigenproblems

Electronic

$$\left(-\frac{\hbar^2}{2m}\nabla^2 + V\right)\psi = E\psi$$

nonlinear eigenproblem (V depends on e density  $|\psi|^2$ )

(+ nasty quantum entanglement)

Photonic

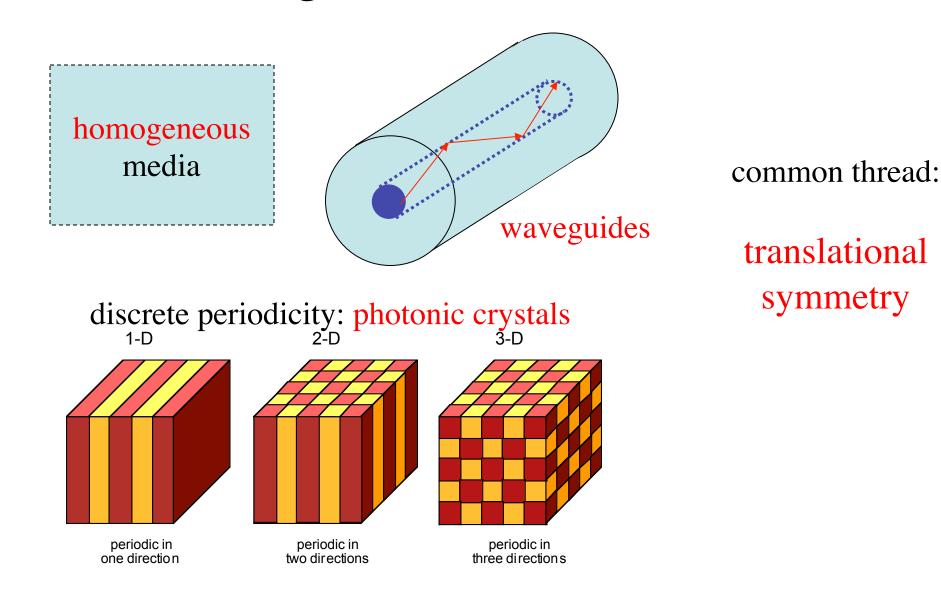
$$\nabla \times \frac{1}{\varepsilon} \nabla \times \vec{H} = \left(\frac{\omega}{c}\right)^2 \vec{H}$$

simple linear eigenproblem (for linear materials with negligible dispersion)

#### —many well-known computational techniques

*Hermitian* ... real  $E \& \omega$ , ... *Periodicity* = *Bloch's theorem*...

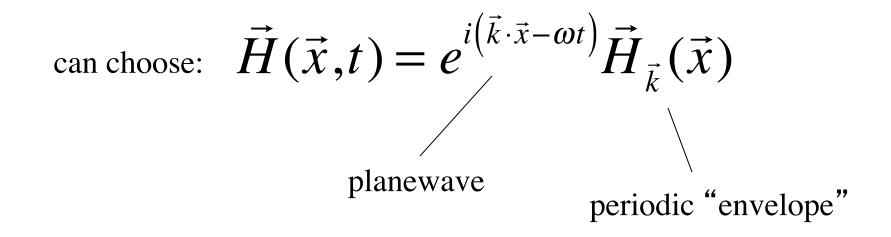
#### Building Blocks: Periodic Media



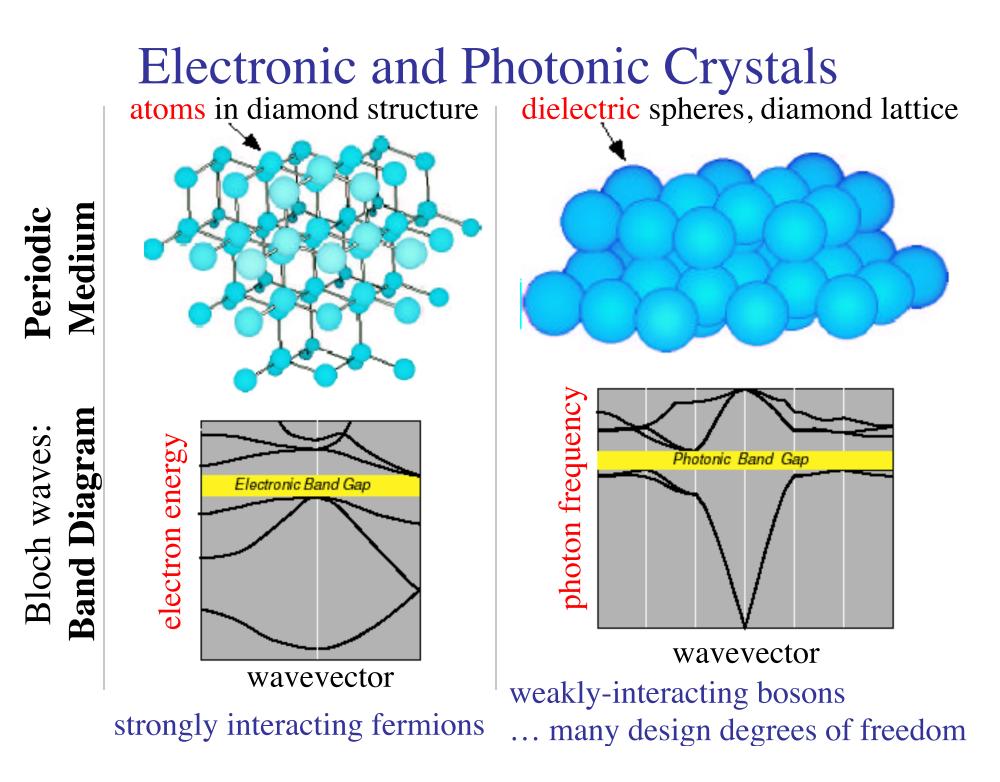
#### Periodic Hermitian Eigenproblems

[ G. Floquet, "Sur les équations différentielles linéaries à coefficients périodiques," *Ann. École Norm. Sup.* **12**, 47–88 (1883). ] [ F. Bloch, "Über die quantenmechanik der electronen in kristallgittern," *Z. Physik* **52**, 555–600 (1928). ]

if eigen-operator is periodic, then Bloch-Floquet solutions:



Corollary 1: **k** is conserved, *i.e.* no scattering of Bloch wave Corollary 2:  $\vec{H}_{\vec{k}}$  given by finite unit cell,  $\vec{P}_{\vec{k}} = \vec{P}_{\vec{k}}$  so *w* are discrete  $\omega_n(\mathbf{k})$ 

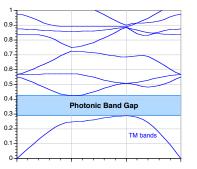


#### A 2d Model System dielectric "atom" ε=12 (e.g. Si) square lattice, period *a* a a $\bullet E$ TM H

#### Solving the Maxwell Eigenproblem

*Finite* cell  $\rightarrow$  *discrete* eigenvalues  $\omega_n$ 

Want to solve for  $\omega_n(\mathbf{k})$ , & plot vs. "all" **k** for "all" *n*,



$$(\nabla + i\mathbf{k}) \times \frac{1}{\varepsilon} (\nabla + i\mathbf{k}) \times \mathbf{H}_n = \frac{\omega_n^2}{c^2} \mathbf{H}_n$$
  
constraint:  $(\nabla + i\mathbf{k}) \cdot \mathbf{H}_n = 0$ 

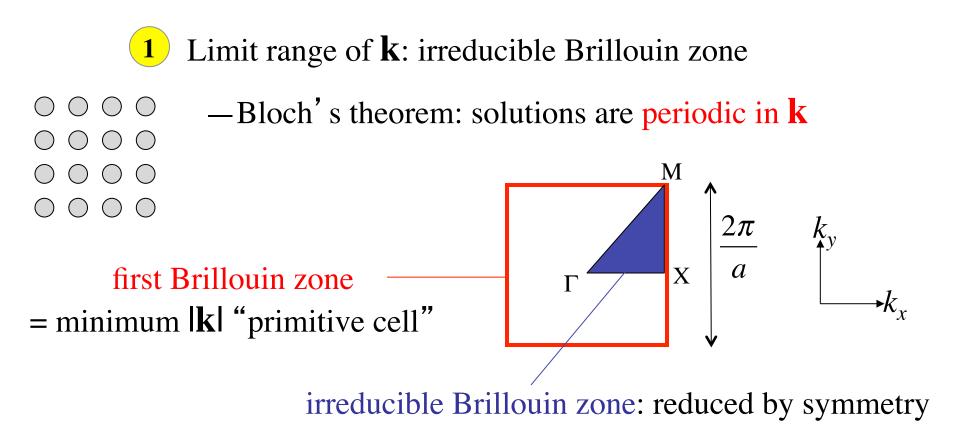
where field = 
$$\mathbf{H}_{n}(\mathbf{x}) e^{i(\mathbf{k}\cdot\mathbf{x} - \omega t)}$$

Limit range of  $\mathbf{k}$ : irreducible Brillouin zone

2 Limit degrees of freedom: expand **H** in finite basis

**3** Efficiently solve eigenproblem: iterative methods

#### Solving the Maxwell Eigenproblem: 1



2 Limit degrees of freedom: expand **H** in finite basis

3) Efficiently solve eigenproblem: iterative methods

#### Solving the Maxwell Eigenproblem: 2a

1 Limit range of **k**: irreducible Brillouin zone  
2 Limit degrees of freedom: expand **H** in finite basis (*N*)  

$$|\mathbf{H}\rangle = \mathbf{H}(\mathbf{x}_t) = \sum_{m=1}^{N} h_m \mathbf{b}_m(\mathbf{x}_t) \text{ solve: } \hat{A} |\mathbf{H}\rangle = \omega^2 |\mathbf{H}\rangle$$
  
finite matrix problem:  $Ah = \omega^2 Bh$ 

inner product:  $\langle \mathbf{f} | \mathbf{g} \rangle = \int \mathbf{f}^* \cdot \mathbf{g}$   $A_{ml} = \langle \mathbf{b}_m | \hat{A} | \mathbf{b}_l \rangle$   $B_{ml} = \langle \mathbf{b}_m | \mathbf{b}_l \rangle$ 

**3** Efficiently solve eigenproblem: iterative methods

# Solving the Maxwell Eigenproblem: 2b

1) Limit range of  $\mathbf{k}$ : irreducible Brillouin zone

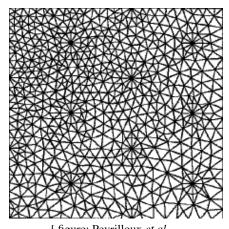
2 Limit degrees of freedom: expand **H** in finite basis — must satisfy constraint:  $(\nabla + i\mathbf{k}) \cdot \mathbf{H} = 0$ 

#### Planewave (FFT) basis

$$\mathbf{H}(\mathbf{x}_t) = \sum_{\mathbf{G}} \mathbf{H}_{\mathbf{G}} e^{i\mathbf{G}\cdot\mathbf{x}_t}$$

constraint:  $\mathbf{H}_{\mathbf{G}} \cdot (\mathbf{G} + \mathbf{k}) = 0$ 

uniform "grid," periodic boundaries, simple code, O(N log N)



[ figure: Peyrilloux *et al.*, *J. Lightwave Tech.* **21**, 536 (2003) ]

#### Finite-element basis

constraint, boundary conditions:

Nédélec elements

[ Nédélec, *Numerische Math*. **35**, 315 (1980) ]

nonuniform mesh, more arbitrary boundaries, complex code & mesh, O(*N*)

3 Efficiently solve eigenproblem: iterative methods

## Solving the Maxwell Eigenproblem: 3a

**1** Limit range of  $\mathbf{k}$ : irreducible Brillouin zone

2 Limit degrees of freedom: expand **H** in finite basis



Efficiently solve eigenproblem: iterative methods

$$Ah = \omega^2 Bh$$

Slow way: compute A & B, ask LAPACK for eigenvalues — requires  $O(N^2)$  storage,  $O(N^3)$  time

Faster way:

- start with *initial guess* eigenvector  $h_0$
- *iteratively* improve

- O(Np) storage, ~ O(Np<sup>2</sup>) time for p eigenvectors

(p smallest eigenvalues)

# Solving the Maxwell Eigenproblem: 3b

**1** Limit range of  $\mathbf{k}$ : irreducible Brillouin zone

2 Limit degrees of freedom: expand **H** in finite basis



Efficiently solve eigenproblem: iterative methods

$$Ah = \omega^2 Bh$$

Many iterative methods:

 Arnoldi, Lanczos, Davidson, Jacobi-Davidson, ..., Rayleigh-quotient minimization

## Solving the Maxwell Eigenproblem: 3c

**1** Limit range of  $\mathbf{k}$ : irreducible Brillouin zone





Efficiently solve eigenproblem: iterative methods

$$Ah = \omega^2 Bh$$

Many iterative methods:

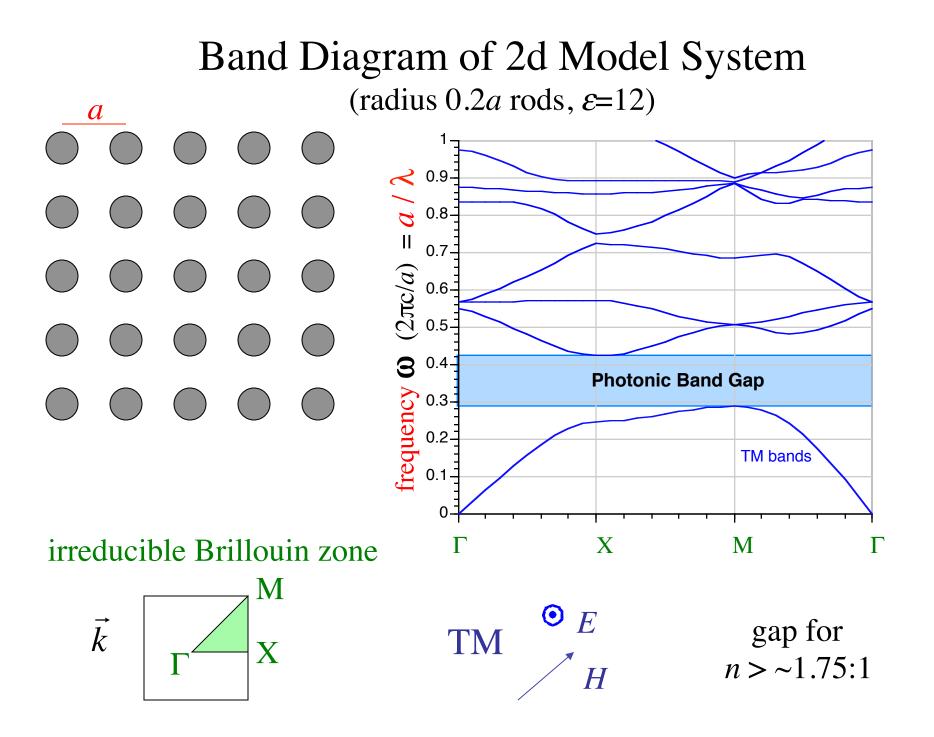
Arnoldi, Lanczos, Davidson, Jacobi-Davidson, ...,
 Rayleigh-quotient minimization

for Hermitian matrices, smallest eigenvalue  $\omega_0$  minimizes:

variational / min–max theorem

$$\omega_0^2 = \min_h \frac{h^* A h}{h^* B h}$$

minimize by preconditioned conjugate-gradient (or...)



The Iteration Scheme is *Important* (minimizing function of 10<sup>4</sup>–10<sup>8</sup>+ variables!)

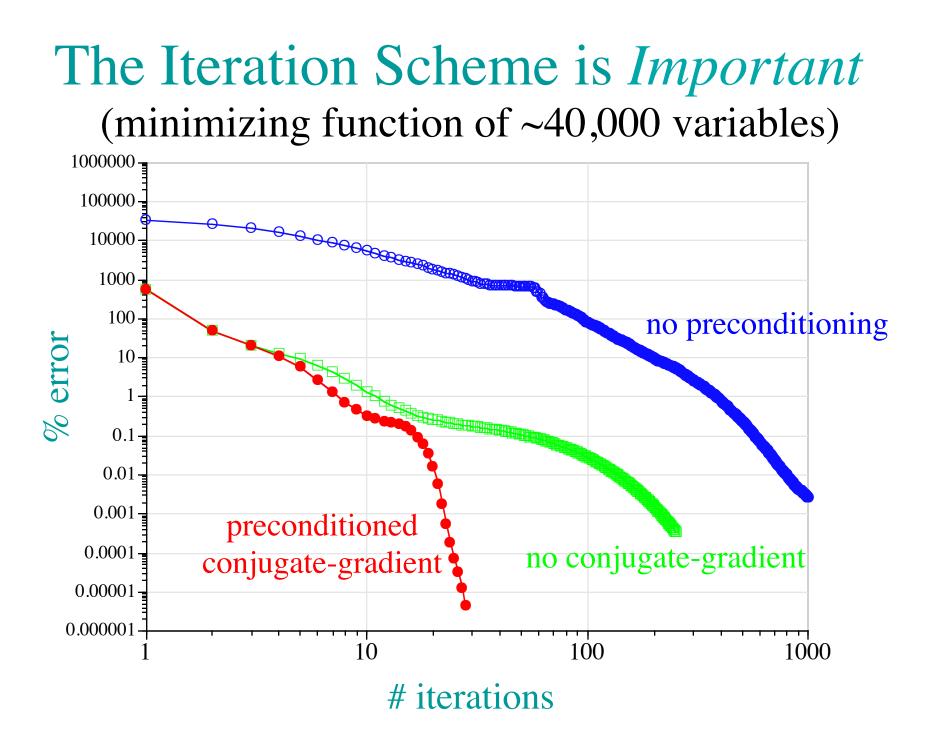
$$\omega_0^2 = \min_h \frac{h^* A h}{h^* B h} = f(h)$$

**Steepest-descent:** minimize  $(h + \alpha \nabla f)$  over  $\alpha$  ... repeat

Conjugate-gradient: minimize  $(h + \alpha d)$ - *d* is  $\nabla f$  + (stuff): *conjugate* to previous search dirs

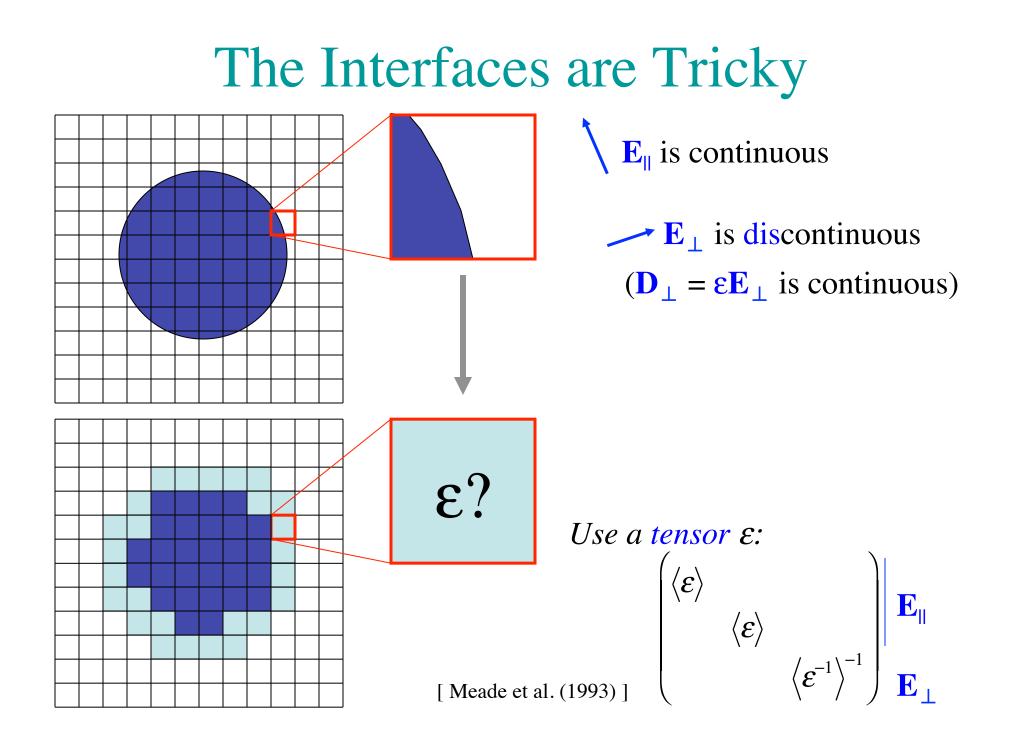
Preconditioned steepest descent: minimize  $(h + \alpha d)$ -  $d = (approximate A^{-1}) \nabla f \sim Newton's method$ 

Preconditioned conjugate-gradient: minimize  $(h + \alpha d)$ - *d* is (approximate A<sup>-1</sup>) [ $\nabla f$  + (stuff)]

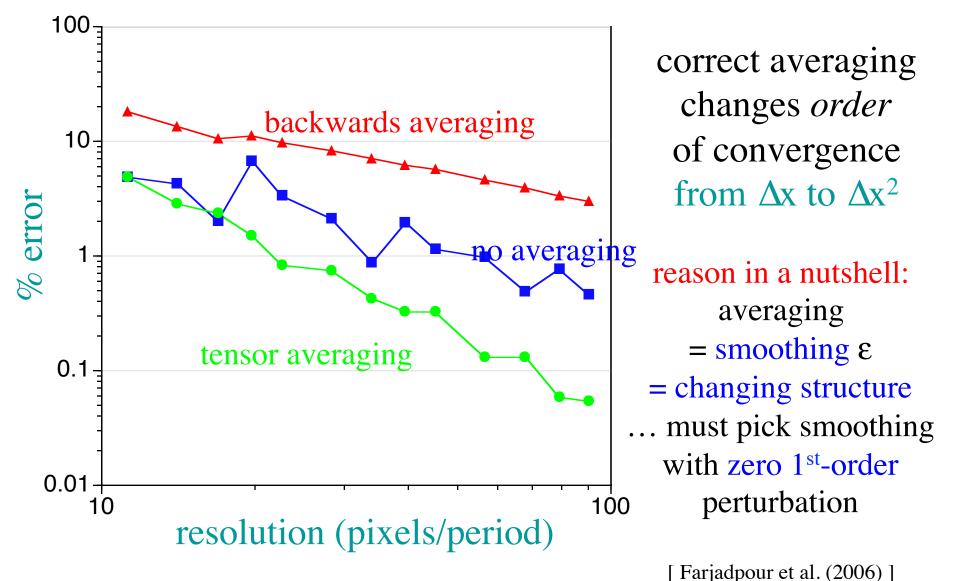


# Much more on iterative solvers: 18.335 at MIT

See also Numerical Linear Algebra (Trefethen & Bau), Templates for the Solution of Linear Systems, Templates for the Solution of Algebraic Eigenproblems, PETSc and SLEPc libraries, etc.



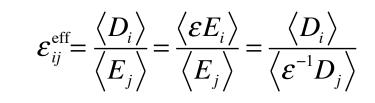
#### The *\varepsilon*-averaging is *Important*



# Closely related to anisotropic metamaterial, e.g. multilayer film in large- $\lambda$ limit

a

 $\lambda >> a$ 



key to anisotropy is differing continuity conditions on **E**:

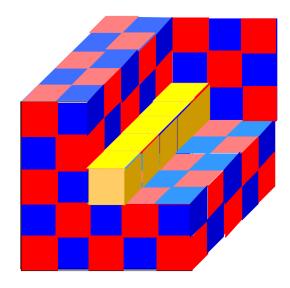
 $\oint E_{\parallel} \text{ continuous } \Rightarrow \epsilon_{\parallel} = <\epsilon >$ 

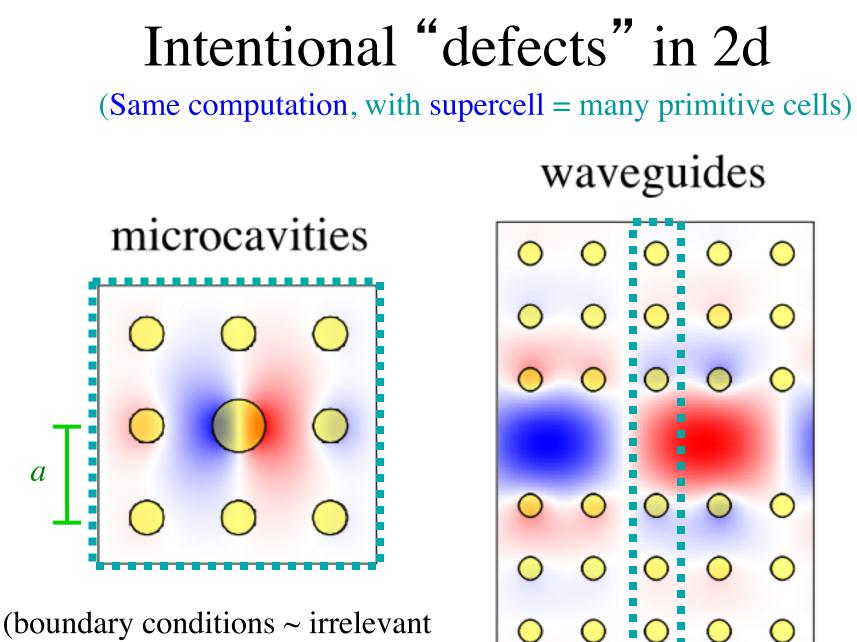
 $D_{\perp} = \varepsilon E_{\perp}$  continuous  $\Rightarrow \varepsilon_{\perp} = \langle \varepsilon^{-1} \rangle^{-1}$ 

#### Intentional "defects" are good

#### microcavities

#### waveguides ("wires")





for exponentially localized modes)

#### Computational Nanophotonics: Cavities and Resonant Devices

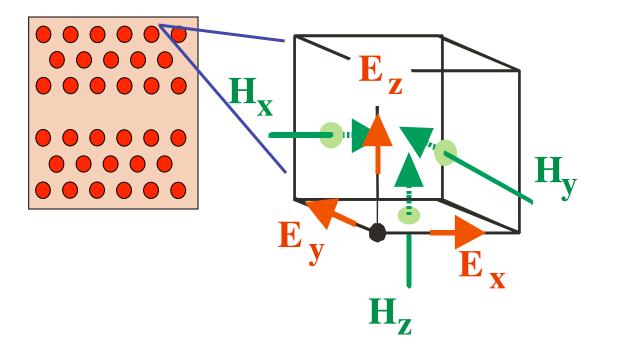
Steven G. Johnson MIT Applied Mathematics

#### FDTD: finite difference time domain

Finite-difference-time-domain (FDTD) is a method to model Maxwell' s equations on a **discrete time** & **space grid** using finite centered differences

$$\nabla \times \mathbf{E} = -\frac{\partial \mathbf{B}}{\partial t}$$
  $\nabla \times \mathbf{H} = \frac{\partial \mathbf{D}}{\partial t} + \mathbf{J}$ 

 $\mathbf{D} = \varepsilon \mathbf{E}$   $\mathbf{B} = \mu \mathbf{H}$ 



K.S. Yee 1966

A. Taflove & S.C. Hagness 2005

### FDTD: Yee leapfrog algorithm

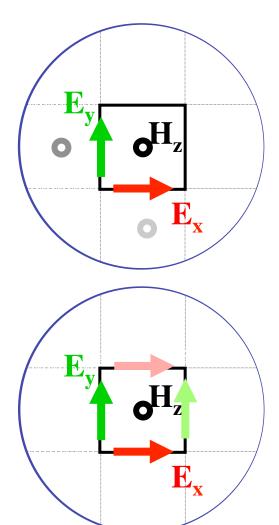
#### 2d example:

1) at time t: Update D fields everywhere using spatial derivatives of H, then find  $E=\epsilon^{-1}D$ 

$$\mathbf{E}_{\mathbf{x}} \coloneqq \frac{\Delta t}{\varepsilon \Delta y} \left( \mathbf{H}_{\mathbf{Z}}^{j+0.5} - \mathbf{H}_{\mathbf{Z}}^{j-0.5} \right)$$
$$\mathbf{E}_{\mathbf{y}} \coloneqq \frac{\Delta t}{\varepsilon \Delta x} \left( \mathbf{H}_{\mathbf{Z}}^{i+0.5} - \mathbf{H}_{\mathbf{Z}}^{i-0.5} \right)$$

2) at time t+0.5: Update H fields everywhere using spatial derivatives of E

$$\mathbf{H}_{z} = \frac{\Delta t}{\mu} \left( \underbrace{\mathbf{E}_{x}^{j+1} - \mathbf{E}_{x}^{j}}_{\Delta y} + \underbrace{\mathbf{E}_{y}^{i} - \mathbf{E}_{y}^{i+1}}_{\Delta x} \right)$$



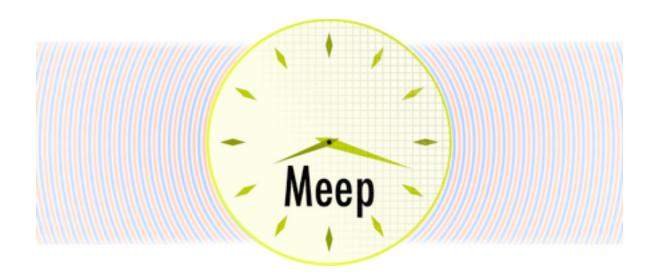
CFL/Von Neumann stability:  $c\Delta t < 1 / \sqrt{\Delta x^{-2} + \Delta y^{-2}}$ 

### Free software: MEEP

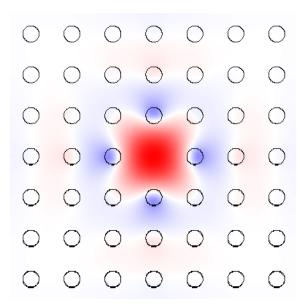
http://ab-initio.mit.edu/meep

- FDTD Maxwell solver: 1d/2d/3d/cylindrical
- Parallel, scriptable, integrated optimization, signal processing
- Arbitrary geometries, anisotropy, dispersion, nonlinearity
- Bloch-periodic boundaries, symmetry boundary conditions,

+ PML absorbing boundary layers...



### Microcavity Blues

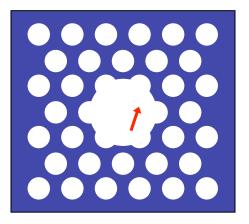


For cavities (*point defects*) frequency-domain has its drawbacks:

- Best methods compute lowest-ω eigenvals, but N<sup>d</sup> supercells have N<sup>d</sup> modes below the cavity mode – *expensive*
- Best methods are for Hermitian operators, but losses requires non-Hermitian

# Time-Domain Eigensolvers

(finite-difference time-domain = FDTD)



Simulate Maxwell's equations on a discrete grid, + absorbing boundaries (leakage loss)

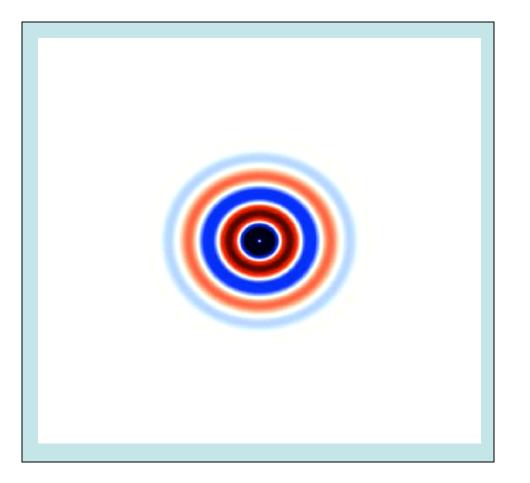
• Excite with broad-spectrum dipole (1) source

 $\Delta \omega$ 

decay rate in time gives loss

# Absorbing boundaries?

Finite-difference/finite-element volume discretizations need to artificially truncate space for a computer simulation.



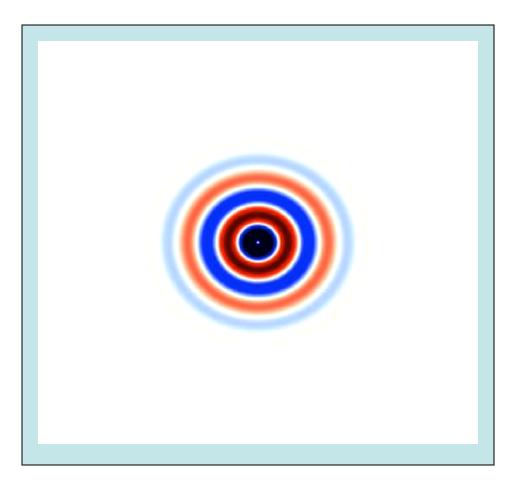
In a wave equation, a hard-wall truncation gives reflection artifacts.

An old goal: "absorbing boundary condition" (ABC) that absorbs outgoing waves.

**Problem**: good ABCs are hard to find in > 1d.

# Perfectly Matched Layers (PMLs)

Bérenger, 1994: design an *artificial* absorbing layer that is analytically reflectionless



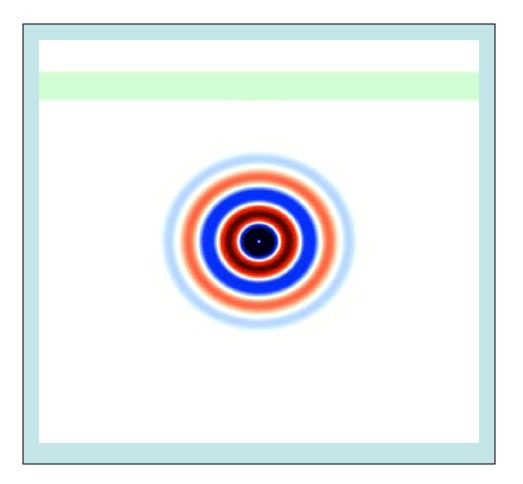
Works *remarkably well*.

Now **ubiquitous** in FD/FEM wave-equation solvers.

Several derivations, cleanest & most general via "complex coordinate stretching" [ Chew & Weedon (1994) ]

# Perfectly Matched Layers (PMLs)

Bérenger, 1994: design an *artificial* absorbing layer that is analytically reflectionless

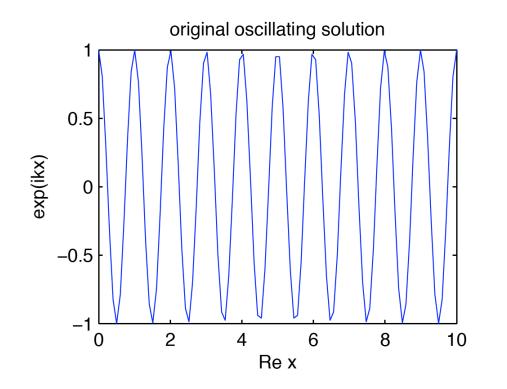


Even works in inhomogeneous media (e.g. waveguides).

### PML Starting point: propagating wave

• Say we want to absorb wave traveling in +x direction in an x-invariant medium at a frequency  $\omega > 0$ .

fields ~ 
$$f(y,z)e^{i(kx-\omega t)}$$



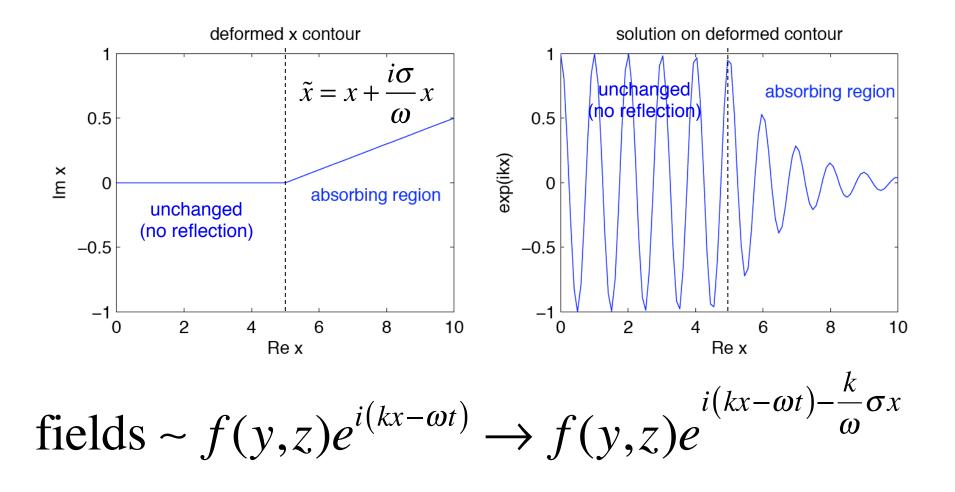
(usually, k > 0)

```
[ rare "backward-wave"
cases defeat PML
(Loh, 2009) ]
```

(only x in wave equation is via  $\partial / \partial x$ terms.)

### PML step 1: Analytically continue

Electromagnetic fields & equations are *analytic* in x, so we can evaluate at complex x & still solve same equations



### PML step 2: Coordinate transformation

Weird to solve equations for complex coordinates  $\tilde{x}$ , so do coordinate transformation back to real x.

$$\tilde{x}(x) = x + \int_{-\infty}^{x} \frac{i\sigma(x')}{\omega} dx'$$

(allow *x*-dependent PML strength s)

$$\frac{\partial}{\partial x} \xrightarrow{1} \frac{\partial}{\partial \tilde{x}} \xrightarrow{2} \left[ \frac{1}{1 + \frac{i\sigma(x)}{\omega}} \right] \frac{\partial}{\partial x}$$

fields ~ 
$$f(y,z)e^{i(kx-\omega t)} \rightarrow f(y,z)e^{i(kx-\omega t)}$$

nondispersive materials:  $k/\omega \sim \text{constant}$ so decay rate independent of  $\omega$ (at a given incidence angle)

### PML Step 3: Effective materials

In Maxwell's equations,  $\nabla \times \mathbf{E} = i\omega\mu\mathbf{H}$ ,  $\nabla \times \mathbf{H} = -i\omega\varepsilon\mathbf{E} + \mathbf{J}$ , coordinate transformations are *equivalent* to transformed *materials* (Ward & Pendry, 1996: "transformational optics")

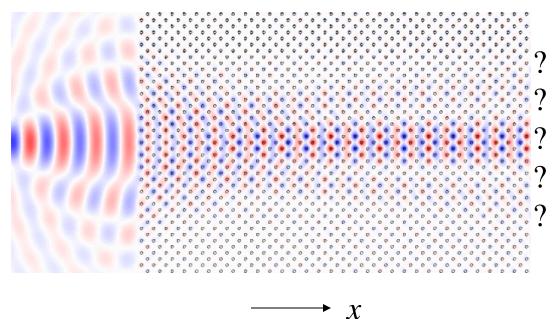
$$\{\varepsilon,\mu\} \rightarrow \frac{J\{\varepsilon,\mu\}J^T}{\det J}$$

x PML Jacobian  $J = \begin{pmatrix} (1+i\sigma/\omega)^{-1} \\ & 1 \\ & & 1 \end{pmatrix}$   $\{\varepsilon, \mu\} \to \{\varepsilon, \mu\} \begin{pmatrix} (1+i\sigma/\omega)^{-1} \\ & 1+i\sigma/\omega \\ & 1+i\sigma/\omega \end{pmatrix}$   $(\partial x)$ 

PML = effective anisotropic "absorbing"  $\varepsilon, \mu$ 

### Photonic-crystal PML?

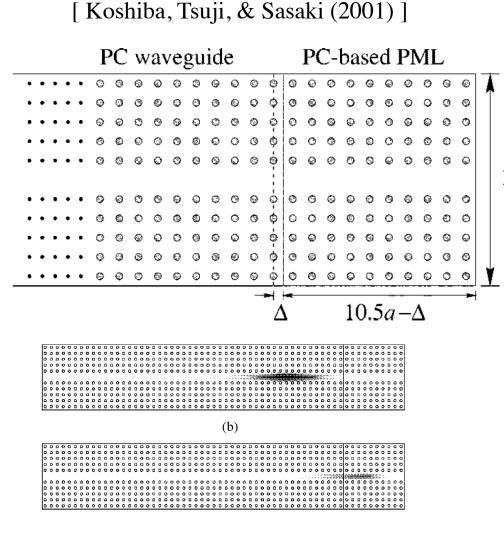
FDTD (Meep) simulation:



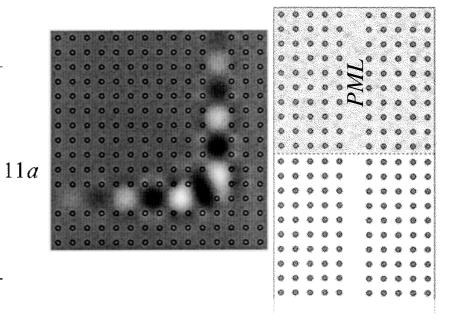
*E* not even *continuous* in *x* direction, much less analytic!

Analytic continuation of Maxwell's equations is hopeless — no reason to think that PML technique should work

### Photonic-crystal PMLs: Magic?



[Kosmidou et al (2003)]



... & several other authors ...
Low reflections claimed

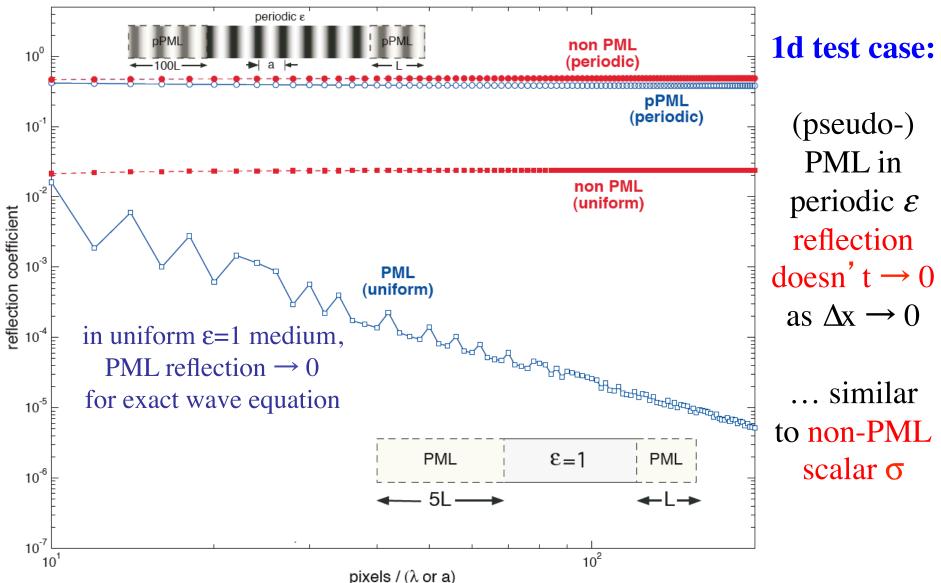
is PML working?

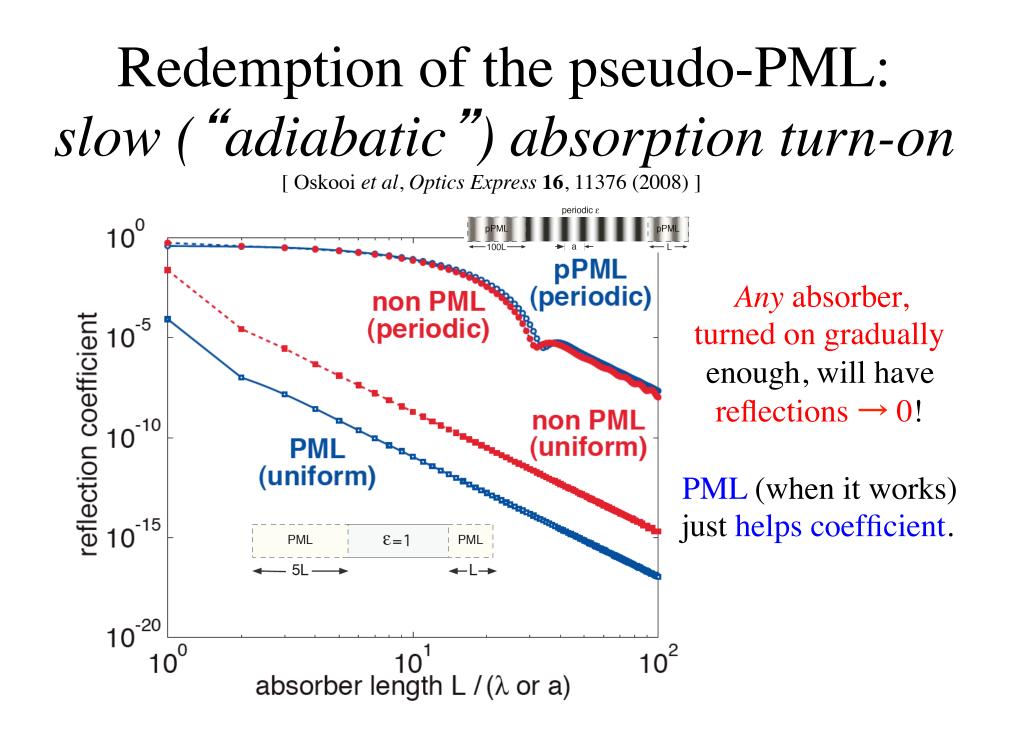
Something suspicious:

very thick absorbers.

#### Failure of Photonic-crystal "pseudo-PML"

[Oskooi et al, Optics Express 16, 11376 (2008)]





### Back to absorption tapers

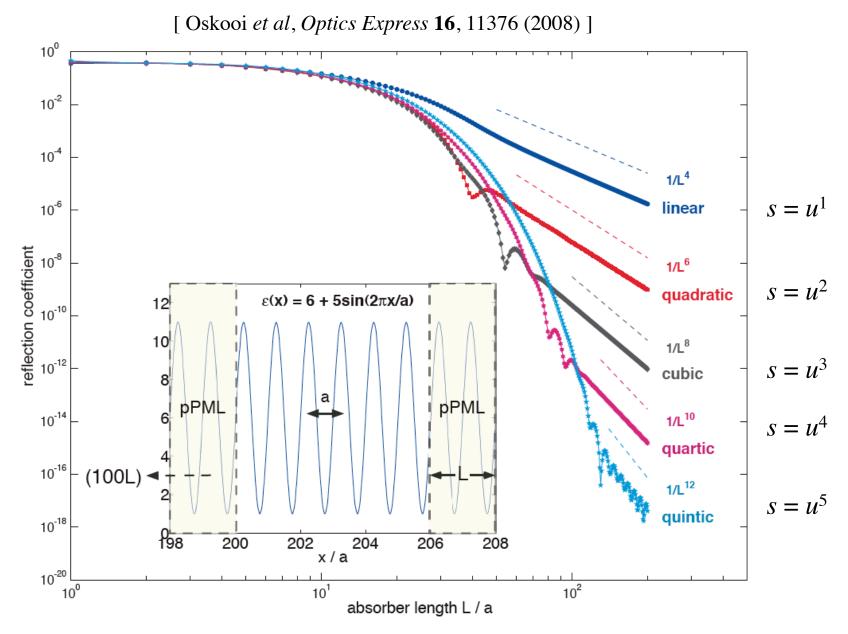
• Suppose absorption is:  $\sigma(x) = \sigma_0 s(x/L)$ , say  $s(u) = u^d$ 

• Fix the round-trip reflection: 
$$R_{\text{round-trip}} = e^{-\#L\sigma_0 \int_0^1 s(u) du} \Rightarrow \sigma_0 \sim \frac{1}{L}$$

 $\Rightarrow \dots \Rightarrow$  transition reflections ~  $O(L^{-2d-2})$ 

[Oskooi et al, Optics Express 16, 11376 (2008)]

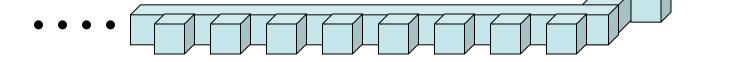
### Reflection vs. Absorber Thickness



# What about DtN / RCWA / Blochmode-expansion / SIE methods?

 useful, nice methods that can impose outgoing boundary conditions exactly, once the Green's function / Bloch modes computed

challenge problem for any method: periodic 3d dielectric waveguide bend in air (note: both guided and radiating modes!)

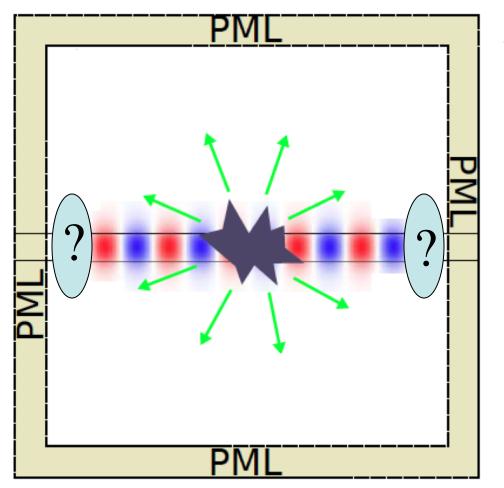


... DtN / Green' s function / Bloch modes (incl. radiation!) expensive

Computational Nanophotonics: Sources & Integral Equations

> Steven G. Johnson MIT Applied Mathematics

# How can we excite a desired incident wave?

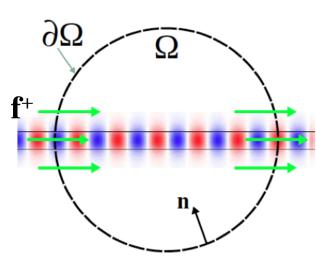


Want some current source to excite incident waveguide mode, planewave, etc...

- also called transparent source since waves do not scatter from it (thanks to linearity)
- vs. hard source = Dirichlet field condition

# Equivalent currents ("total-field/scattered-field" approach)

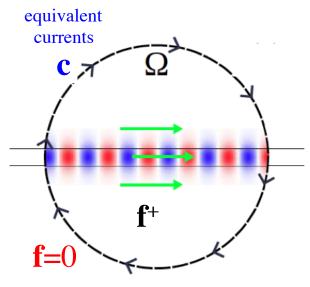
[ review article: arXiv:1301.5366 ]



known incident fields

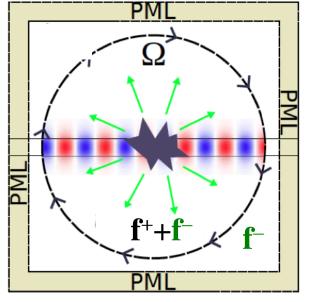
 $\mathbf{f}^+ = \begin{pmatrix} \mathbf{E} \\ \mathbf{H} \end{pmatrix}$ 

in ambient medium (possibly inhomogeneous, e.g. waveguide or photonic crystal)



want to construct surface currents  $\mathbf{c} = \begin{pmatrix} \mathbf{J} \\ \mathbf{K} \end{pmatrix}$ 

giving same  $f^+$  in  $\Omega$ 



do simulations
in finite domain
+ inhomogeneities
 / interactions
= scattered field f<sup>-</sup>

## The *Principle of Equivalence* in classical EM

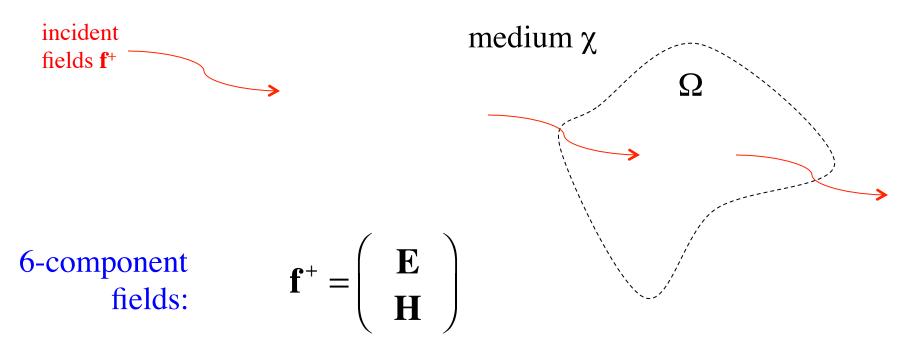
(or Stratton–Chu equivalence principle) (formalizes Huygens' Principle) (or total-field/scattered-field, TFSF)

(close connection to Schur complement [Kuchment])

[ see e.g. Harrington, *Time-Harmonic Electromagnetic Fields* ]

[ review article: arXiv:1301.5366 ]

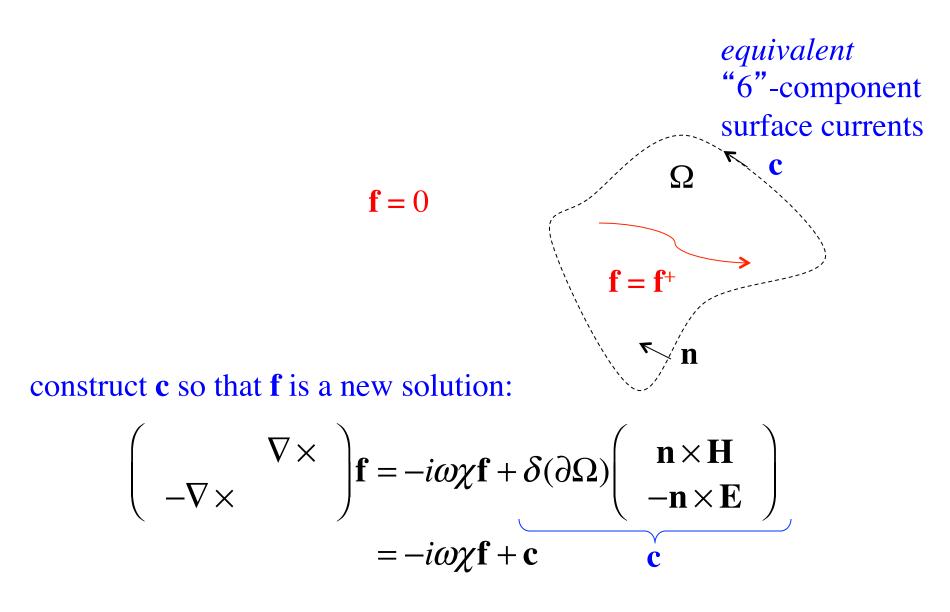
### starting point: solution in all space



solve (source-free) Maxwell PDE (in frequency domain):

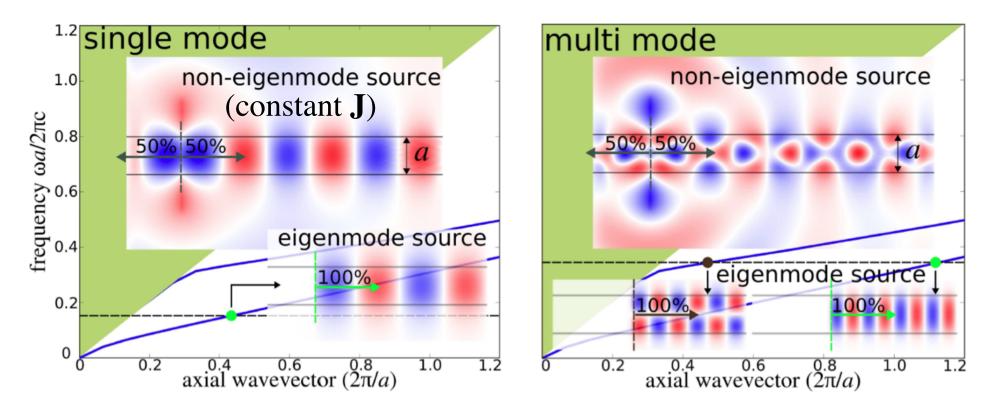
$$\begin{pmatrix} \nabla \times \\ -\nabla \times \end{pmatrix} \mathbf{f}^{+} = -i\omega \begin{pmatrix} \varepsilon \\ \mu \end{pmatrix} \mathbf{f}^{+} = -i\omega\chi\mathbf{f}^{+}$$

### constructing solution in $\Omega$



# Exciting a waveguide mode in FDTD

- compute mode in MPB, then use as source in MEEP



[ review article: arXiv:1301.5366 ]

### Problems with equivalent sources

(if not solved, undesired excitation of other waves) [review article: arXiv:1301.5366]

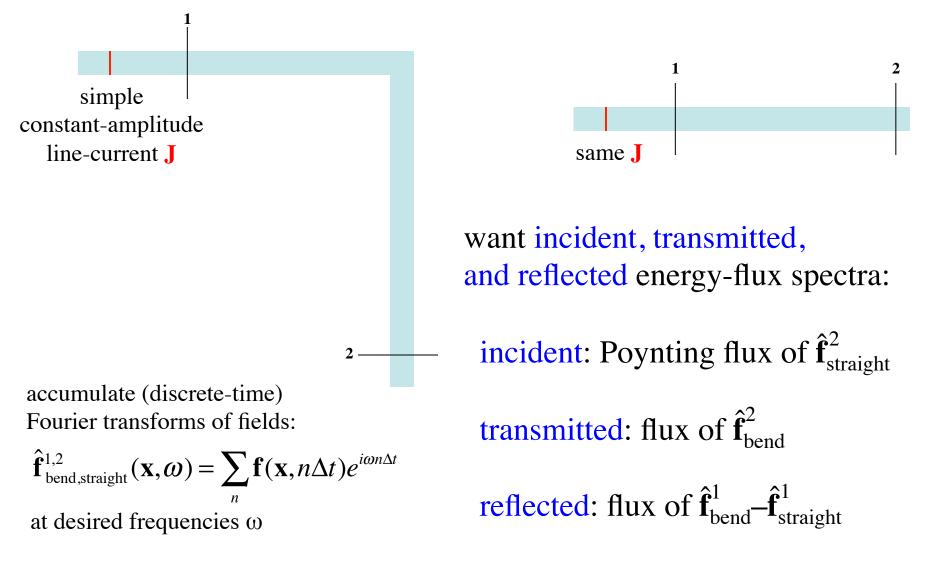
- Discretization mismatch: at finite resolution, solutions from one technique (MPB) don't exactly match discrete modes in another technique (Meep) — leads to small imperfections — solvable by using the same discretization to find modes
- Dispersion: mode profile varies with  $\omega$ , so injecting a pulse p(t) requires a convolution with  $\hat{\mathbf{c}}(\mathbf{x},\omega) \underset{\text{Fourier}}{\leftrightarrow} \mathbf{c}(\mathbf{x},t)$

 $\operatorname{currents}(\mathbf{x},t) = p(t) * \mathbf{c}(\mathbf{x},t) \approx p(t) \, \hat{\mathbf{c}}(\mathbf{x},\omega)$  *narrow*-bandwidth

- convolutions expensive, can be approximated by finite-time (FIR/IIR) calculations using DSP techniques
- specialized methods are known for planewave sources

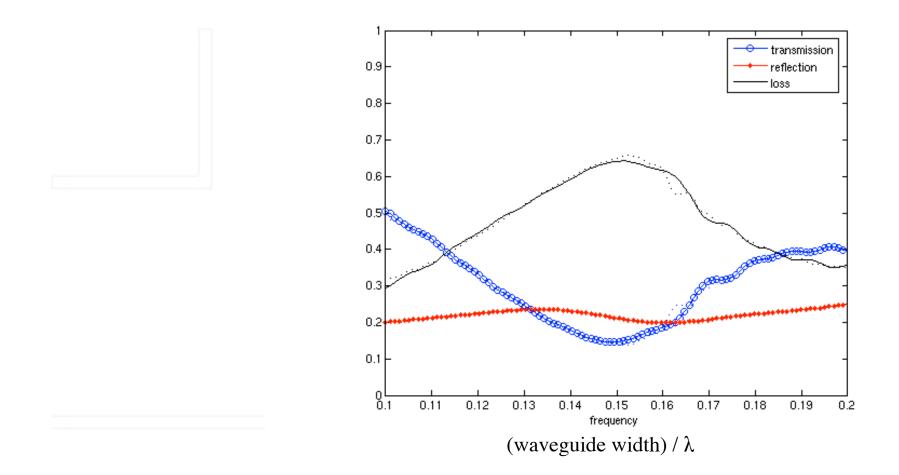
### Shortcut: Subtract two simulations

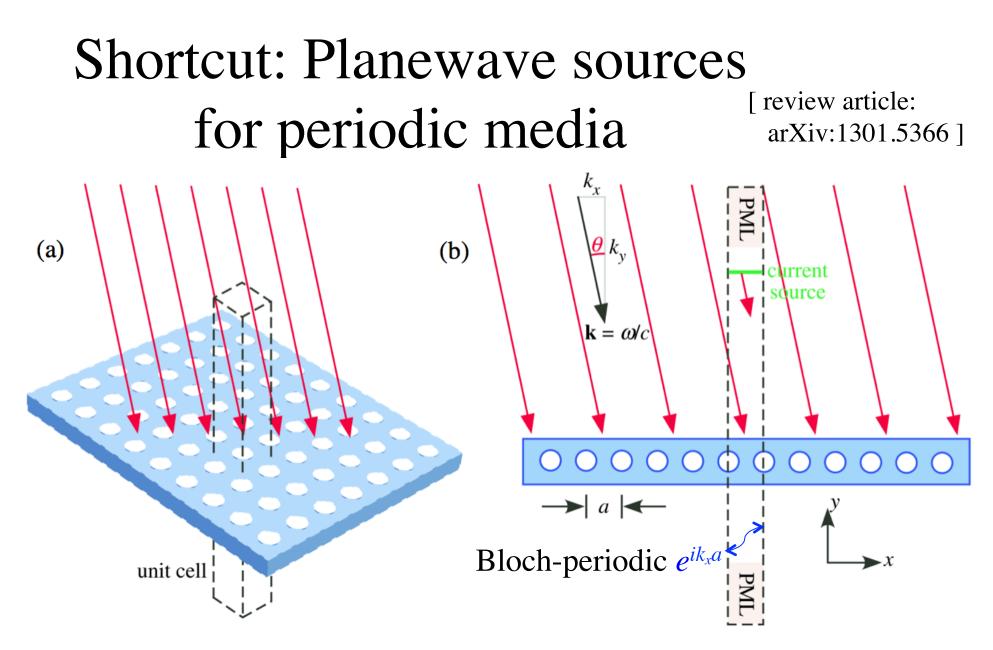
example: 90° bend of single-mode dielectric waveguide



### Shortcut: Subtract two simulations

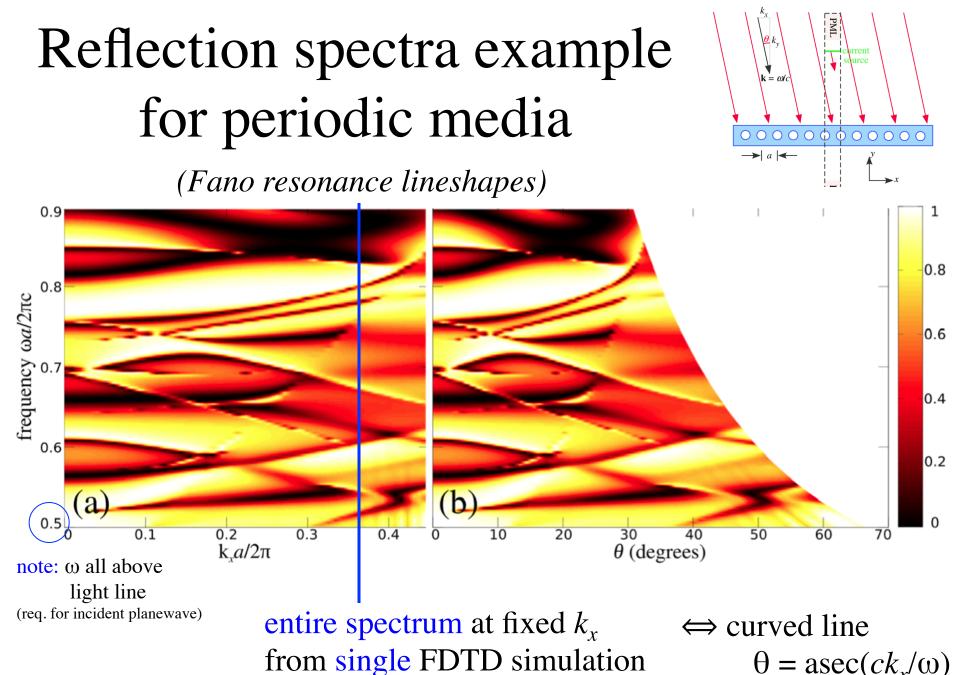
example: 90° bend of single-mode dielectric waveguide





trick #1: incident & scattered fields are Bloch-periodic/quasiperiodic

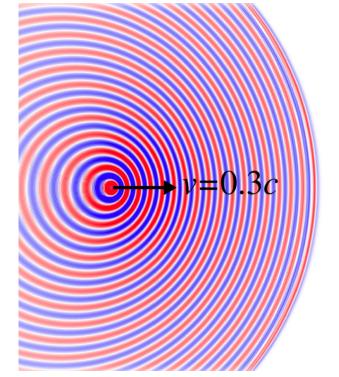
trick #2:  $e^{ik_xx}$  current source produces planewave



(Fourier transform of pulse)

 $\theta = \operatorname{asec}(ck_x/\omega)$ in  $(\omega, \theta)$  plot

# Fun possibilities in FDTD: moving sources [= just some currents J(x,t)]

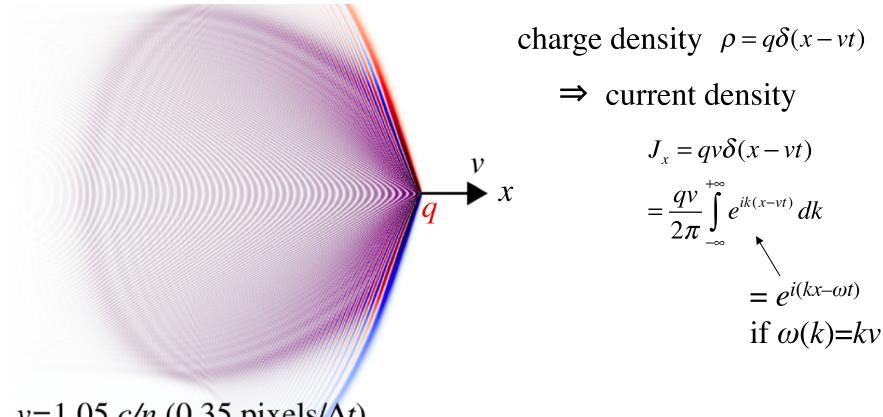


 $v = 1.05 \ c/n \ (0.35 \ \text{pixels}/\Delta t)$ 

Doppler shift from moving oscillating dipole

Cerenkov radiation from moving point charge in dielectric medium

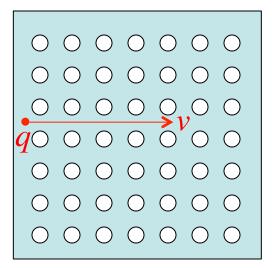
### Cerenkov radiation



 $v = 1.05 c/n (0.35 pixels/\Delta t)$ 

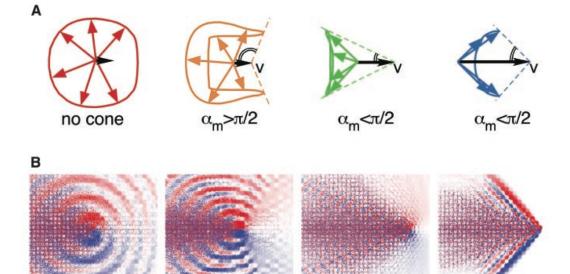
excites radiating mode  $\omega(k_x,k_y)$ if  $v = \omega(k_x, k_y)/k_x$ = phase velocity in x direction  $\geq c/n$  in index-*n* medium

# Cerenkov radiation in photonic crystal



excites radiating mode  $\omega(k_x,k_y)$ if  $v = \omega(k_x,k_y)/(k_x + 2\pi m/a)$ for any integer *m* 

⇒ no minimum v
[ Smith–Purcell effect ]



very different radiation
patterns & directions
depending on *v*,
due to interactions with
2d PhC dispersion curves

[ Luo, Ibanescu, Johnson,& Joannopoulos (Science, 2002) ]

# Surface-integral equations (SIEs) and

### boundary-element methods (BEMs)

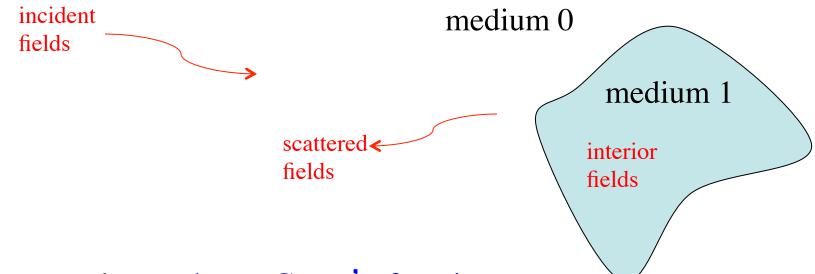
[ see e.g. Harrington, Time-Harmonic Electromagnetic Fields ]

Harrington, "Boundary integral formulations for homogeneous material bodies," J. Electromagnetic Waves Appl. 3, 1–15 (1989)

Chew et al., Fast and Efficient Algorithms in Computational Electromagnetics (2001)].

# Exploiting partial knowledge of Green's functions

a typical scattering problem:



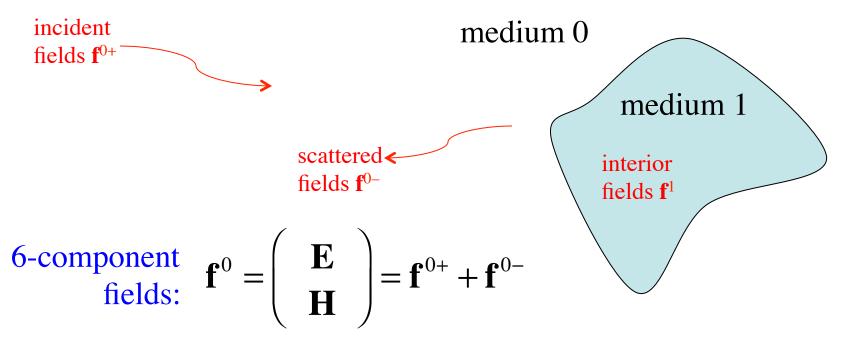
suppose that we know Green's functions in infinite medium 0 or medium 1

- known analytically for homogeneous media
- computable by *much smaller* calculation in periodic medium

Can exploit this to derive integral equation for surface unknowns only.

# The *Principle of Equivalence* in classical EM

[ see e.g. Harrington, Time-Harmonic Electromagnetic Fields ]

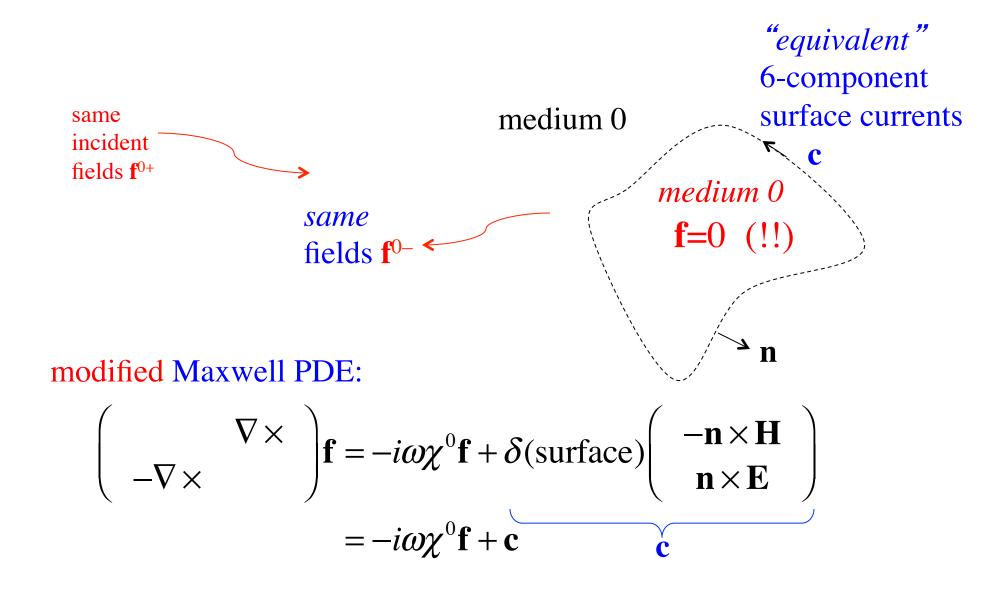


Maxwell PDE:

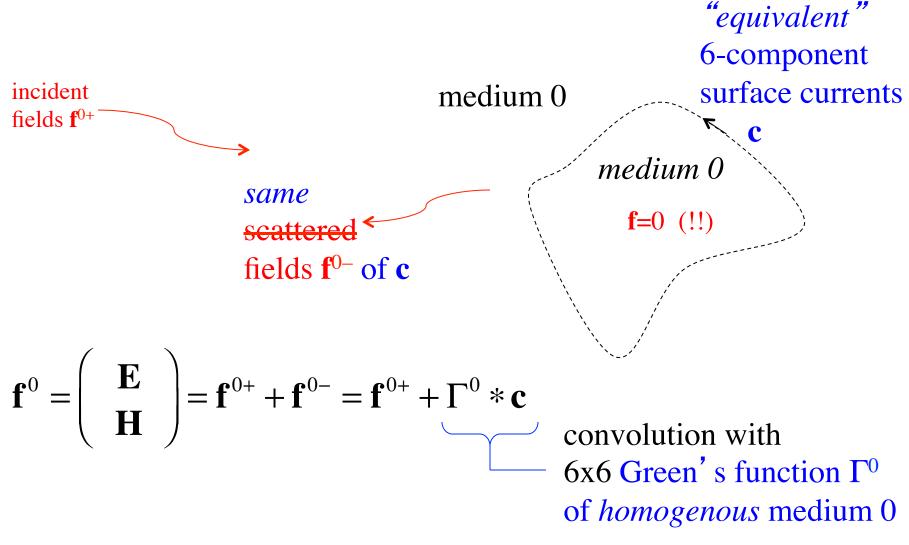
$$\begin{pmatrix} \nabla \times \\ -\nabla \times \end{pmatrix} \mathbf{f} = -i\omega \boldsymbol{\chi}^{(0,1)} \mathbf{f}$$

... we want to partition *into* separate *medium* 0/1 *problems* & enforce continuity...

## Constructing a medium-0 solution

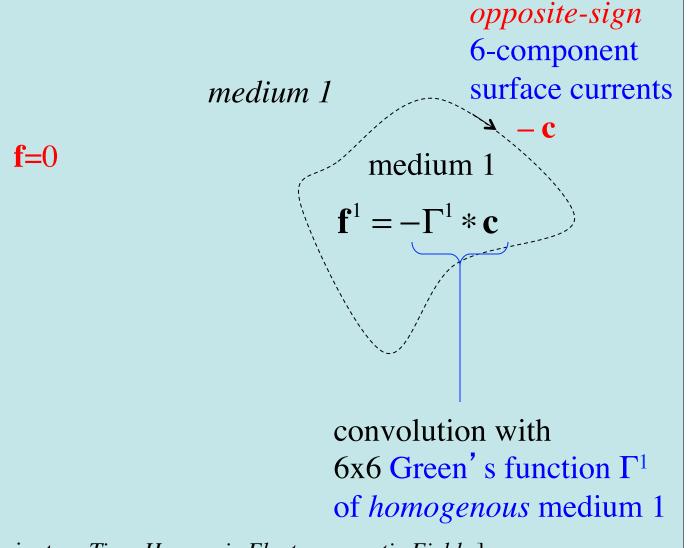


# The Principle of Equivalence I



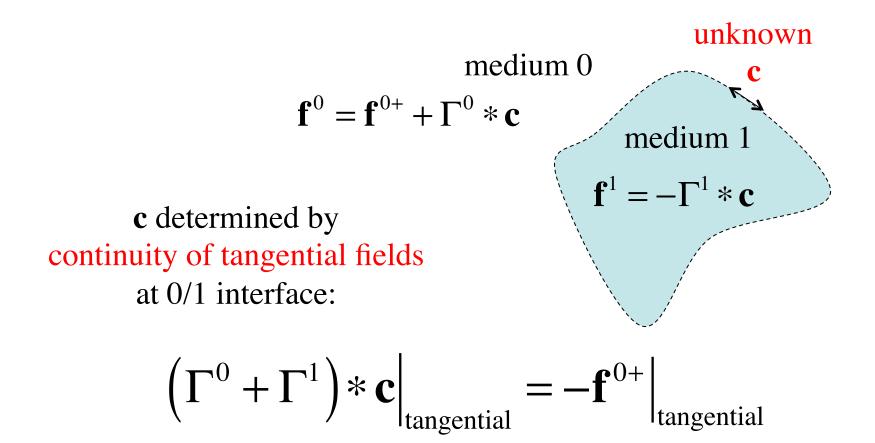
[e.g. Harrington, Time-Harmonic Electromagnetic Fields]

### The Principle of Equivalence II



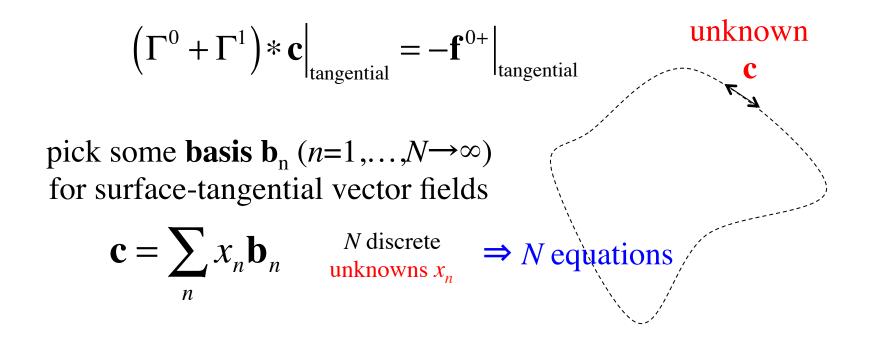
[e.g. Harrington, Time-Harmonic Electromagnetic Fields]

# Surface-Integral Equations (SIE)



[e.g. Harrington, Time-Harmonic Electromagnetic Fields]

## Discretizing the Maxwell SIE



[ e.g. Harrington, Time-Harmonic Electromagnetic Fields ]

### Discretizing the Maxwell SIE

Galerkin method — require error  $\perp$  basis:

$$\left\langle \mathbf{b}_{m} \middle| \left( \Gamma^{0} + \Gamma^{1} \right) \ast \left( \sum_{n} x_{n} \mathbf{b}_{n} \right) \right\rangle = \left\langle \mathbf{b}_{m} \middle| -\mathbf{f}^{0+} \right\rangle \qquad \text{unknown}$$

pick some basis  $\mathbf{b}_n$   $(n=1,\ldots,N \rightarrow \infty)$ for surface-tangential vector fields

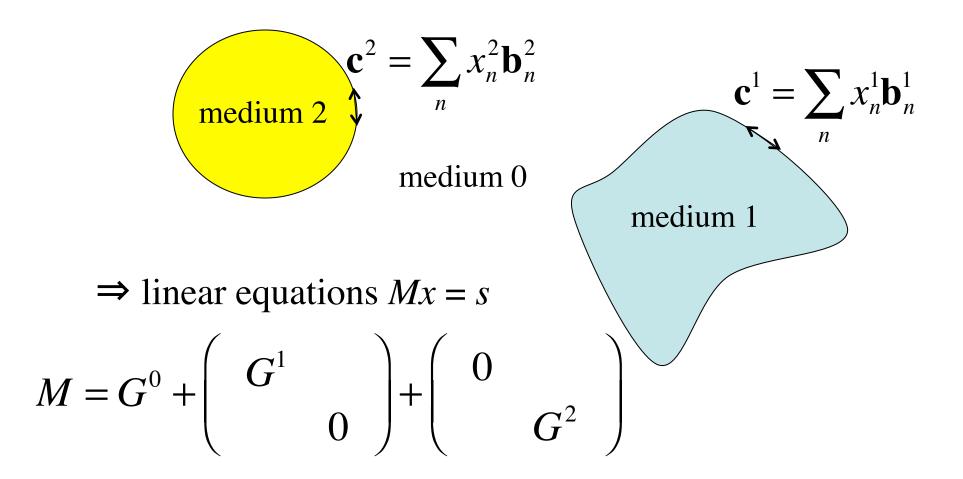
> $\mathbf{c} = \sum x_n \mathbf{b}_n \qquad \begin{array}{c} N \text{ discrete} \\ \text{unknowns } x_n \end{array}$ n

$$\Rightarrow$$
 N equations  $Mx = s$ 

$$M_{mn} = \left\langle \mathbf{b}_{m} \left| \left( \Gamma^{0} + \Gamma^{1} \right) * \mathbf{b}_{n} \right\rangle = G_{mn}^{0} + G_{mn}^{1} \right.$$
$$s_{m} = \left\langle \mathbf{b}_{m} \right| - \mathbf{f}^{0+} \right\rangle$$

[e.g. Harrington, Time-Harmonic Electromagnetic Fields]

## Discretized SIE: Two Objects

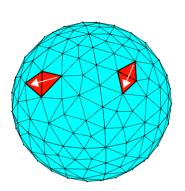


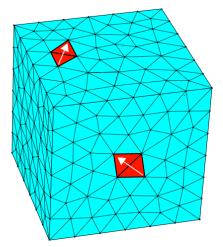
... + straightforward generalizations to more objects, nested objects, etcetera

# SIE basis choices

- Can use *any* basis for c = any basis of surface functions
   ... basis is *not* incoming/outgoing waves
   & need *not* satisfy *any wave equation*
- Spectral bases: spherical harmonics, Fourier series, ... ... nice for high symmetry
  - ~ uniform spatial resolution
- Boundary Element Methods (BEM):

localized basis functions defined on irregular mesh





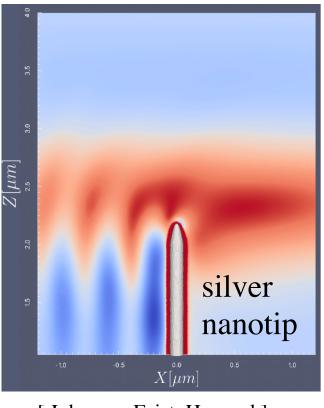
"**RWG**" basis (1982):

vector-valued  $\mathbf{b}_n$  defined on *pairs* of adjacent triangles via degree-1 polynomials

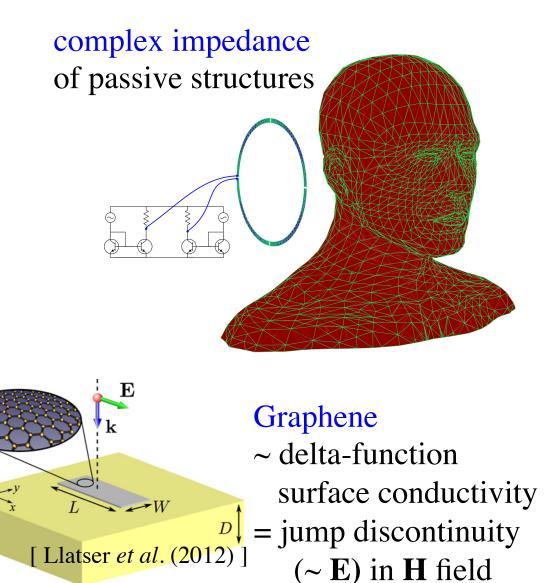
# BEM strengths

especially small surface areas in a large (many- $\lambda$ ) volume, e.g.:

surface plasmons (metals): extremely sub- $\lambda$  fields



[Johannes Feist, Harvard]



## The bad news of BEM

• Not well-suited for nonlinear, time-varying, or non-piecewise-constant media

• BEM system matrix 
$$M_{mn} = \left\langle \mathbf{b}_{m} \middle| \left( \Gamma^{0} + \Gamma^{1} \right) * \mathbf{b}_{n} \right\rangle = G_{mn}^{0} + G_{mn}^{1}$$

*singular* integrals for overlapping b<sub>m</sub>, b<sub>n</sub>
 ...special numerical integration techniques
 *M* is *not sparse*, but:

 often small enough for dense solvers (≤ 10<sup>4</sup>×10<sup>4</sup>)
 + "fast solvers:" approximate sparse factorizations (fast multipole method, etc.)

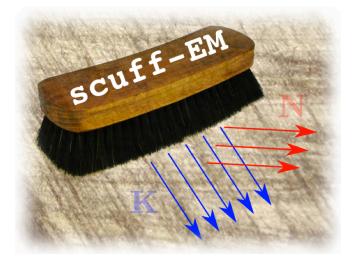
 lots of work every time you change Γ

 (e.g. 3d vs. 2d, periodic boundaries, anisotropic, ...)
 but independent of geometry

### The good news of BEM: You don't have to write it yourself



Free software developed by Dr. Homer Reid (collaboration with Prof. Jacob White @ MIT)



### **SCUFF-EM**

[ http://homerreid.ath.cx/scuff-EM ]

Surface-**CU**rrent / **Field** Formulation of Electro-Magnetism

SCUFF-EM is a free, open-source software implementation of the boundary-element method of electromagnetic scattering.

SCUFF-EM supports a wide range of geometries, including compact scatterers, infinitely extended scatterers, and multi-material junctions.

The SCUFF-EM suite includes 8 standalone application codes for specialized problems in EM scattering, fluctuation physics, and RF engineering.

The SCUFF-EM suite also includes a core library with C++ and PYTHON APIs for designing homemade applications.

### http://homerreid.com/scuff-EM

\* to be released by end of October-ish

## SCUFF usage outline

The steps involved in solving any BEM scattering problem:

1. Mesh object surfaces into triangles.

Not done by SCUFF-EM; high-quality free meshing packages exist (e.g. GMSH).

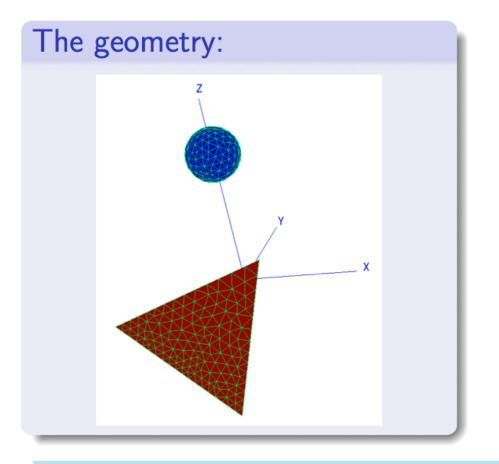
- 2. Assemble the BEM matrix **M** and RHS vector **v**. SCUFF-EM does this.
- 3. Solve the linear system Mk = v for the surface currents k. SCUFF-EM uses LAPACK for this.
- 4. Post-process to compute scattered fields  $\{E, H\}^{\text{scat}}$  from k. SCUFF-EM does this.

Innovations unique to **SCUFF-EM**:

- Bypass step 4: Compute scattered/absorbed power, force, and torque directly from k
- Bypass steps 3 and 4: Compute Casimir forces and heat transfer directly from M

# Geometries in SCUFF

A gold sphere and a displaced and rotated SiO2 tetrahedron:



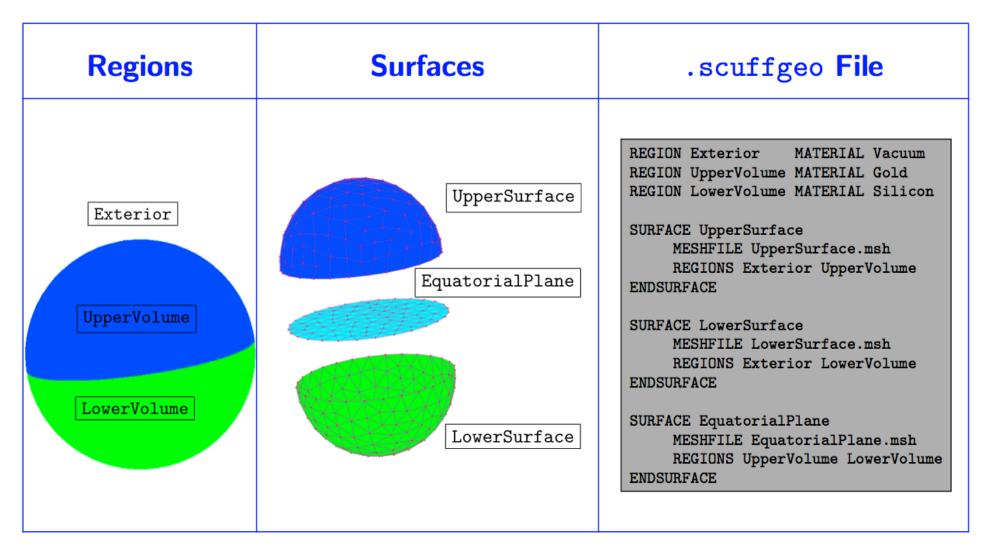
#### The .scuffgeo file:

OBJECT TheSphere MESHFILE Sphere.msh MATERIAL Gold ENDOBJECT

OBJECT ThePyramid MESHFILE Pyramid.msh MATERIAL SiO2 DISPLACED 0 0 -1 ROTATED 45 ABOUT 0 1 0 ENDOBJECT

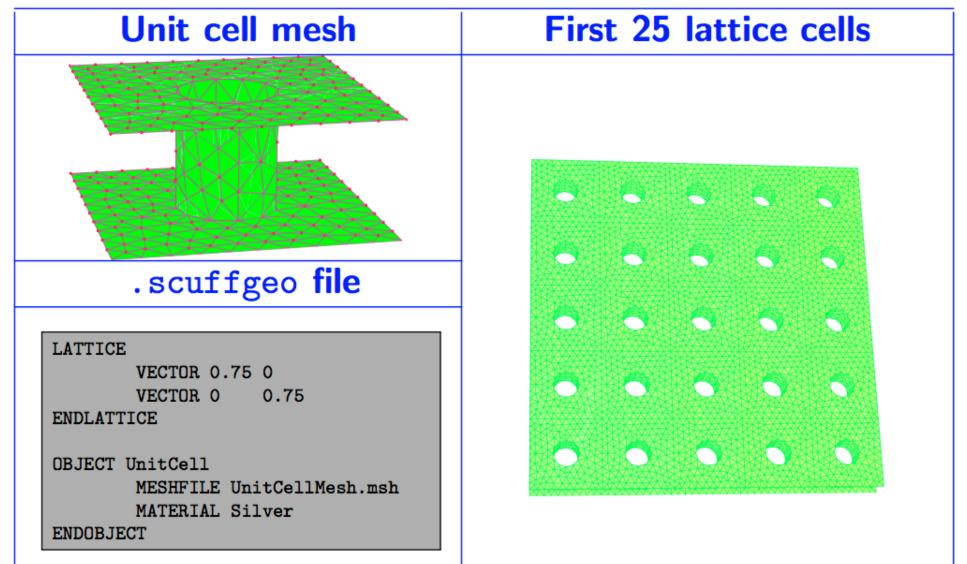
→ Handle displacements and rotations without re-meshing.

# Geometries in SCUFF



(discretization of SIE at junctions of 3+ materials is a bit tricky)

### Periodic geometries in SCUFF



(implementing periodicity is nontrivial: changes Green's function! SCUFF: periodic  $\Gamma = \Sigma$ (nearest neighbors) + Ewald summation)

# Using SIE/BEM solutions

Solving the SIE gives the surface currents  $\mathbf{c}$ , and from these (via  $\Gamma^* \mathbf{c}$ ) one can obtain any desired fields, but...

It is much more efficient to compute as much as possible directly from  $\mathbf{c}$  (~  $\mathbf{n}$  × surface fields). Examples:

- Scattering matrices (e.g. spherical-harmonic waves in → out): obtain directly from multipole moments of "currents"
- Any bilinear function of the surface fields can be computed directly from bilinear functions of **c**:
  - scattered/absorbed power, force, torque, ...
- Net effects of quantum/thermal fluctuations in matter can be computed from norm/det/trace of M or M<sup>-1</sup>:

- thermal radiation, Casimir (van der Waals) forces, ...

# Resonant modes (and eigenvalues)

• BEM scattering problems are of the form  $M(\omega)x = s$ . Resonances (and eigenvalues) are  $\omega$  where this system is singular, i.e. the **nonlinear eigenproblem** 

det  $M(\omega) = 0$ 

For passive ( $\Rightarrow$  causal) systems, solutions can only occur for Im  $\omega \le 0$ .

• Various algorithms exist, including an intriguing algorithm using contour integrals of  $M(\omega)$  [Beyn (2012)].

Computational Nanophotonics: Optimization and "Inverse Design"

> Steven G. Johnson MIT Applied Mathematics

Many, many papers that parameterize by a *few* degrees of freedom and optimize...

Today, focus is on *large-scale optimization*, also called *inverse design*: so many degrees of freedom (10<sup>2</sup>–10<sup>6</sup>) that computer is "discovering" new designs.

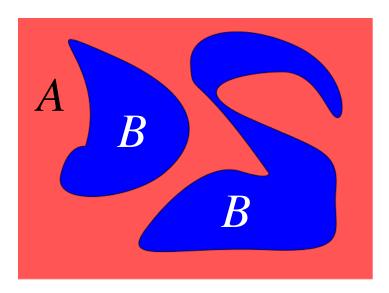
# Outline

- Brief overview/examples of large-scale optimization work in photonics
- Overview of optimization terminology, problem types, and techniques.
- Some more detailed photonics examples.

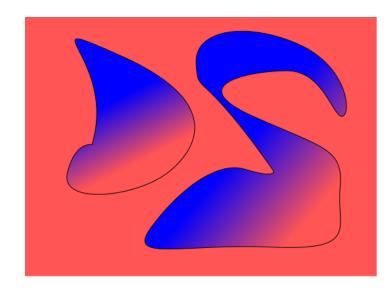
### Outline

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# Topology optimization



Given two (or more) materials A and B, determine what arrangement — including what topology optimizes some objective/constraints.

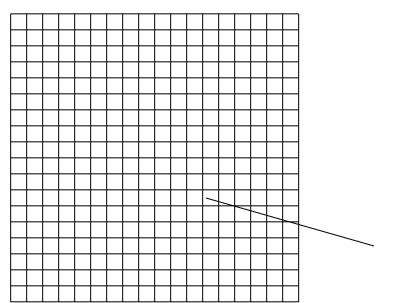


Continuous relaxation: allow material to vary in [*A*,*B*] continously at every point

- Not uncommon for optimum to yield *A* or *B* almost everywhere
- Possible to add "penalty" to objective for intermediate values

# Discretizing Topology Optimization

for computer, need finite-dimensional parameter space



some computational grid

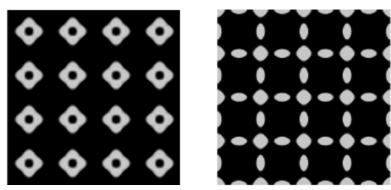
Level-set method: value of "level-set" function  $\phi(\mathbf{x})$  varies continuously at each pixel  $\Rightarrow$  material *A* or *B* if  $\phi > 0$  or < 0

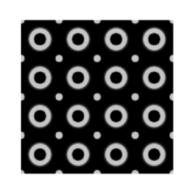
...*01*...

Continuous relaxation: material varies in [*A*,*B*] at each pixel

e.g. in electromagnetism, let  $\varepsilon$  at each pixel vary in [*A*,*B*].

### Dobson et al. (Texas A&M)





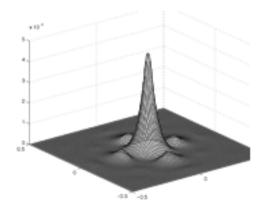
(maximizes  $\sim \Delta \omega$ , not fractional gap!)

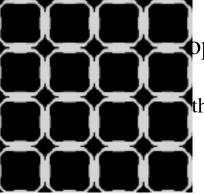
(square lattices only)

TM gap, bands 3 & 4 TM bands 6 & 7

SIAM J. Appl. Math. 59, 2108 (1999)



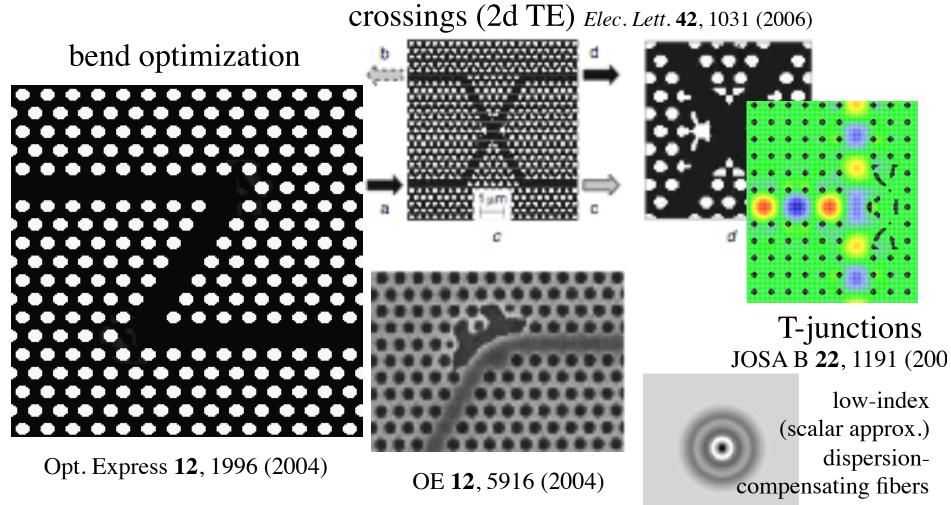




optimized TE gaps square lattice thousands of iterations & still not optimal!

optimize TM localization in supercell SIAM J. Appl. Math **64**, 762 (2004) J. Comput. Phys **158**, 214 (2000)

### 2d (TE or TM) transmission optimization Sigmund, Jensen, Pederson et al. [<u>www.topopt.dtu.dk</u>]



JOSA B 25, 88 (2008)

### Dispersion optimization Sigmund, Jensen, Pederson et al. [<u>www.topopt.dtu.dk</u>]

0.3

0.2

0.1

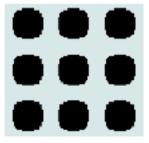
0.1

Normalized frequency or (a/).

b)



low-index (scalar approx.) dispersioncompensating fibers JOSA B **25**, 88 (2008)



optimized 2d scalar phononic crystals [ Phil. Trans. Roy. Soc. London A **361**, 1001 (2003) ]

optimized phononic gap  $\Delta \omega$ bands 1 & 2 constant group-velocity band in 2d TE line-defect

Wavenumber k (a/2n)

0.3

0.4

0.5

0.2

# · · · · · · · · ·

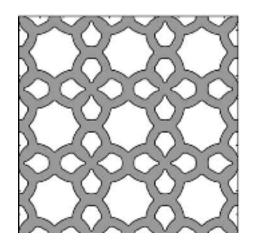
... also band gaps for 2d (scalar) phononic crystals...

# Kao, Osher, and Yablonovitch 2d TM and TE square-lattice gaps via level set

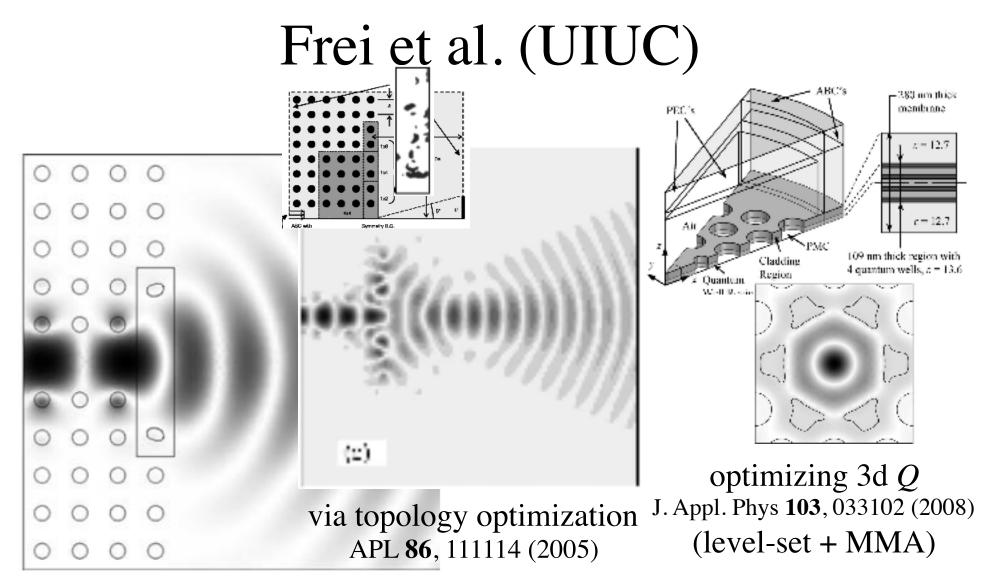
Appl. Phys. B 81, 235 (2005)

	N. C.Y. 199 (1997)	N 35 900
0	0	•
000	000	000
0	0	•
		0
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000	000	000
۲	•	•

TM gap, bands 6 & 7 (maximizes  $\Delta \omega$ , not fractional gap!)

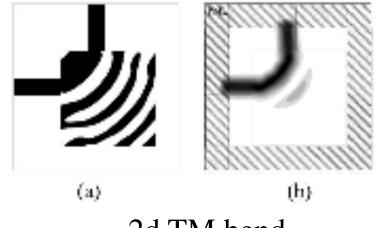


TE gap, bands 5 & 6

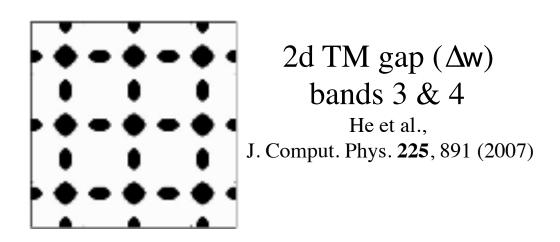


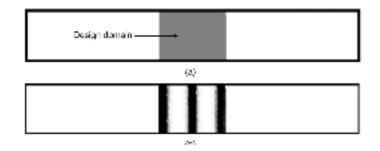
2d TM "directional" emission via level-set method Frei, Opt. Lett. **32**, 77 (2007)

# Other Topology Optimizers



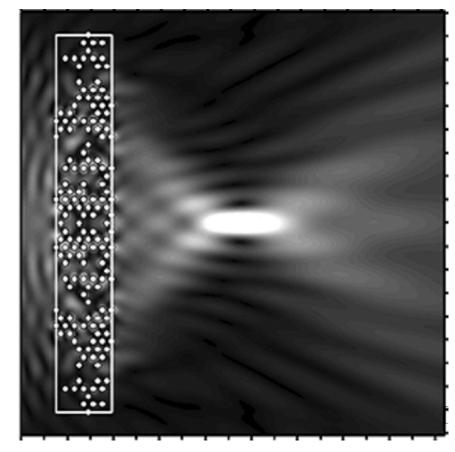
2d TM bend [ Tsuji, Phot. Tech. Lett. 20, 982 (2008) ]

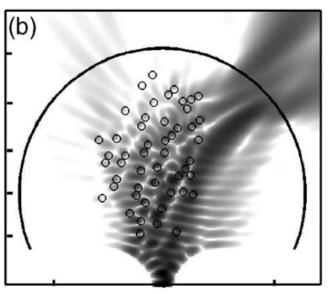




"2d" (really 1d) TE filter Byun, IEEE Trans. Magnetics 43, 1573 (2007)

### Optimization with many discrete degrees of freedom





2d TM "bender" moving cylinders around (steepest-descent) Seliger, J. Appl. Phys. **100**, 034310 (2006) ]

2d TM "lens" design genetic algorithms: moving cylinders around [Håkansson, IEEE J. Sel. Ar. Commun. 23, 1365 (2005)

## Outline

- Brief overview/examples of large-scale optimization work in photonics
- Overview of optimization terminology, problem types, and techniques.
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# A general optimization problem

 $\min_{x\in\mathbb{R}^n}f_0(x)$ 

subject to *m* constraints

 $f_i(x) \le 0$ 

$$i = 1, 2, ..., m$$

*x* is a *feasible point* if it satisfies all the constraints *feasible region* = set of all feasible *x* 

minimize an objective function  $f_0$ with respect to *n* design parameters *x* (also called *decision parameters*, *optimization variables*, etc.)

> - note that *maximizing* g(x)corresponds to  $f_0(x) = -g(x)$

note that an *equality constraint*  h(x) = 0yields two inequality constraints  $f_i(x) = h(x)$  and  $f_{i+1}(x) = -h(x)$ (although, in practical algorithms, equality constraints typically require special handling)

## Important considerations

- *Global* versus *local* optimization
- *Convex* vs. non-convex optimization
- Unconstrained or box-constrained optimization, and other special-case constraints
- Special classes of functions (linear, etc.)
- Differentiable vs. non-differentiable functions
- Gradient-based vs. derivative-free algorithms
- •
- Zillions of different algorithms, usually restricted to various special cases, each with strengths/weaknesses

# Global vs. Local Optimization

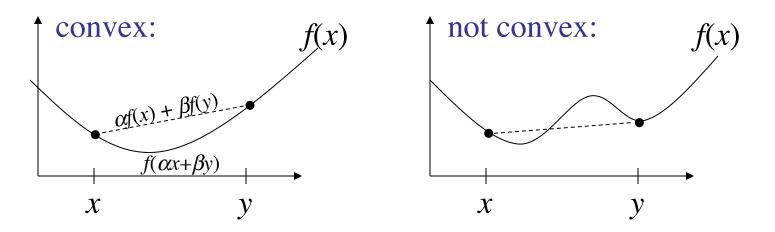
- For *general nonlinear* functions, *most* algorithms only guarantee a local optimum
  - that is, a feasible  $x_0$  such that  $f_0(x_0) \le f_0(x)$  for all feasible x within some neighborhood  $||x-x_0|| < R$  (for some small R)
- A *much harder* problem is to find a global optimum: the minimum of  $f_0$  for *all* feasible *x* 
  - exponentially increasing difficulty with increasing n, practically impossible to *guarantee* that you have found global minimum without knowing some special property of  $f_0$
  - many available algorithms, problem-dependent efficiencies
    - *not* just genetic algorithms or simulated annealing (which are popular, easy to implement, and thought-provoking, but usually *very slow*!)
    - for example, non-random systematic search algorithms (e.g. DIRECT), partially randomized searches (e.g. CRS2), repeated local searches from different starting points ("multistart" algorithms, e.g. MLSL), ...

## **Convex Optimization**

[ good reference: *Convex Optimization* by Boyd and Vandenberghe, free online at <u>www.stanford.edu/~boyd/cvxbook</u> ]

All the functions  $f_i$  (*i*=0...*m*) are *convex*:

 $f_i(\alpha x + \beta y) \le \alpha f_i(x) + \beta f_i(y) \quad \text{where} \quad \begin{array}{l} \alpha + \beta = 1\\ \alpha, \beta \in [0, 1] \end{array}$ 



For a convex problem (convex objective & constraints) *any* local optimum *must* be a global optimum ⇒ efficient, robust solution methods available

#### Important Convex Problems

- LP (linear programming): the objective and constraints are *affine*:  $f_i(x) = a_i^T x + \alpha_i$
- QP (quadratic programming): affine constraints + convexquadratic objective  $x^{T}Ax+b^{T}x$
- SOCP (second-order cone program): LP + *cone* constraints  $||Ax+b||_2 \le a^Tx + \alpha$
- SDP (semidefinite programming): constraints are that  $\Sigma A_k x_k$  is positive-semidefinite

all of these have very efficient, specialized solution methods

## Non-convex local optimization: a typical generic outline

[ many, many variations in details !!! ]



At current **x**, construct approximate model of  $f_i$ -e.g. affine, quadratic, ... often convex



Optimize the model problem ⇒ new x — use a *trust region* to prevent large steps



Evaluate new **x**:

- if "acceptable," go to 1
- if bad step (or bad model), update trust region / model and go to 2

### Important special constraints

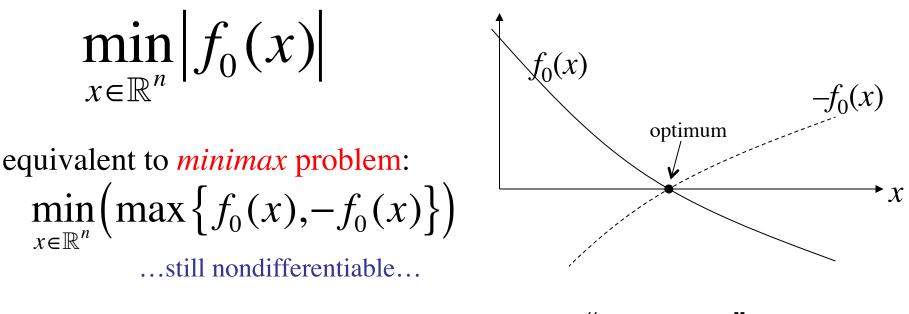
- Simplest case is the *unconstrained* optimization problem: *m*=0
  - e.g., line-search methods like steepest-descent, nonlinear conjugate gradients, Newton methods ...
- Next-simplest are *box constraints* (also called *bound constraints*):  $x_k^{\min} \le x_k \le x_k^{\max}$ 
  - easily incorporated into line-search methods and many other algorithms
  - many algorithms/software *only* handle box constraints
- ...
- Linear equality constraints *Ax=b* 
  - for example, can be explicitly eliminated from the problem by writing x=Ny+x, where x is a solution to Ax=b and N is a basis for the nullspace of A

### Derivatives of $f_i$

- Most-efficient algorithms typically require user to supply the gradients  $\nabla_x f_i$  of objective/constraints
  - you should *always* compute these analytically
    - rather than use finite-difference approximations, better to just use a derivative-free optimization algorithm
    - in principle, one can always compute  $\nabla_x f_i$  with about the same cost as  $f_i$ , using adjoint methods
  - gradient-based methods can find (local) optima of problems with millions of design parameters
- Derivative-free methods: only require  $f_i$  values
  - easier to use, can work with complicated "black-box" functions where computing gradients is inconvenient
  - *may* be only possibility for nondifferentiable problems
  - need > n function evaluations, bad for large n

#### Removable non-differentiability

consider the non-differentiable unconstrained problem:

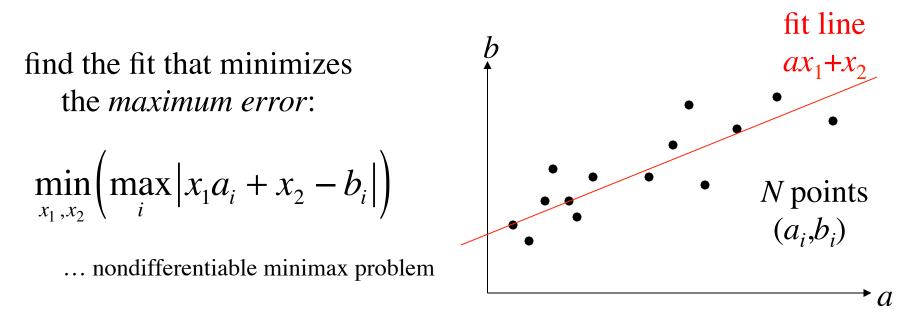


...equivalent to *constrained* problem with a "temporary" variable *t*:

$$\min_{x \in \mathbb{R}^n, t \in \mathbb{R}} t \quad \text{subject to:} \quad t \ge f_0(x) \quad (f_1(x) = f_0(x) - t)$$

$$t \ge -f_0(x) \quad (f_2(x) = -f_0(x) - t)$$

#### Example: Chebyshev linear fitting



equivalent to a *linear programming* problem (LP):

 $\min_{x_1, x_2, t} t$  subject to 2N constraints:  $x_1 a_i + x_2 - b_i - t \le 0$   $b_i - x_1 a_i - x_2 - t \le 0$ 

#### Gap Optimization via nonlinear constraints

nt: 
$$\max_{\varepsilon} \left( 2 \frac{\left[ \min_{\mathbf{k}} \boldsymbol{\omega}_{n+1}(\mathbf{k}) \right] - \left[ \max_{\mathbf{k}} \boldsymbol{\omega}_{n}(\mathbf{k}) \right]}{\left[ \min_{\mathbf{k}} \boldsymbol{\omega}_{n+1}(\mathbf{k}) \right] + \left[ \max_{\mathbf{k}} \boldsymbol{\omega}_{n}(\mathbf{k}) \right]} \right)$$

we wan

not differentiable at accidental degeneracies

an equivalent problem:

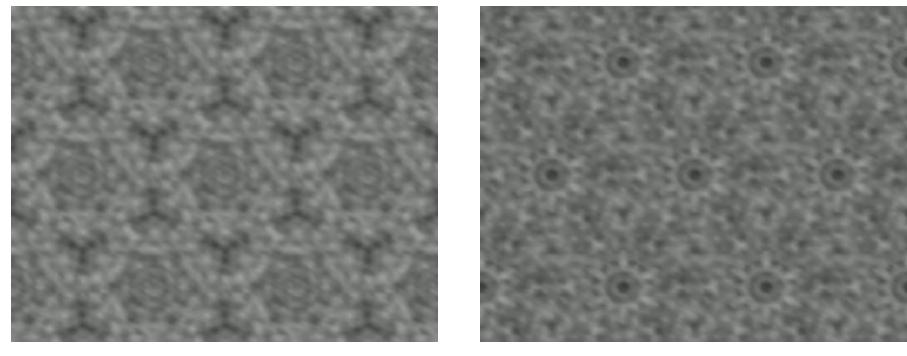
$$\max_{\varepsilon} \left( 2 \frac{f_2 - f_1}{f_2 + f_1} \right)$$

...with (mostly) differentiable nonlinear constraints:  $f_2 \leq \omega$ 

subject to:

$$f_1 \ge \omega_n(\mathbf{k})$$
$$f_2 \le \omega_{n+1}(\mathbf{k})$$

#### Optimizing 1st TM and TE gaps for a triangular lattice with 6-fold symmetry (between bands 1 & 2)

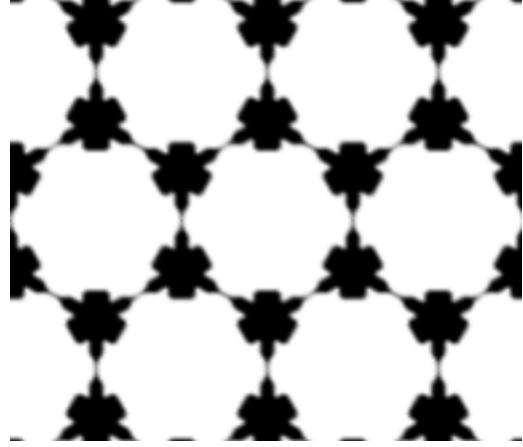


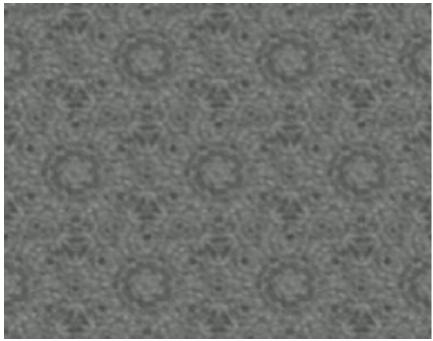
48.3% TM gap (e = 12:1)

51.4% TE gap (e = 12:1)

30 iterations of optimizer

## Optimizing 1st complete (TE +TM) 2d gap

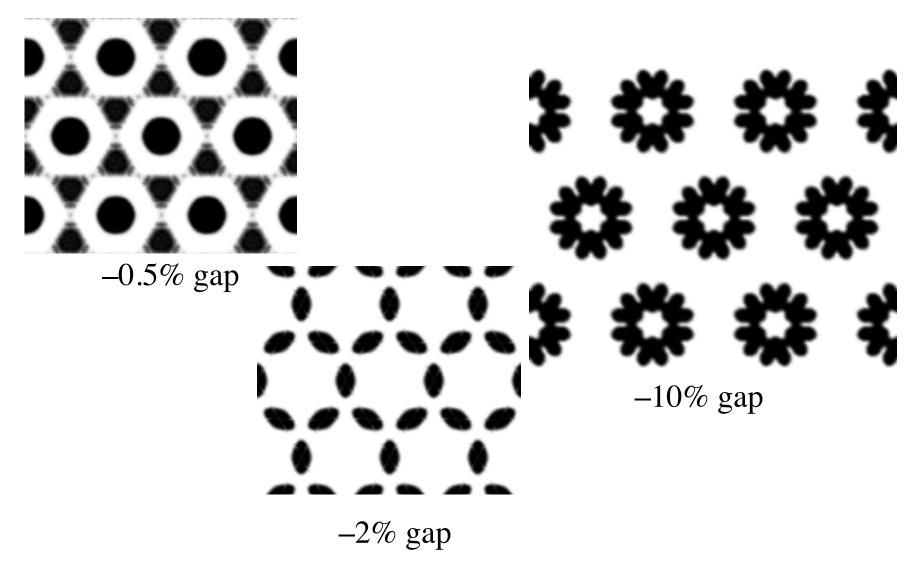




20.7% gap (e = 12:1)

21.1% gap (e = 12:1)

#### + some local minima



good news: only a handful of minima (in 10<sup>3</sup>-dimensional space!)

#### Relaxations of Integer Programming

If x is integer-valued rather than real-valued (e.g.  $x \in \{0,1\}^n$ ), the resulting *integer programming* or *combinatorial optimization* problem becomes *much harder* in general (often NP-complete).

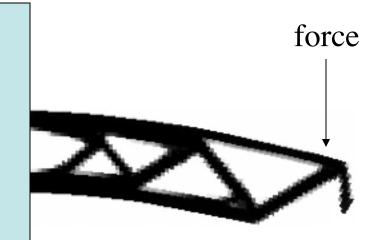
However, useful results can often be obtained by a *continuous relaxation* of the problem — e.g., going from  $x \in \{0,1\}^n$  to  $x \in [0,1]^n$ ... at the very least, this gives an lower bound on the optimum  $f_0$ ... and penalty methods (e.g. SIMP) can be used to gradually eliminate intermediate x values.

## Early Topology Optimization

design a structure to do something, made of material A or B... let *every pixel* of discretized structure vary *continuously* from A to B

density of each pixel varies continuously from 0 (air) to max

ex: design a cantilever to support maximum weight with a fixed amount of material



optimized structure, deformed under load

[Buhl et al, Struct. Multidisc. Optim. 19, 93-104 (2000)]

#### Some Sources of Software

- Decision tree for optimization software: <u>http://plato.asu.edu/guide.html</u>
  - lists many packages for many problems
- CVX: general convex-optimization package <u>http://www.stanford.edu/~boyd/cvx</u>
- NLopt: implements many nonlinear optimization algorithms (global/local, constrained/unconstrained, derivative/no-derivative) <u>http://ab-initio.mit.edu/nlopt</u>

#### Outline

- Brief overview/examples of large-scale optimization work in photonics
- Overview of optimization terminology, problem types, and techniques.
- Some more detailed photonics examples.

# Key questions occur *before* choosing optimization algorithm:

- How to parameterize the degrees of freedom

  how much knowledge of solution to build in?
- Which objective function & constraints? — many choices for a given design goal,

... can make an enormous difference in the computational feasibility & the robustness of the result.

#### Today: Three Examples

- Optimizing photonics without solving Maxwell's equations — transformational inverse design
- Ensuring manufacturability of narrow-band devices — robust optimization in photonics design
- Optimizing eigenvalues without eigensolvers — microcavity design and the frequency-averaged local density of states

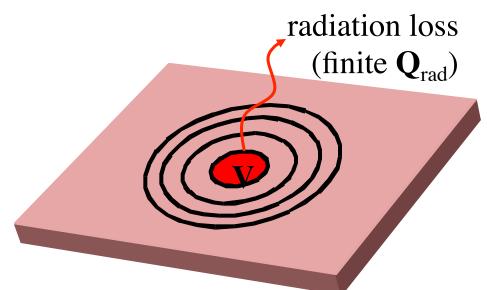
#### Today: Three Examples

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- Optimizing eigenvalues without eigensolvers — microcavity design and the frequency-averaged local density of states

[X. Liang et al., manuscript in preparation]

#### 3d Microcavity Design Problem

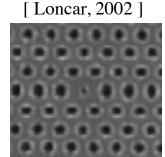


Want some 2d pattern that will confine light in 3d with maximal lifetime (" $Q_{rad}$ ") and minimal modal volume ("V")

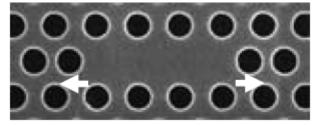
Many *ad hoc* designs, trading off  $O_{red}$  and V...



410 nm 420 nm 410 nm 410 nm 420 nm 410 nm 41



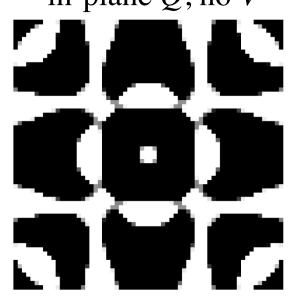
("defects" in periodic structures)

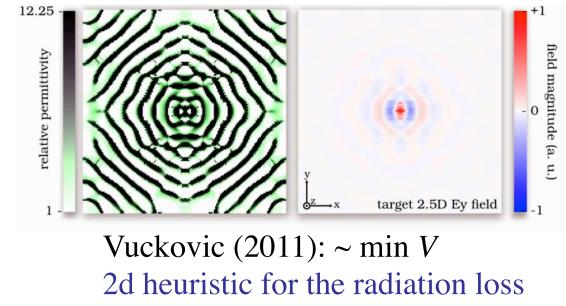


[Akahane, 2003]

### Topology optimization? Mostly 2d...

[Kao and Santosa, 2008] in-plane Q, no V





Can we formulate a *practical* approach to solve the *full* problem, computing the *true* 3d radiation loss?

Goals: understand ultimate limits on cavity performance, & eventually push cavity design into new regimes

#### Not just maximizing Q or Q/V!

Typical figure of merit is "Purcell factor" Q/V(~ enhancement of light-matter coupling)

Naively, should we maximize Q/V?

Trivial design problem: maximum  $Q/V = \infty$ [ e.g. perfect ring resonator of  $\infty$  radius ]

$$V = \frac{\int \boldsymbol{\varepsilon} |\mathbf{E}|^2}{\max \boldsymbol{\varepsilon} |\mathbf{E}|^2}$$



$$V \sim R$$
$$Q_{\rm rad} \sim \exp(\# R)$$

#### Real design problem:

maximize Qsuch that  $V \le V_0$ 

or

minimize V such that  $Q \ge Q_0$ set by bandwidth, loss tolerance, & fabrication capabilities

#### Transforming the problem...

a series of nonobvious transformations makes the problem *much easier* 

minimize modal volume V subject to  $Q \ge Q_0$ 

turn difficult eigenproblem into easier scattering problem: Q/V is really just LDOS

Maximize mean LDOS (local density of states) (= power of dipole) over bandwidth  $\omega_0/Q_0$ 

Maximize LDOS at complex  $\omega = \omega_0 (1 + i/2Q_0)$ 

complex analysis: contour integration + causality

technical issue: avoid optimizing along "narrow ridge" (avoid ill-conditioned Hessian)

Minimize 1/LDOS at  $\omega_0(1+i/2Q_0)$ 

#### LDOS: Local Density of States

[ review: arXiv:1301.5366 ]

Maxwell eigenproblem:

Maxwell vector-Helmholtz:

 $\frac{1}{\varepsilon} \nabla \times \frac{1}{\mu} \nabla \times E \triangleq \Theta E = \omega^2 E$  $\langle E, E' \rangle = \int E^* \cdot \varepsilon E'$ 

 $\boldsymbol{E}=i\boldsymbol{\omega}(\boldsymbol{\Theta}-\boldsymbol{\omega}^2)^{-1}\boldsymbol{\varepsilon}^{-1}\boldsymbol{J}$ 

Power radiated by a current **J** (Poynting's theorem)

$$P = -\frac{1}{2} \operatorname{Re} \int \boldsymbol{E}^* \cdot \boldsymbol{J} \, d^3 \boldsymbol{x} = -\frac{1}{2} \operatorname{Re} \langle \boldsymbol{E}, \boldsymbol{\varepsilon}^{-1} \boldsymbol{J} \rangle$$

special case of a dipole source: LDOS

$$\boldsymbol{J}(\boldsymbol{x}) = \boldsymbol{e}_{\ell} \,\delta(\boldsymbol{x} - \boldsymbol{x}_0) \qquad \text{LDOS}_{\ell}(\boldsymbol{x}_0, \boldsymbol{\omega}) = \frac{4}{\pi} \,\varepsilon(\boldsymbol{x}_0) P_{\ell}(\boldsymbol{x}_0, \boldsymbol{\omega})$$

## Why a "density of states"

[ review: arXiv:1301.5366 ]

$$\frac{1}{\varepsilon} \nabla \times \frac{1}{\mu} \nabla \times \boldsymbol{E} \triangleq \boldsymbol{\Theta} \boldsymbol{E} = \boldsymbol{\omega}^2 \boldsymbol{E}$$
$$\langle \boldsymbol{E}, \boldsymbol{E'} \rangle = \int \boldsymbol{E} \cdot \boldsymbol{\varepsilon} \boldsymbol{E'}$$

countable eigenfunctions  $\mathbf{E}^{(n)}$  and frequencies  $\omega^{(n)} + i\gamma^{(n)}$ 

consider a finite domain (periodic/Dirichlet) + small absorption

$$E = i\omega(\Theta - \omega^2)^{-1} \varepsilon^{-1} J$$
$$P = -\frac{1}{2} \operatorname{Re} \langle E, \varepsilon^{-1} J \rangle$$
$$\varepsilon^{-1} J = \sum_{n} E^{(n)} \langle E^{(n)}, \varepsilon^{-1} J \rangle$$

 $loss \rightarrow 0$ : a localized measure of spectral density

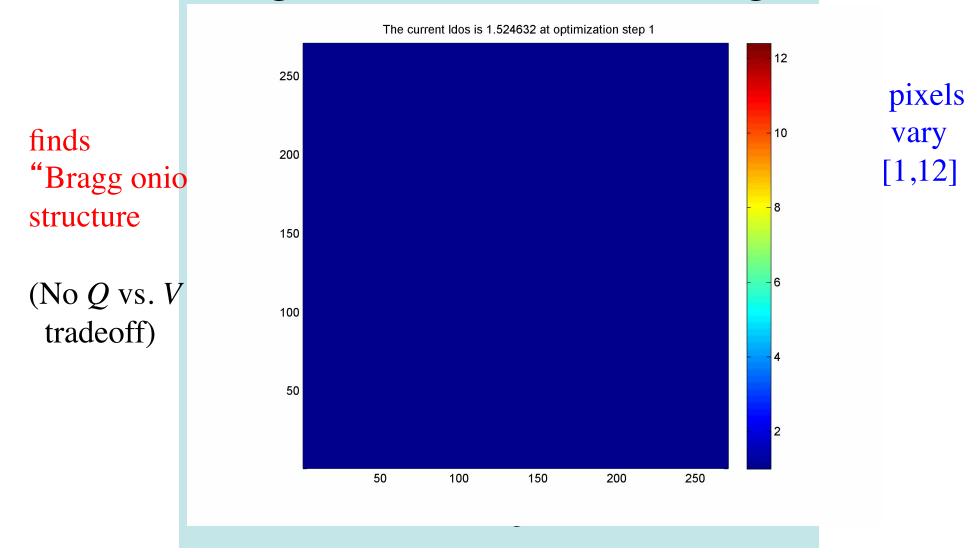
$$LDOS_{\ell}(\boldsymbol{x},\boldsymbol{\omega}) = \sum_{n} \delta(\boldsymbol{\omega} - \boldsymbol{\omega}^{(n)}) \boldsymbol{\varepsilon}(\boldsymbol{x}) |E_{\ell}^{(n)}(\boldsymbol{x})|^{2}$$
  
DOS(\omega) =  $\sum_{n} \delta(\boldsymbol{\omega} - \boldsymbol{\omega}^{(n)})$ 

Minimize 1/LDOS at  $\omega_0(1+i/2Q_0)$ 

...Let every pixel be a degree of freedom (ε in [1,12])
 ~ 10<sup>5</sup> degrees of freedom
 ...Solve with (mostly) standard methods:
 FDFD solver (sparse-direct + GMRES)
 adjoint sensitivity analysis
 quasi-Newton optimization (L-BFGS)

#### Now, a few results...

## 2d test case: Out-of-plane **J**, starting from vacuum initial guess



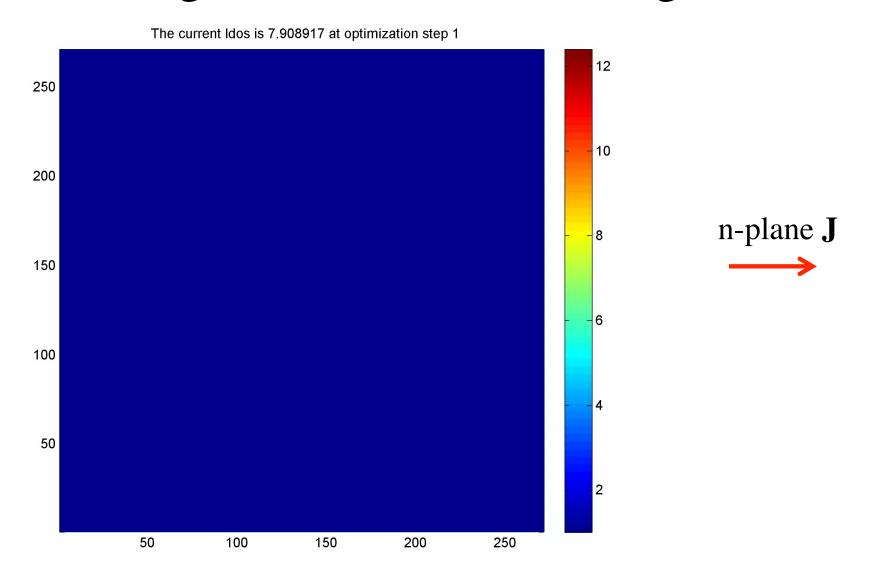
#### 2d test case: Out-of-plane **J**, starting from PhC initial guess

starting guess has PhC resona mode already, but optimizatic converts back to Bragg onion

	0	۰	۰	۰	۰	۰	۰	۰	•	•	۰	۰	۰	•	۰	۰	•			12
250	0	۰	•	•	•	۰	۰	۰	•	•	•	•	•	0	۰	۰	•			
	•	۰	۰	۰	۰	۰	۰	۰	۰	•	•	۰	•	0	۰	۰	•			
200	•	۰	•	•	•	۰	•	•	•	•	•	•	•	0	۰	•	$\bullet$			10
	•	۰	•	•	•	۰	۰	•	•	•	•	•	۰	•	۰	•	ullet			
150	0	۰	•	۰	•	۰	•	۰	•	$\bullet$	۰	•	۰	•	۰	•	۰			
	•	•	•	•	•	۰	•	•	•	•	•	•	•	•	•	•	•	-		8
	•	۰	•	•	•	$\bullet$	•	•	۰	•	$\bullet$	۲	•	0	•	•	•			
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	•	•	۰	۲	•	۲	•	•	۰	•	$\bullet$	•	$\bullet$	•	•	•	$\bullet$	-		4
50	•	$\bullet$	•	•	•	•	•	•	$\bullet$	$\bullet$	$\bullet$	•	•	•	•	$\bullet$	$\bullet$			
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	•	•	0	ø	0	0	•	0	ò	0	0	0	•	ø	0	0	•			
			50			100			150			200				250				•

The current Idos is 16.625309 at optimization step 1

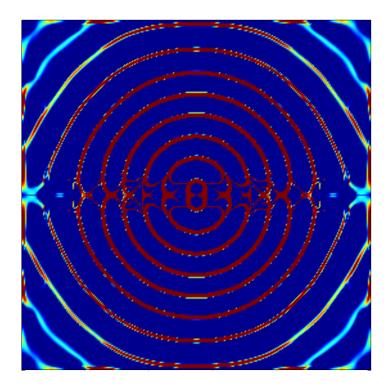
## 2d test case: In-plane J (breaks symmetry), starting from vacuum initial guess

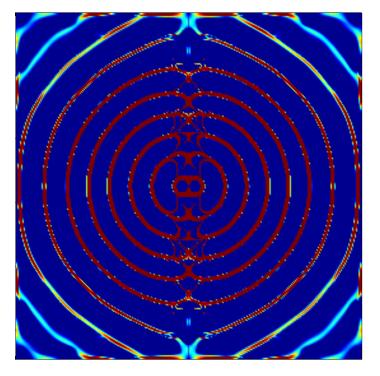


#### in-plane J

Jy

#### Maximizing LDOS for random in-plane J = max[LDOS( $\omega$ ,J<sub>x</sub>)+LDOS( $\omega$ ,J<sub>x</sub>)]/2



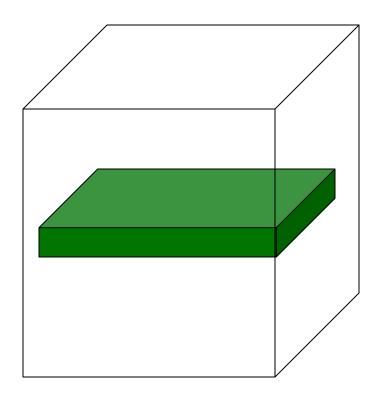


4 out of 10

6 out of 10

Spontaneous symmetry breaking! "Picks" one polarization randomly

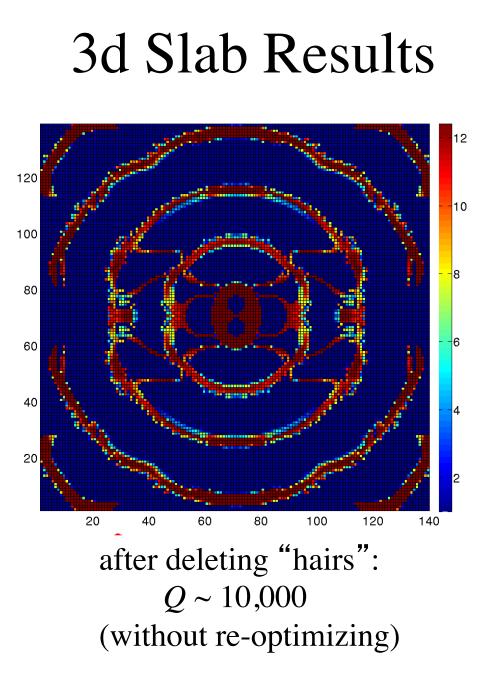
#### 3d results: Photonic-crystal slab

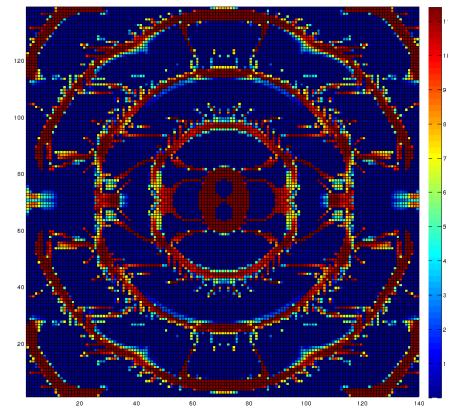


Next: 2d pattern in 3d slab

(including radiation loss via PML absorbing boundaries) Optimize with  $Q_0 = 10^4$ 

i.e. prefer  $Q \ge 10^4$  but after that mainly minimize V





#### $Q \sim 30,000, V \sim 0.06(\lambda/n)^3$

vs. hand-optimized:  $Q \sim 100,000, V \sim 0.7(\lambda/n)^3$   $Q \sim 300,000, V \sim 0.2(\lambda/n)^3$ *and others...* 

#### Today: Three Examples

• Optimizing photonics without solving Maxwell's equations — transformational inverse design

• Ensuring manufacturability of narrow-band devices — robust optimization in photonics design

> [ Oskooi *et al.*, *Optics Express* **20**, 21558 (2012). ] [ Mutapcic *et al.*, *Engineering Optim*. (2009) ]

• Optimizing eigenvalues without eigensolvers — microcavity design and the frequency-averaged local density of states

#### Robustness of optimized designs

a "nominal" optimization problem:

minimize design parameters **p** 

objective(**p**)

#### Robustness of optimized designs

a "nominal" optimization problem:

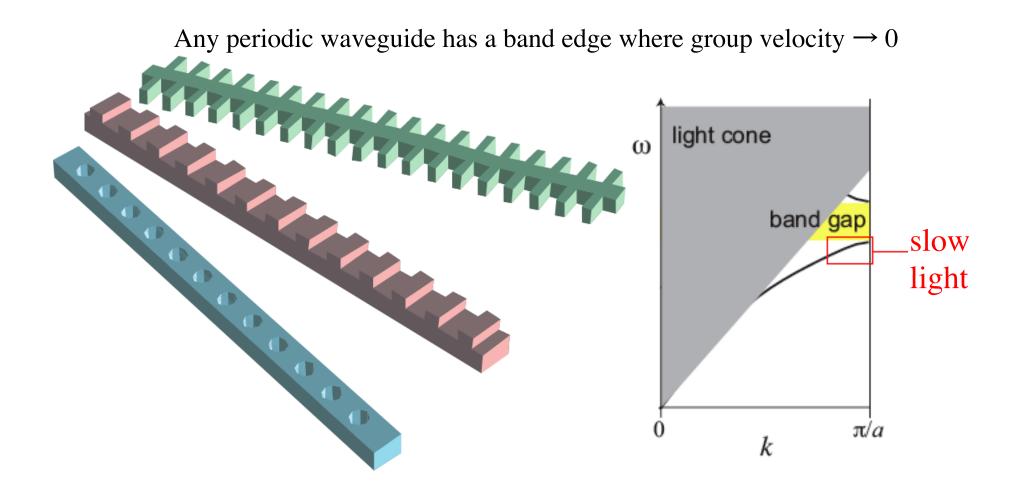
minimize design parameters **p** objective(**p**,**0**)

**Problem:** real objective is inexact, due to uncertainties in modeling, fabrication, materials, etcetera ... is a function objective( $\mathbf{p}, \mathbf{u}$ ) of  $\mathbf{p}$ and unknown/uncertain parameters  $\mathbf{u} \in U$ 

Problem: optimization sometimes finds solutions that are "delicate" and destroyed by uncertainty ... i.e. objective(p, actual u) >> objective(p,0)

... can easily happen in single-frequency wave-optics designs where optimization finds a delicate interference effect...

### Slow light

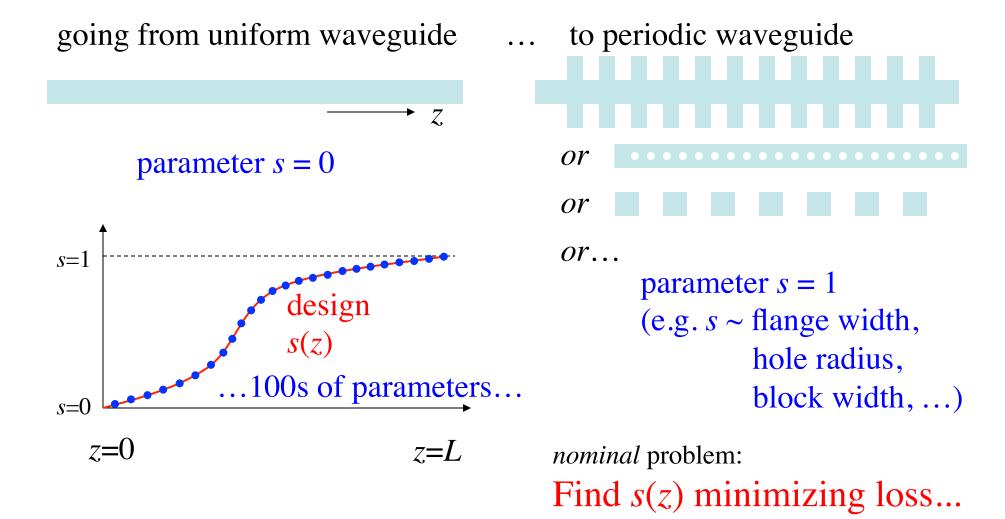


Enhances light-matter interactions, dispersion phenomena, tunable time delays ... but hard to couple to ordinary waveguide: large "impedance mismatch"

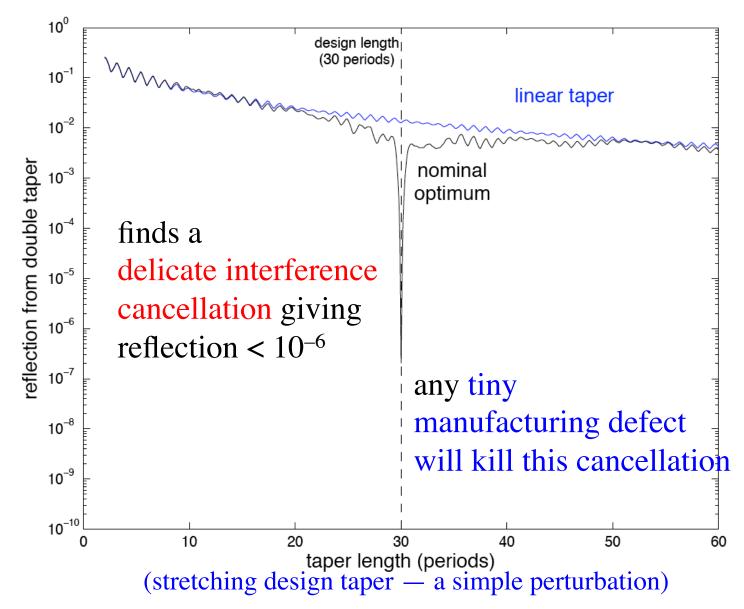
#### A slow-light optimization problem

[ Povinelli, Johnson, Joannopoulos (2005) ]

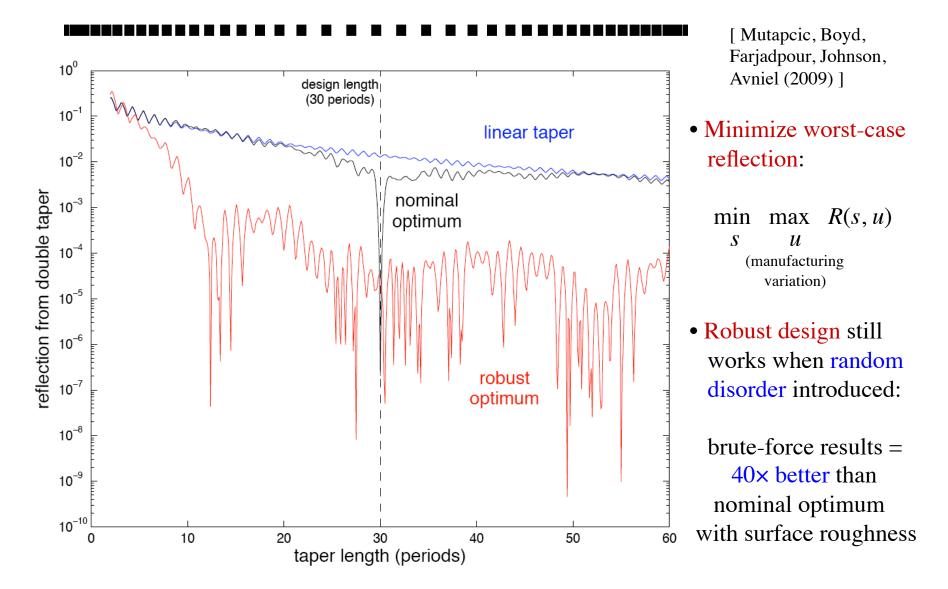
[ Mutapcic, Boyd, Farjadpour, Johnson, Avniel (2009) ] [ Oskooi *et al.*, *Optics Express* **20**, 21558 (2012). ]



#### A nominal optimum



#### The solution: Robust optimization (worst-case minimax)



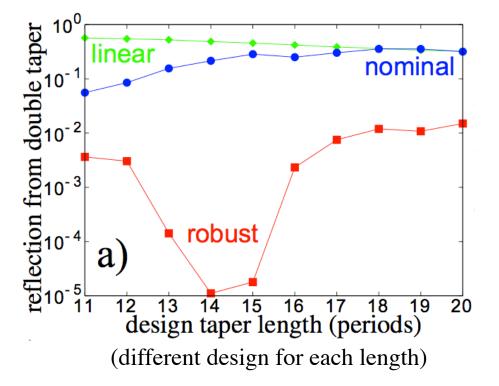
#### A more realistic, slow-light structure

[Oskooi et al., Optics Express 20, 21558 (2012).]



Slow-light waveguide for TE (in-plane polarization), tapers contain no narrow gaps, corresponds to contiguous, low-aspect ratio structure in 3d.

... Operate close to band edge, group velocity c/34.



In the presence of disorder, robust is orders of magnitude better than nominal optimum.

Nominal optimum is worthless: reflections > 10%.

Making taper too long makes things worse: disorder kills you.

#### Today: Three Examples

• Optimizing photonics without solving Maxwell's equations — transformational inverse design

> [Gabrielli, Liu, Johnson & Lipson, *Nature Commun*. (2012)] [Liu *et al.*, manuscript in preparation.]

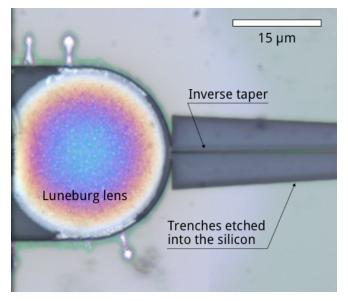
- Ensuring manufacturability of narrow-band devices — robust optimization in photonics design
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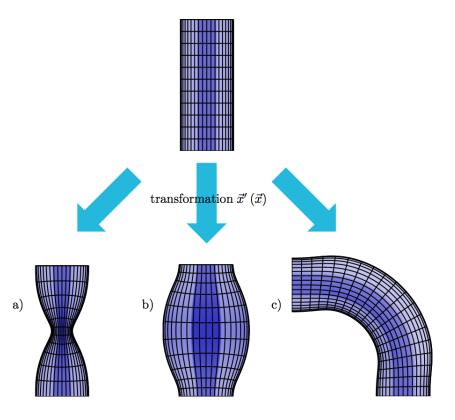
#### Gradient-index Multimode Optics

#### Lipson group @ Cornell

can make smoothly varying "gradient-index" structures by grayscale lithography (variable-thickness waveguide

= gradient effective index)



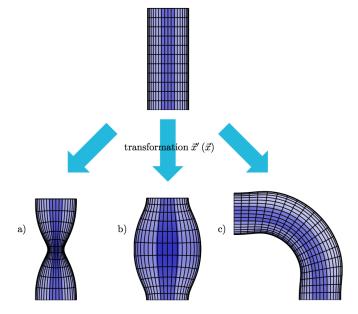


Transformation optics: design materials that mathematically mimic coordinate transformations

#### **Transformational Optics**

[Ward & Pendry (1996)]

Idea: warping light with x'(x)



= material transformations

 $\varepsilon' = \varepsilon \frac{JJ^T}{\det J}$   $\mu' = \mu \frac{JJ^T}{\det J}$ (J = Jacobian matrix) **Pro:** exact transformation of Maxwell solutions, so no reflections or scattering

 transforms all modes same way, preserving relative phase → multimode optics

**Cons:** most transformations give difficult-to-achieve  $\varepsilon$ ,  $\mu$ :

• anisotropy; 
$$\mu \neq \mu_0$$
,

... "round" to isotropic index

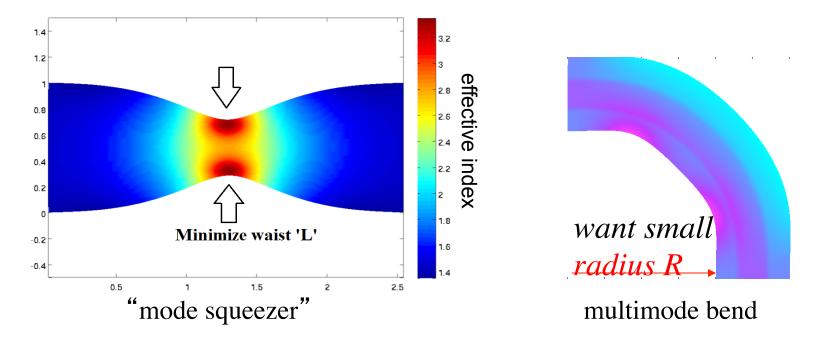
 $n \approx \sqrt{\varepsilon \mu / \varepsilon_0 \mu_0}$ 

• n may be too big / small

### Transformational Inverse Design

Given a transformation x'(x), we can evaluate its manufacturability (need minimal anisotropy, attainable indices) quickly, without solving Maxwell's equations

... so optimization can rapidly search many transformations to find the "best" manufacturable design



#### 

For a given radius R, minimize the maximum anisotropy, subject to index constraints, over "all" transformations  $\mathbf{x}'(\mathbf{x})$ :

$$\min_{\mathbf{x}'(\mathbf{x})} \left[ \max_{\mathbf{x}} \operatorname{anisotropy}(\mathbf{x}) \right] = \min_{\mathbf{x}'(\mathbf{x}), t} t$$

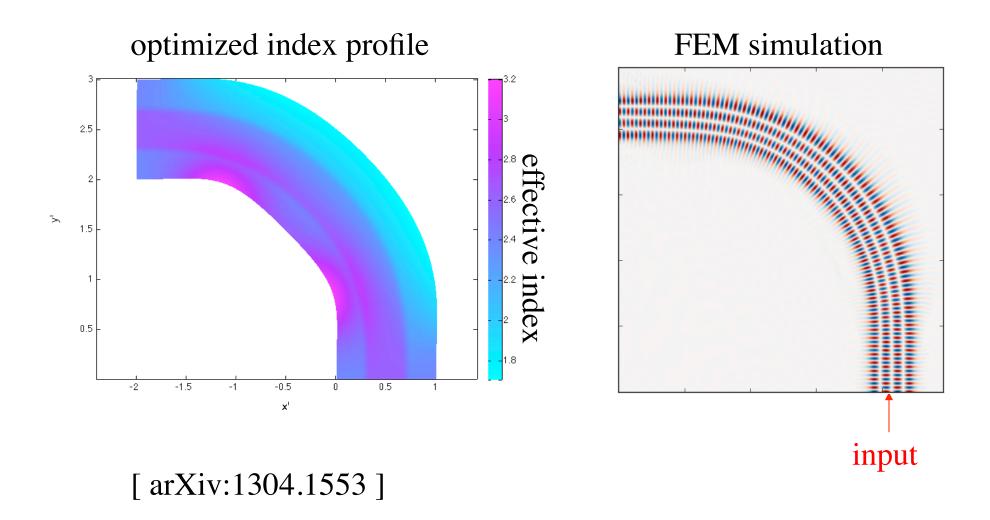
subject to:  $1.6 \le n(\mathbf{x}) \le 3.2$ at all  $\mathbf{x}$   $t \ge anisotropy(\mathbf{x}) (= "Distortion"-1)$  $-1 + tr J^T J / 2 det J \ge 0$ (J = Jacobian) $\sim 30,000$ constraints $(100 \times 100 \mathbf{x} \text{ grid})$ 

where smooth transformations **x**'(**x**) are parameterized by exponentially convergent Chebyshev/sine series

~ 100 parameters

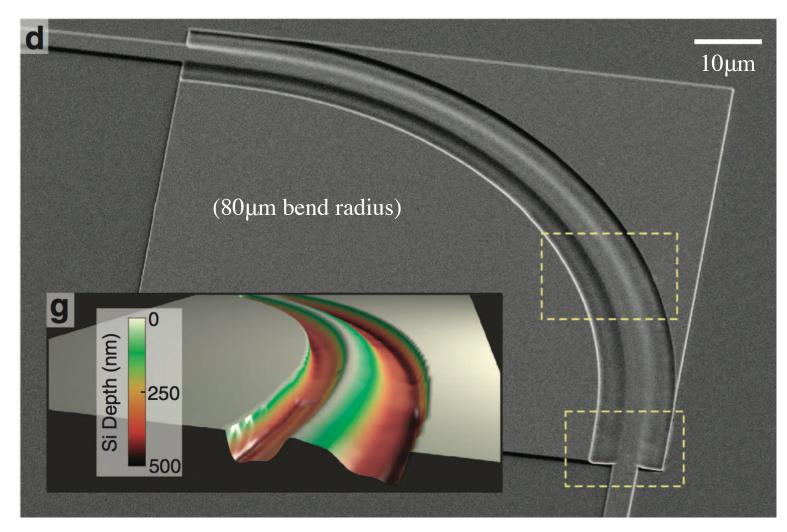
... so cheap that almost any (local) optimization algorithm is okay ... [ use COBYLA derivative-free sequential LP algorithm of Powell (1994) ]

#### An optimized multimode bend



#### Experimental (Si/SiO<sub>2</sub>) Realization

[Gabrielli, Liu, Johnson & Lipson, Nature Commun. (2012)]



measured 14dB reduction in loss (conversion) of the fundamental mode  $(\lambda = 1.55 \mu m)$ VS. circular bend