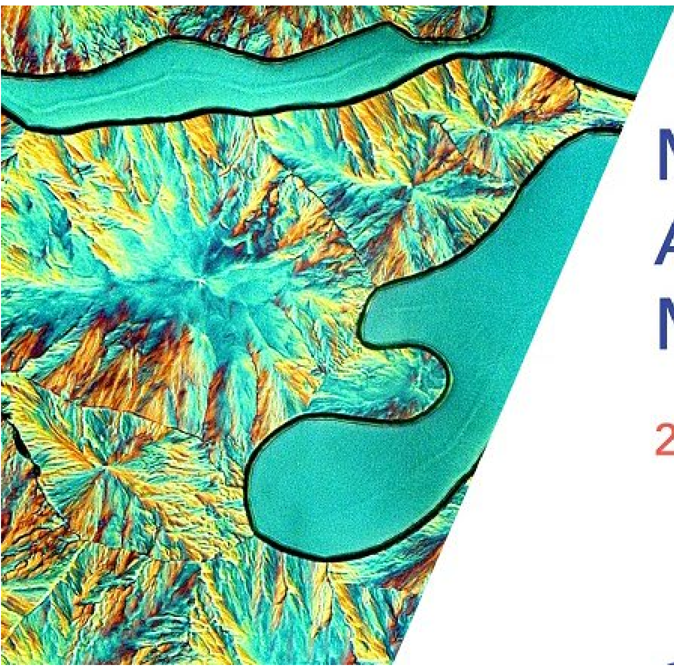
Machine Learning for Accelerated and Inverse Metasurface Design

Presented by:

OSA Photonic Metamaterials Technical Group

The OSA Photonic Metamaterials Technical Group Welcomes You!



MACHINE LEARNING FOR ACCELERATED AND INVERSE METASURFACE DESIGN

2 April 2020 • 13:00 EDT

Photonic
Metamaterials
Technical Group

Technical Group Leadership 2020

Chair

Wei Ting Chen
Harvard Univ.

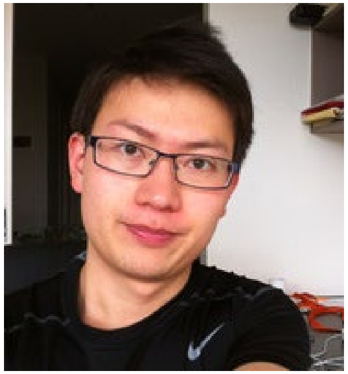
Webinar Officer

Aaron Joseph Pung
Sandia National Laboratories

Webinar Officer

Maxim Shcherbakov
Cornell Univ.

Event Officer



Haoran Ren
LMU Munich

Event Officer

Md Saad-Bin-Alam
University of Ottawa

OSA Photonic Metamaterials Technical Group

Technical Group at a Glance

- Total Members: 1,516 members
  - A part of benefits of OSA membership

- Mission and Focus
  - Serve the community by sharing latest information and providing a pathway for young professionals to greater involvement with mentors and peers

  - OSA Incubator on Flat Optics: Recent Advances and Future Opportunities

#OSAMetamaterialsTG

Join Our Online Community

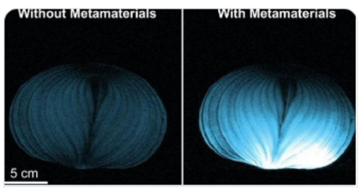
Tweet #OSAMetamaterialsTG

#OSAMetamaterialsTG

Curated Tweets by @hvwalter

Featured tweets from the OSA Photonic Metamaterials Technical Group

AaronJPung
@PungAaron
Mechanical Engineers & Optical Engineers team up to make a new metamaterial for the benefit of MRI! tinyurl.com/y3gbq9kw #OSAMetamaterialsTG #photonics #science #collaboration #photonics



Researchers design 'intelligent' metama…
Boston University researchers have develo…
phys.org

- Upcoming webinars from Prof. Federico Capasso (Harvard) and Prof. Andrea Alu (CUNY)

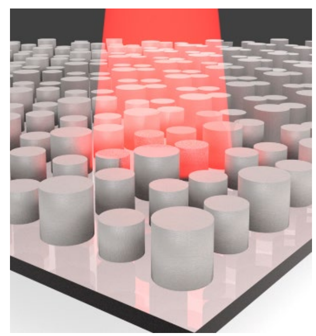
OSA Photonic Metamaterials Technical Group

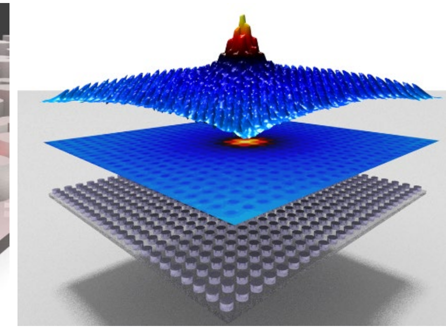
OSA Photonic Metamaterials Technical Group

Webinar Series

Machine Learning for Accelerated and Inverse Metasurface Design

Thursday, April 2nd, 13:00 EDT

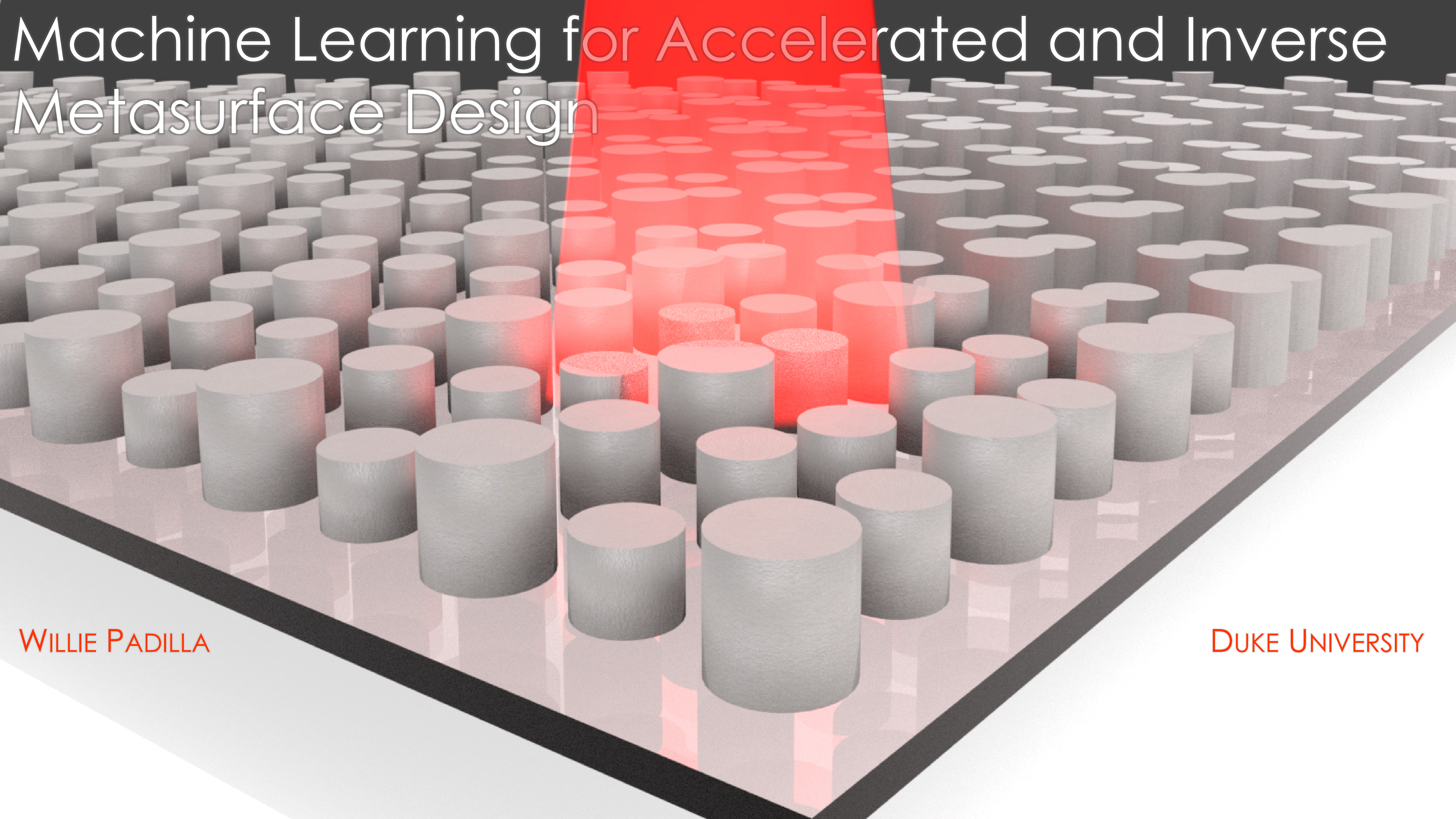




Speaker: Dr. Willie Padilla
Full Professor in the Department of ECE at Duke University

CMIP

Machine Learning for Accelerated and Inverse Metasurface Design



WILLIE PADILLA

DUKE UNIVERSITY

ACKNOWLEDGEMENTS

Graduate Students

Christian Nadell (CoVar Applied Tech)

Simiao Ren (Duke)

Bohao Huang (Duke)

Collaborators

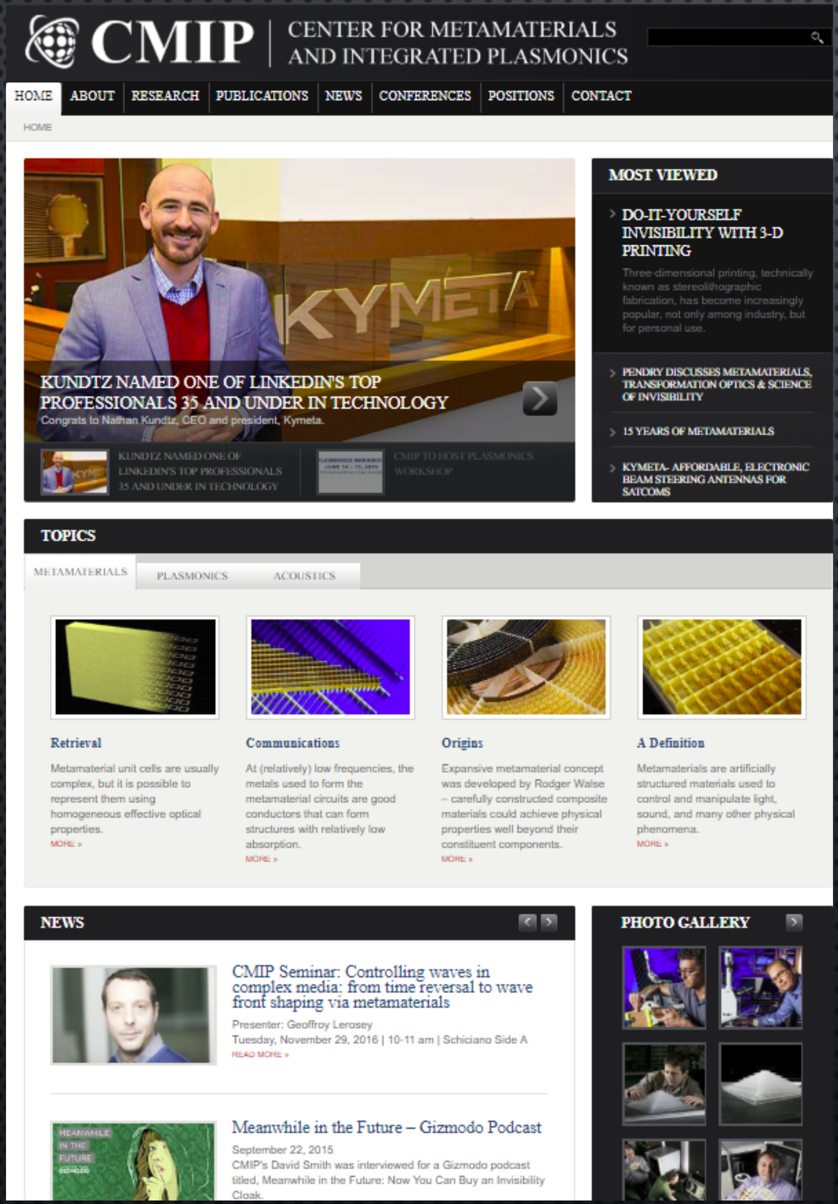
Kebin Fan (Duke)

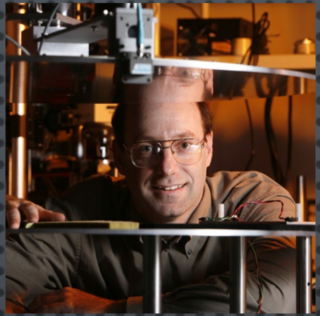
Jordan Malof, (Duke)

Funding

DE-SC0014372

CENTER FOR METAMATERIALS AND INTEGRATED PLASMONICS DUKE UNIVERSITY



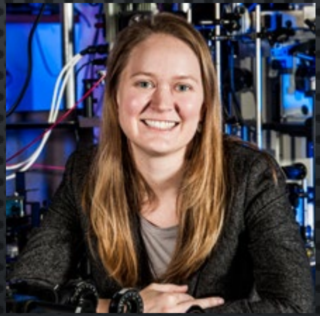


David Smith

Nan Jokerst

Steve Cummer

Natalia Litchinitser

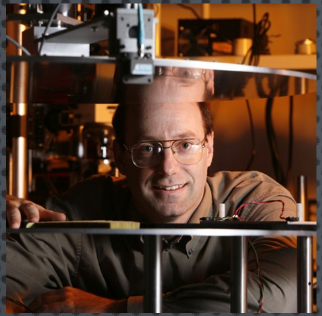


Maiken Mikkelsen

Willie Padilla

Non-linear, integrated nano-systems, acoustical MMs, photonics, plasmonics, absorbers / emitters, topological photonics.

CENTER FOR METAMATERIALS AND INTEGRATED PLASMONICS
DUKE UNIVERSITY



David Smith

Willie Padilla

20 YEARS OF METAMATERIALS

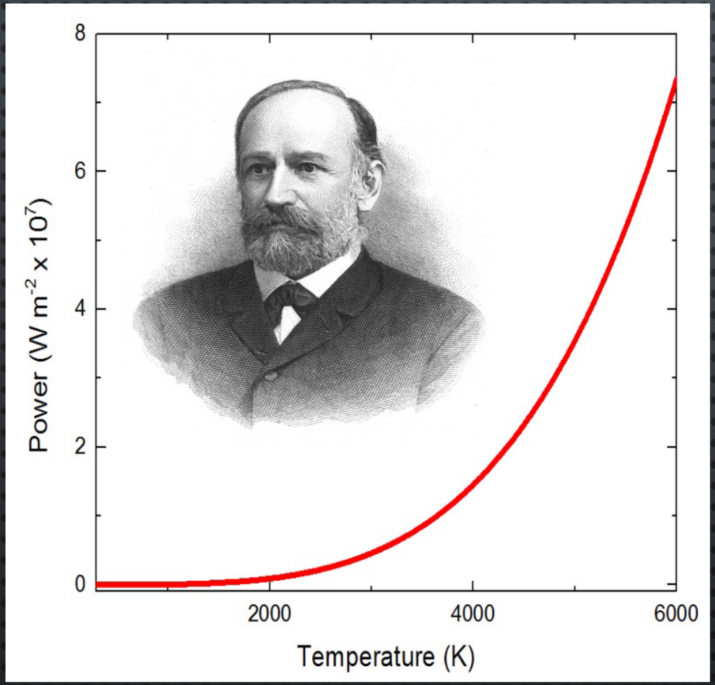
VOLUME 84, NUMBER 18 PHYSICAL REVIEW LETTERS 1 MAY 2000

Composite Medium with Simultaneously Negative Permeability and Permittivity

D. R. Smith,* Willie J. Padilla, D. C. Vier, S. C. Nemat-Nasser, and S. Schultz
Department of Physics, University of California, San Diego, 9500 Gilman Drive, La Jolla, California 92093-0319
(Received 2 December 1999)

We demonstrate a composite medium, based on a periodic array of interspaced conducting nonmagnetic split ring resonators and continuous wires, that exhibits a frequency region in the microwave regime with simultaneously negative values of effective permeability $\mu_{\mathrm{eff}}(\omega)$ and permittivity $\varepsilon_{\mathrm{eff}}(\omega)$. This structure forms a "left-handed" medium, for which it has been predicted that such phenomena as the Doppler effect, Cherenkov radiation, and even Snell's law are inverted. It is now possible through microwave experiments to test for these effects using this new metamaterial.

MOTIVATION – BLACKBODY RADIATION

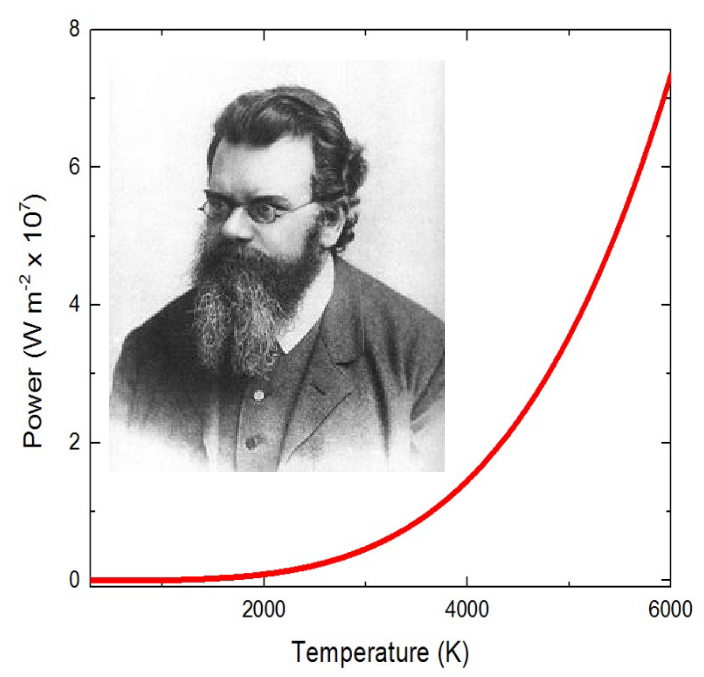


Josef Stefan
(1835 – 1893)

1879 – Total power per unit area emitted at all frequencies by a hot solid was proportional to the fourth power of its absolute temperature *T*.

$$M(T) \propto T^4$$

BLACKBODY RADIATION

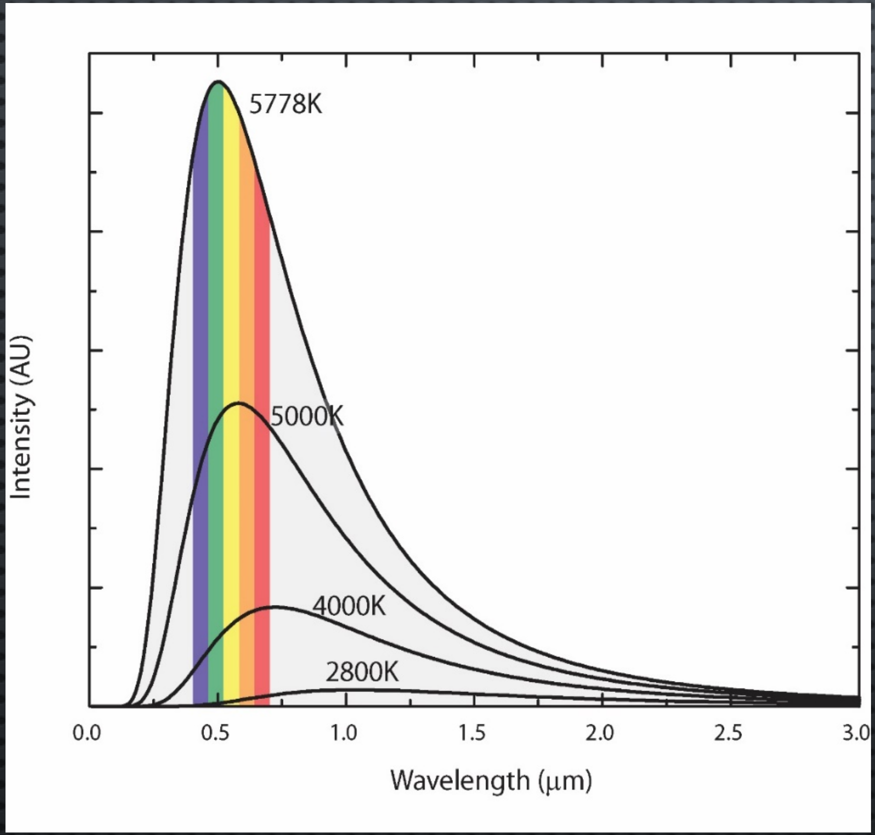


Ludwig Boltzmann
(1844 – 1906)

1884 – Derived Stefan's law from Maxwell's equations and thermodynamics.

$$M(T) = \varepsilon\sigma T^4$$

BLACKBODY RADIATION

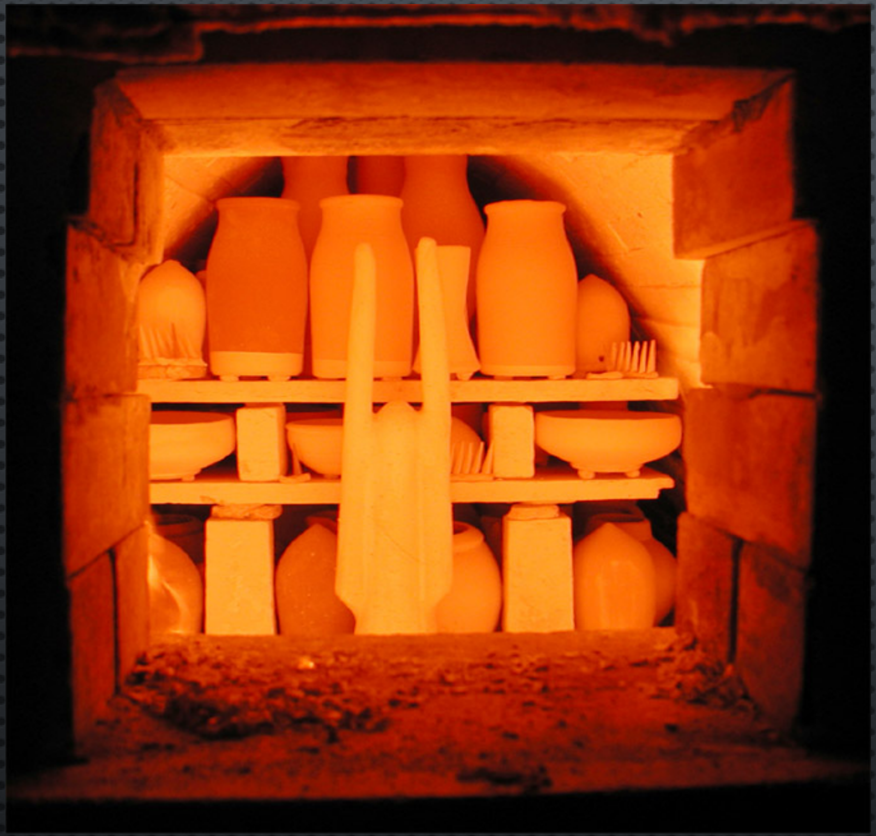


Max Planck
(1858 – 1947)

1900 – Derived the blackbody distribution law from statistical mechanics and Maxwell's equations.

$$B(\lambda, T) = \frac{2\pi hc^2}{\lambda^5} \frac{1}{e^{\frac{hc}{\lambda k_B T}} - 1}$$

BLACKBODY RADIATION



Thomas Wedgwood
(1771 – 1805)

1792 – All the objects in his ovens, regardless of their chemical nature, size, or shape, became red at the same temperature.

Natural materials are limited by the Stefan-Boltzmann law

Engineered materials provide a path forward to overcome SB-law

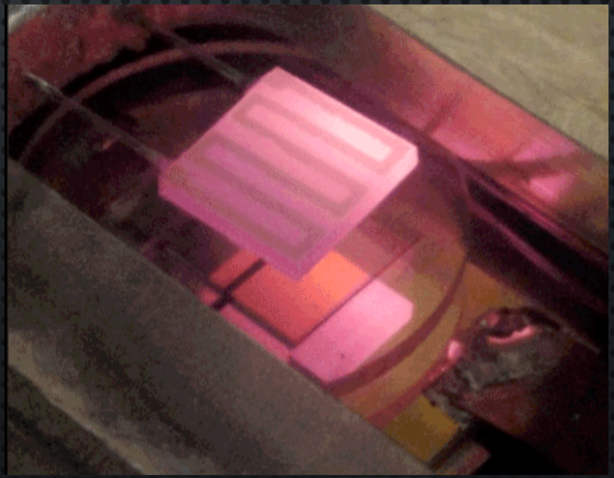
WHY DO WE CARE ABOUT THE BLACKBODY?

•Controlled Incandescence

-Lighting

•Energy Harvesting

-Thermophotovoltaics



PHOTOPIC SENSITIVITY OF THE EYE

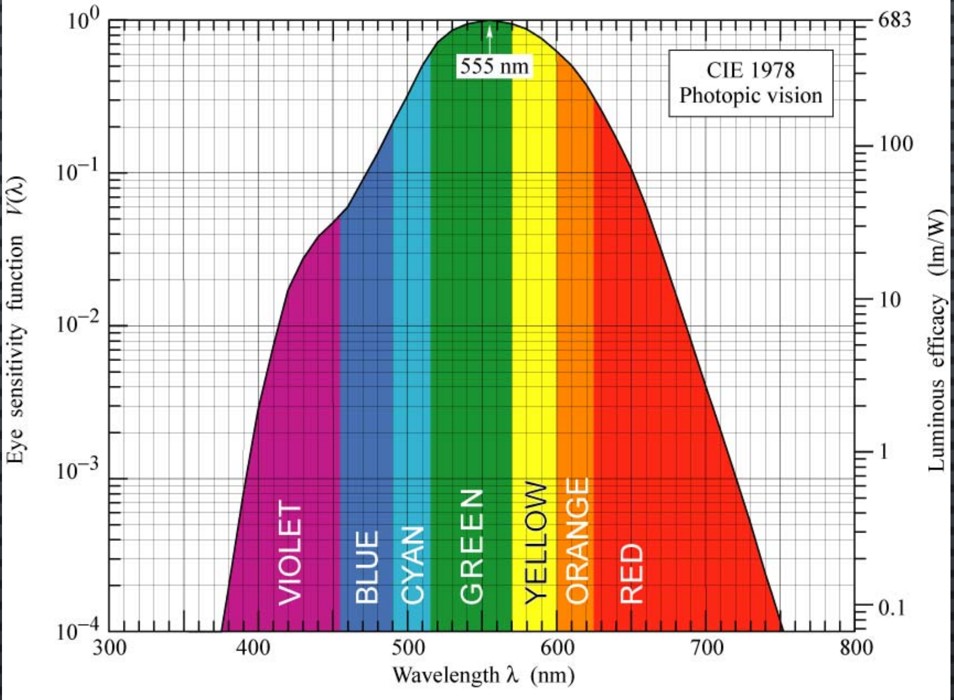
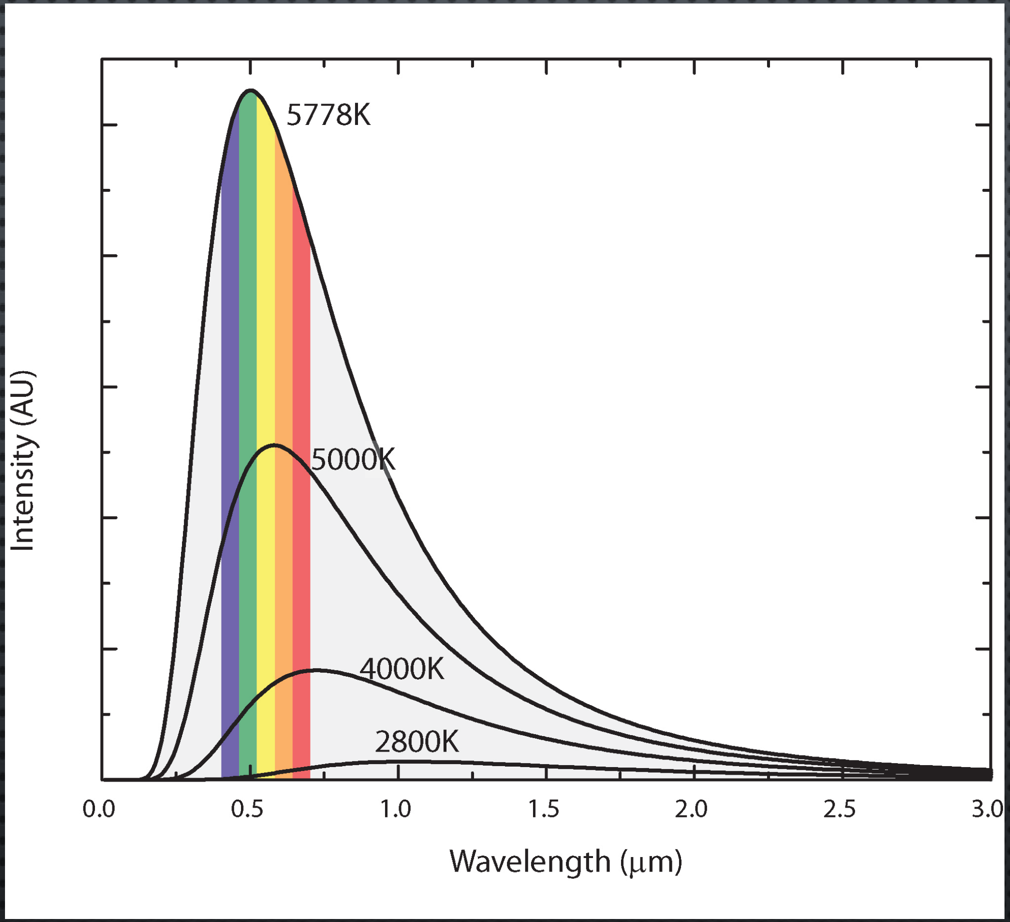


Fig. 16.7. Eye sensitivity function, $V(\lambda)$, (left ordinate) and luminous efficacy, measured in lumens per Watt of optical power (right ordinate). $V(\lambda)$ is greatest at 555 nm. Also given is a polynomial approximation for $V(\lambda)$ (after 1978 CIE data).

E. F. Schubert
Light-Emitting Diodes (Cambridge Univ. Press)
www.LightEmittingDiodes.org

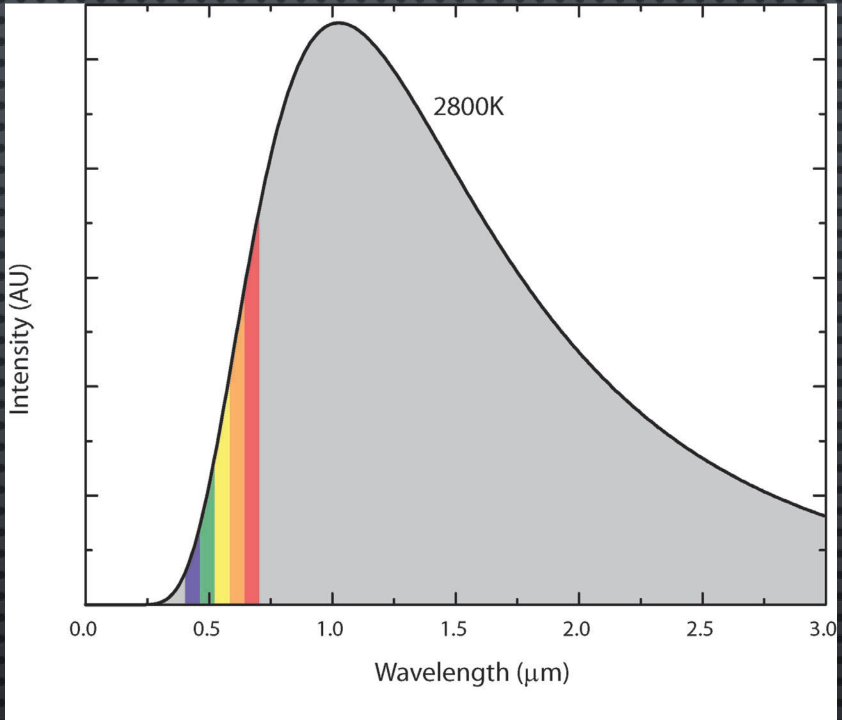
- Photopic (well-lit conditions) sensitivity peaks at 555nm
- Eye sensitivity shifts to shorter wavelengths for low lighting
- CIE 1978 polynomial is standard fit used for lighting

PHOTOPIC SENSITIVITY OF THE EYE



- Human eye optimized for sunlight
- Sun is a blackbody at ~5800K

PHOTOPIC SENSITIVITY OF THE EYE

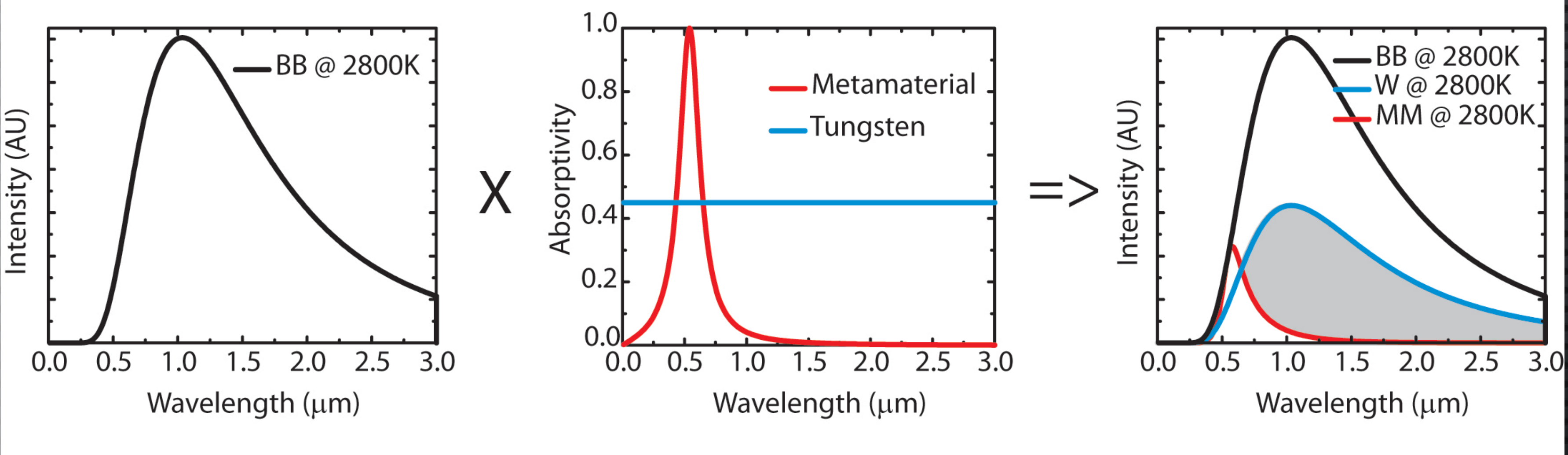


- Tungsten light bulbs operate at 2800K
- Black body peaks in the near infrared
- Generates waste heat
- Emissivity of tungsten is ~45%

HOW TO CONTROL EMISSION WITH METAMATERIALS

Kirchoff's law of thermal radiation - 1859

At thermal equilibrium, the emissivity of a body or surface equals its absorptivity



METAMATERIAL LIGHTING

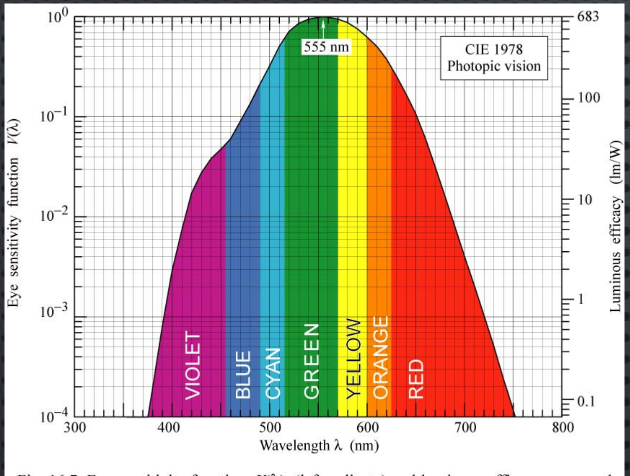
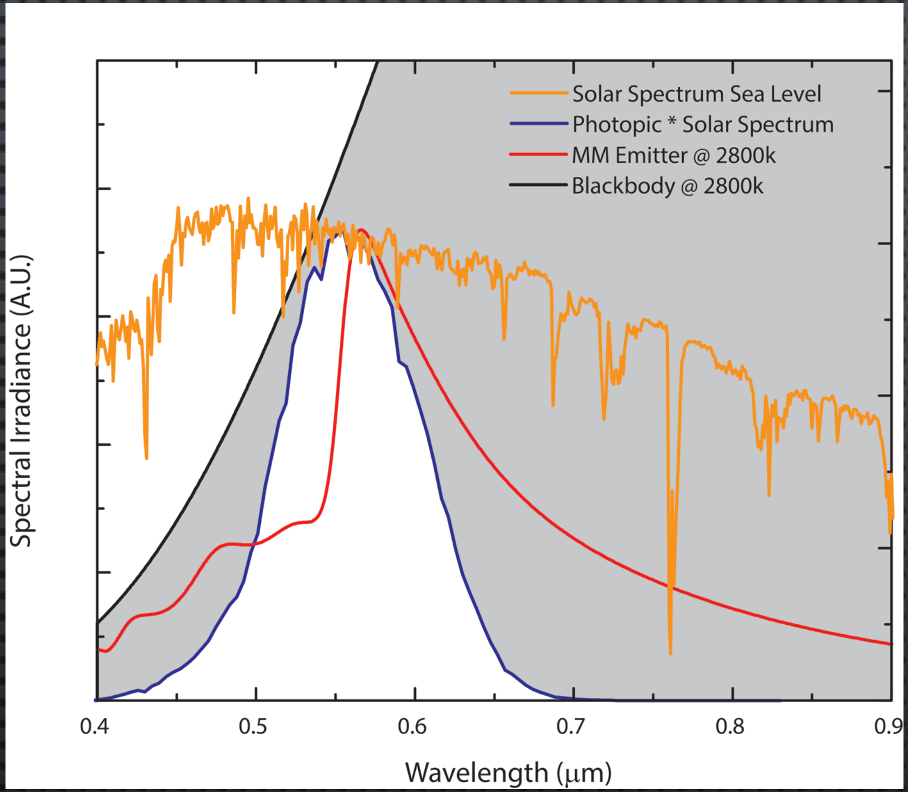
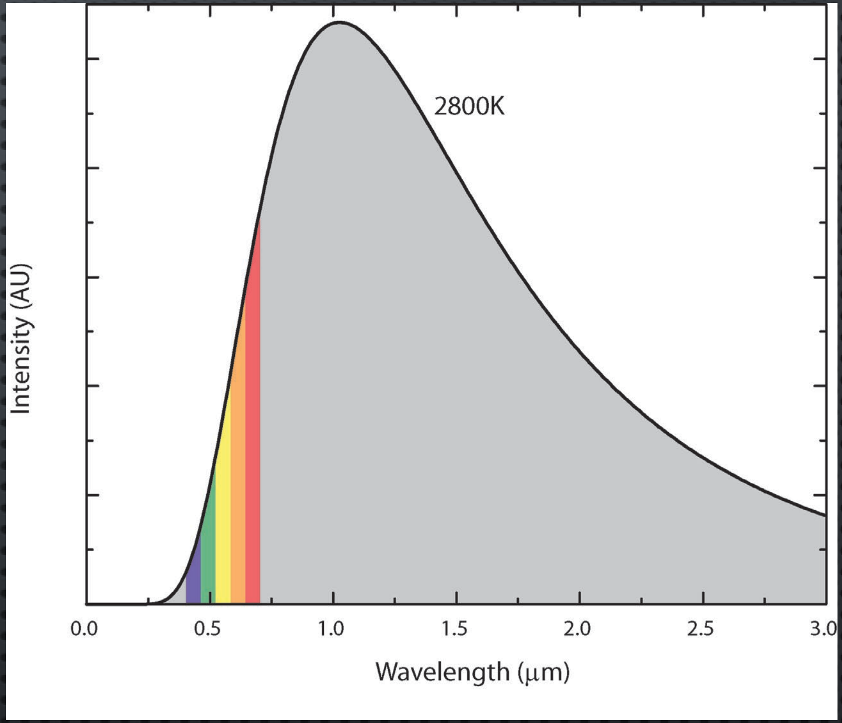
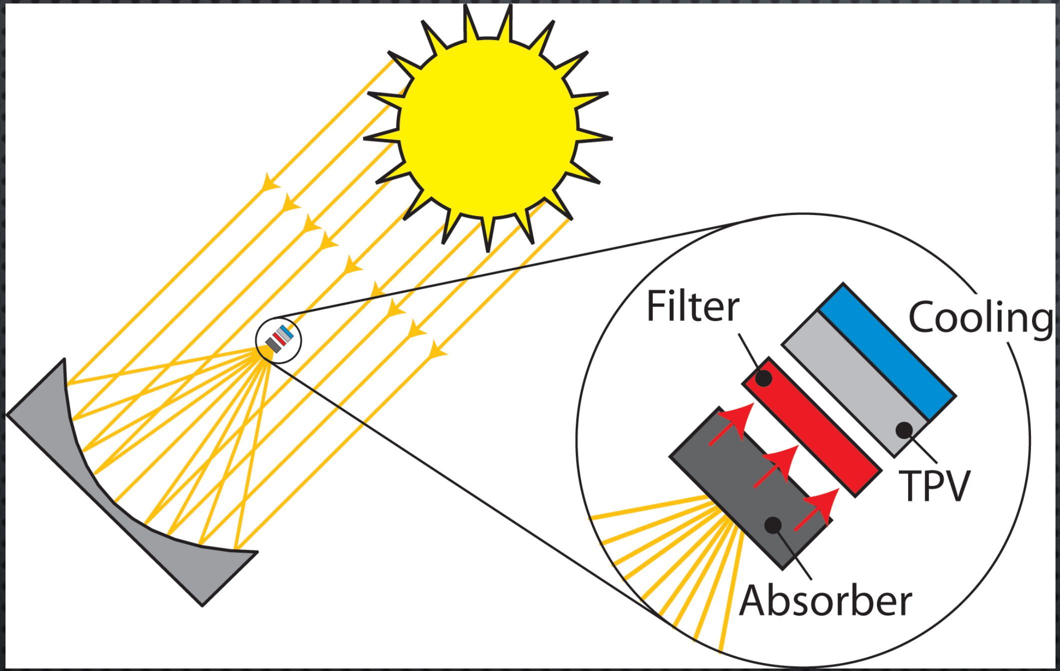


Fig. 16.7. Eye sensitivity function, $V(\lambda)$, (left ordinate) and luminous efficacy, measured in lumens per Watt of optical power (right ordinate). $V(\lambda)$ is greatest at 555 nm. Also given is a polynomial approximation for $V(\lambda)$ (after 1978 CIE data).

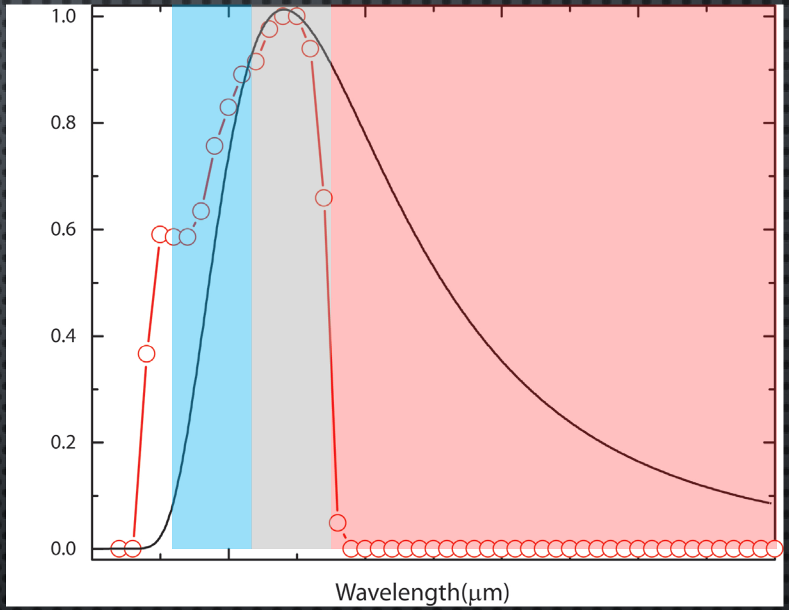




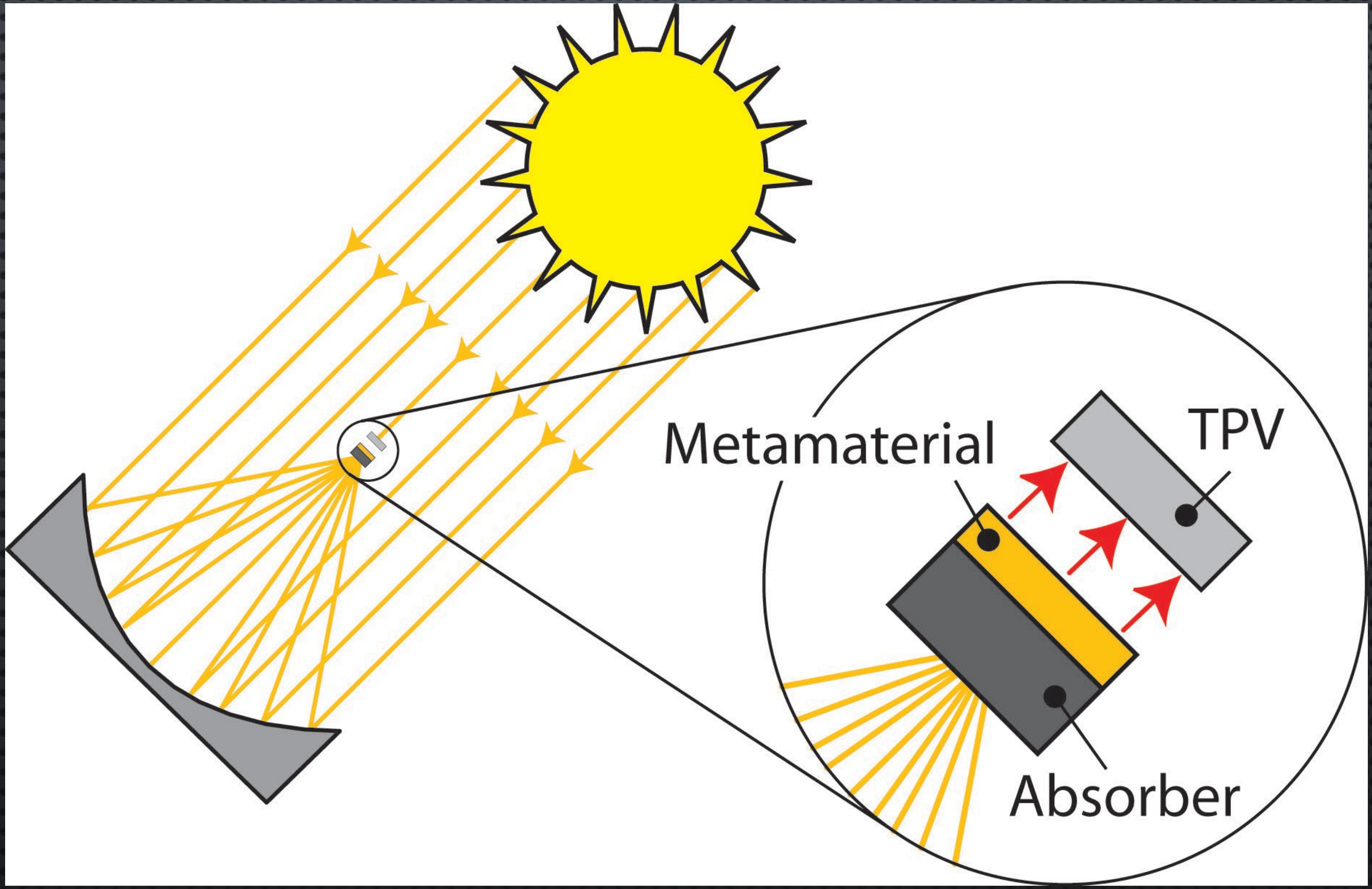
ENERGY HARVESTING - THERMOPHOTOVOLTAICS



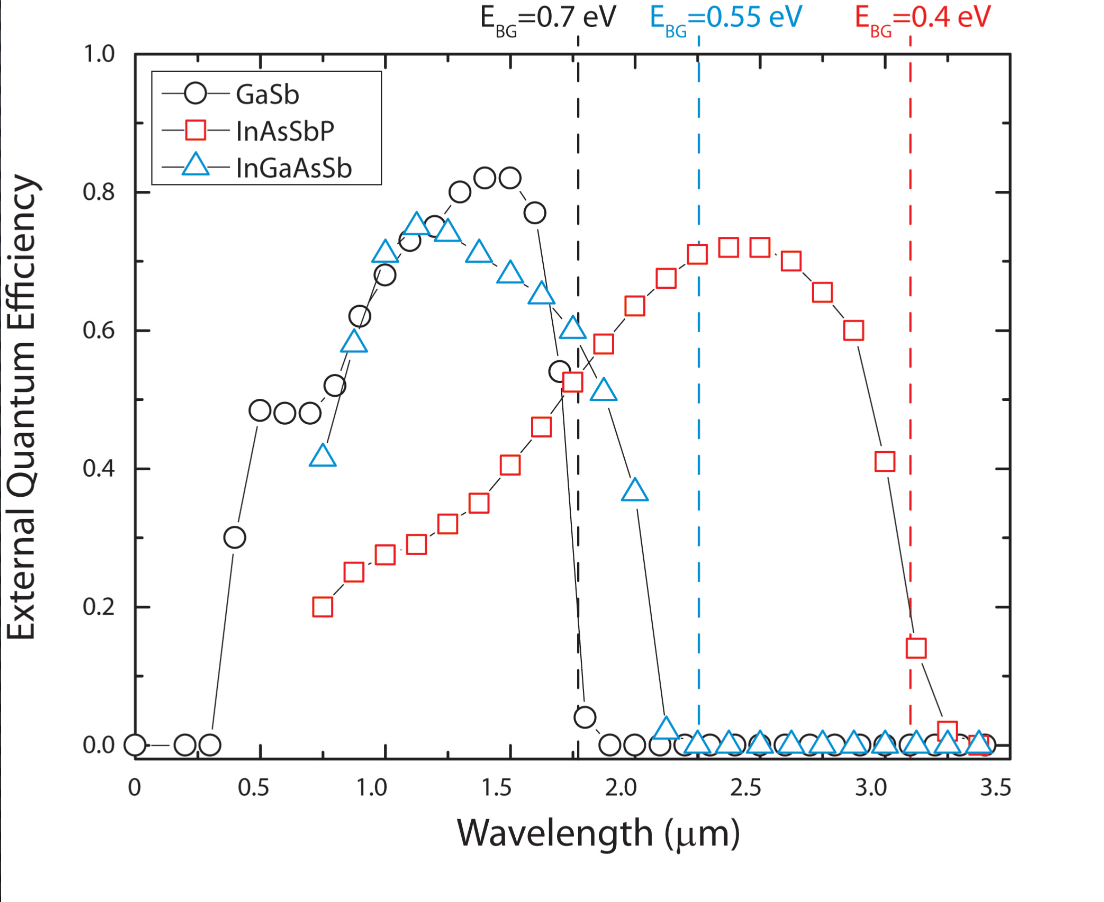
External Quantum Efficiency



ENERGY HARVESTING

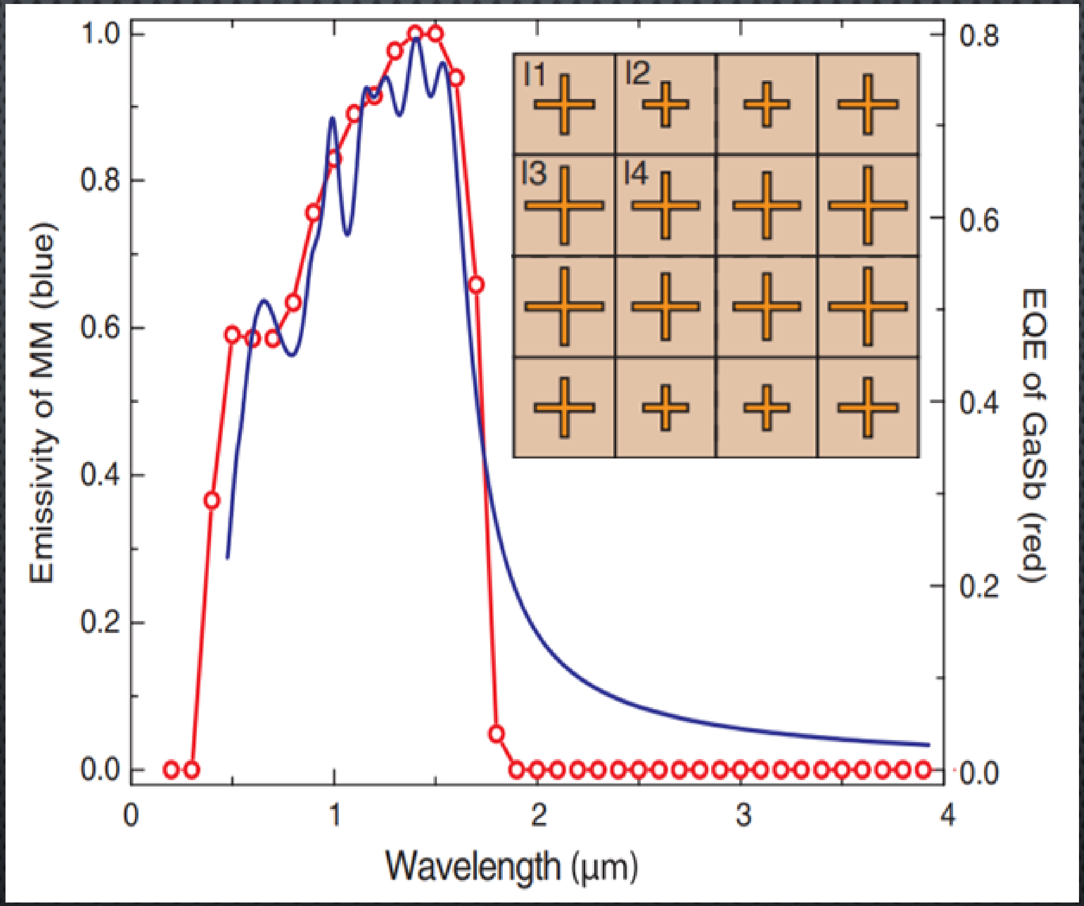


ENERGY HARVESTING



Material	Band Gap Energy (eV) @300K	Wavelength (nm)
SiC	2.86	434
Si	1.12	1107
GaSb	0.7	1771
Ge	0.67	1851
InGaAsSb	0.55	2254
InAsSbP	0.4	3100
PbS	0.37	3351

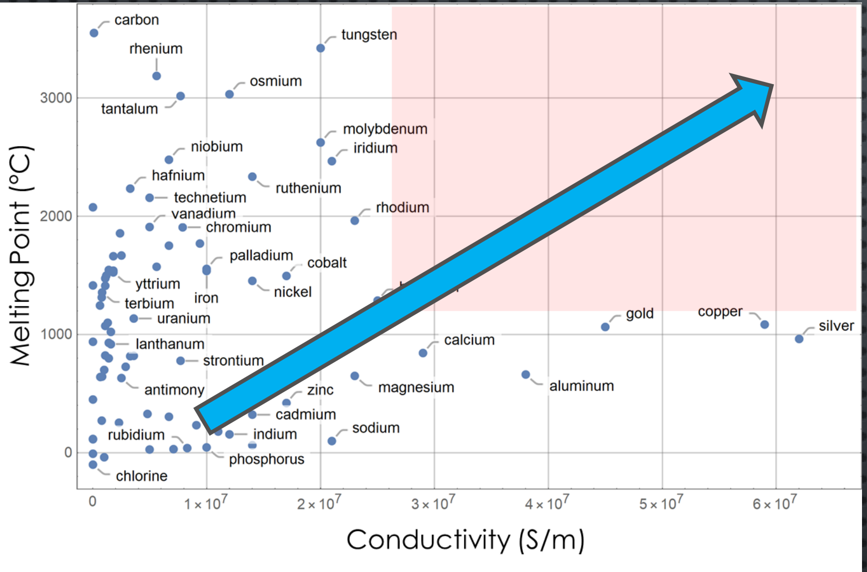
TAMING THE BLACKBODY

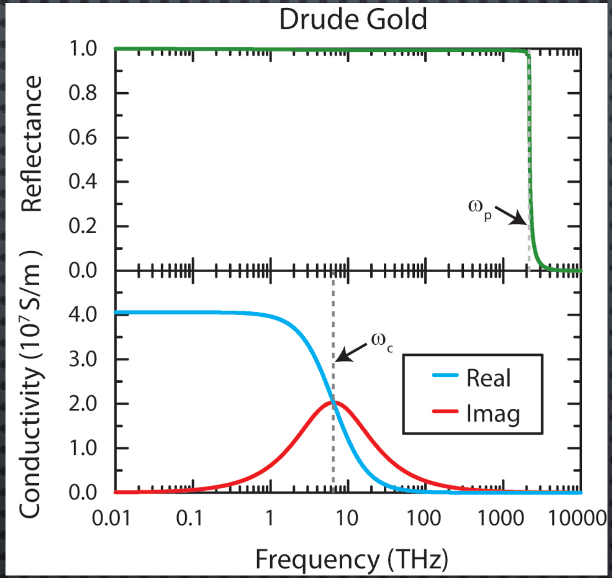


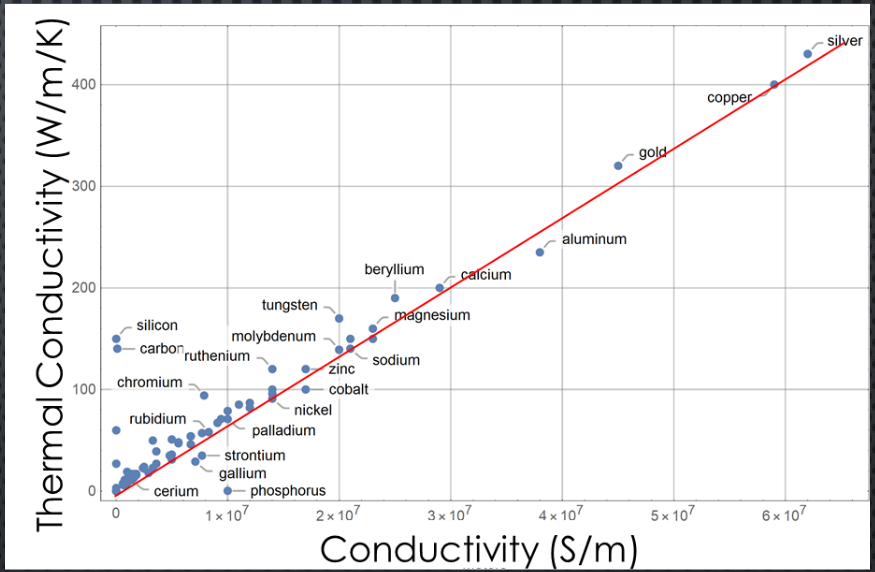
$$M(T) = \varepsilon\sigma T^4$$

X. Liu, T. Tyler, T. Starr, A. F. Starr, N. M. Jokerst, and W. J. Padilla PRL **107**, 045901 (2011)

METAMATERIAL LIMITATIONS







Low Melting Temperatures

$$M(T) = \varepsilon\sigma T^4$$

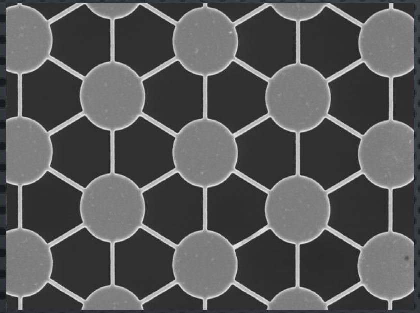
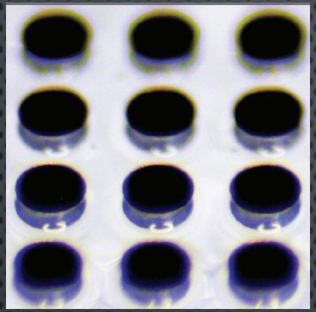
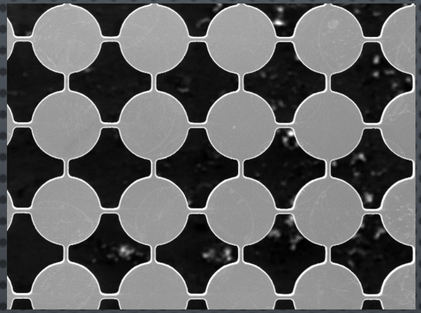
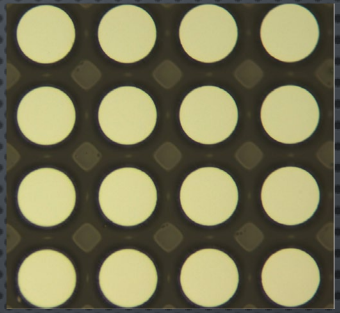
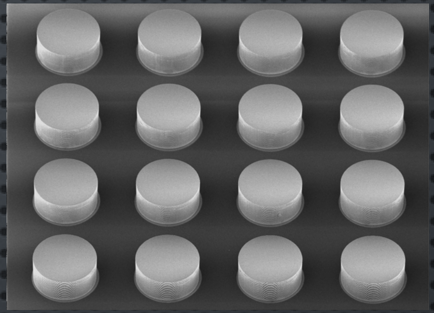
Ohmic Losses

$$\sigma(\omega) = \frac{\sigma_0}{1 - i\omega\tau}$$

High Thermal Conductivities

$$\kappa = \sigma L T$$

FUNDAMENTALLY DIFFERENT APPROACH

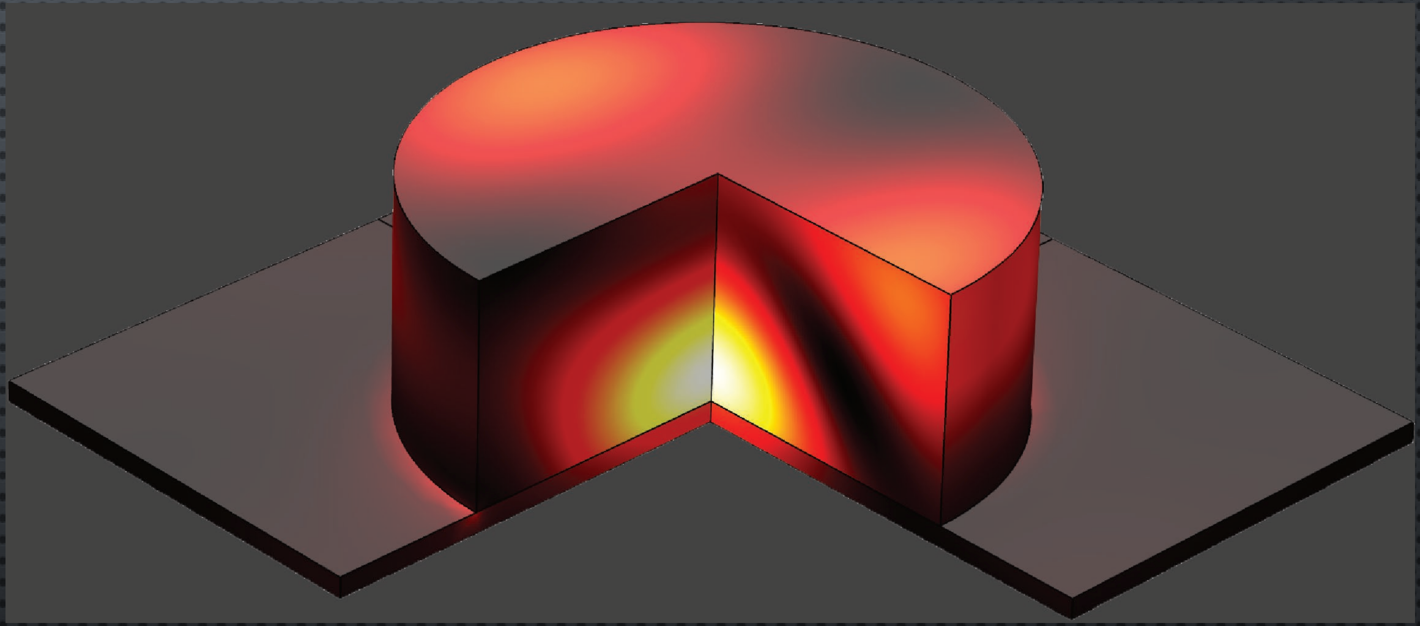
    

1. EM response determined by geometrical parameters
2. Independent and direct control of $\varepsilon(\omega)$ and $\mu(\omega)$
3. Multifunctional properties
4. EM response comes from the 'meta-atom', not from the array

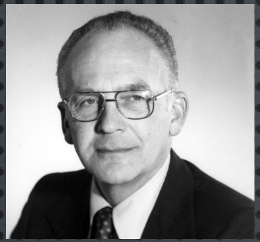
New problems emerge…

OUTLINE

- **All-Dielectric Metasurfaces**
- Machine Learning
- Inverse Design
- Artificial "Intelligence"
- Conclusion

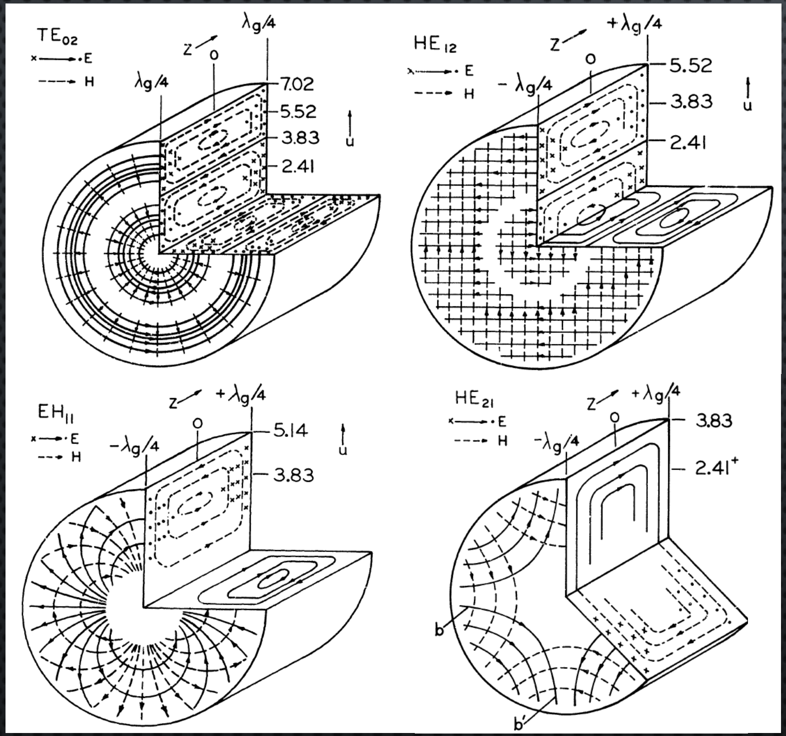


DIELECTRIC WAVEGUIDES AND RESONATORS

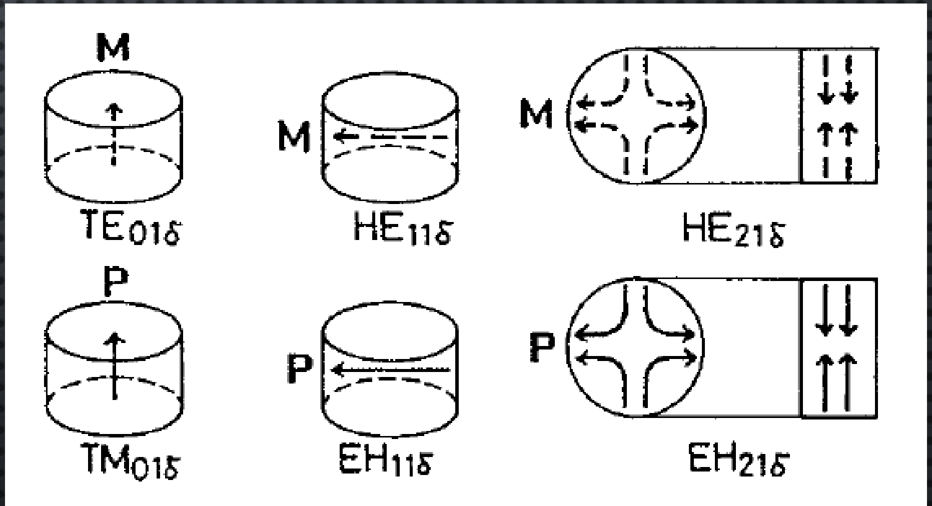


Elias Snitzer

Yoshio Kobayashi



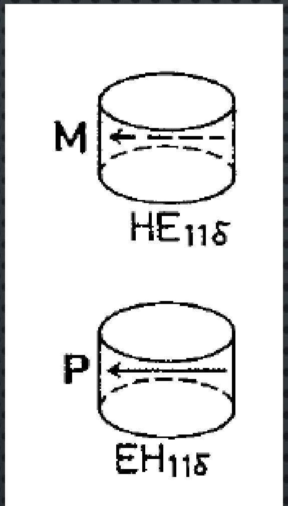
E. Snitzer, “Cylindrical dielectric waveguide modes,” J. Opt. Soc. Amer. 51, 491–498 (1961).



Y. Kobayashi and S. Tanaka, “Resonant Modes of a Dielectric Rod Resonator Short-Circuited at Both Ends by Parallel Conducting Plates,” IEEE Trans. Microw. Theory Techn. 28, 1077–1085 (1980).

DIELECTRIC WAVEGUIDES AND RESONATORS

Z



HE Mode is an approximate TM mode $H_z / E_z << 1$ for the HE Mode

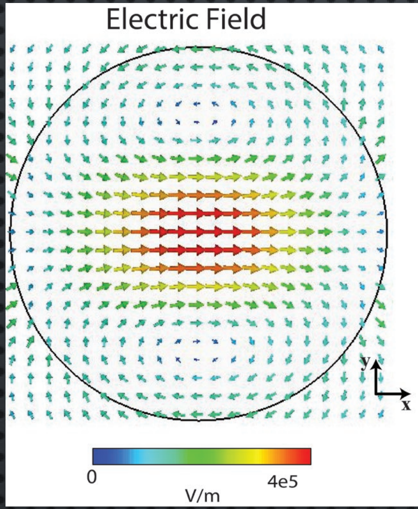
EH Mode is an approximate TE mode $E_z / H_z << 1$ for the EH Mode

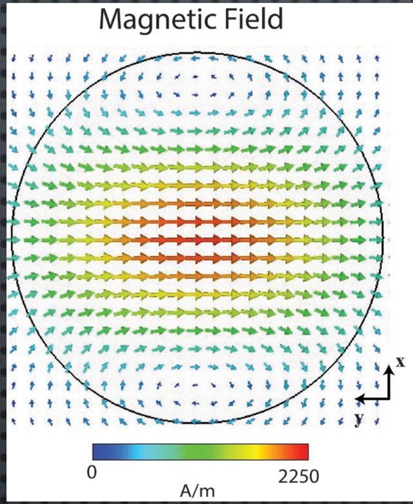
Field variation within the cylinder is denoted by three indices, i.e. HE_{nml} and EH_{nml}

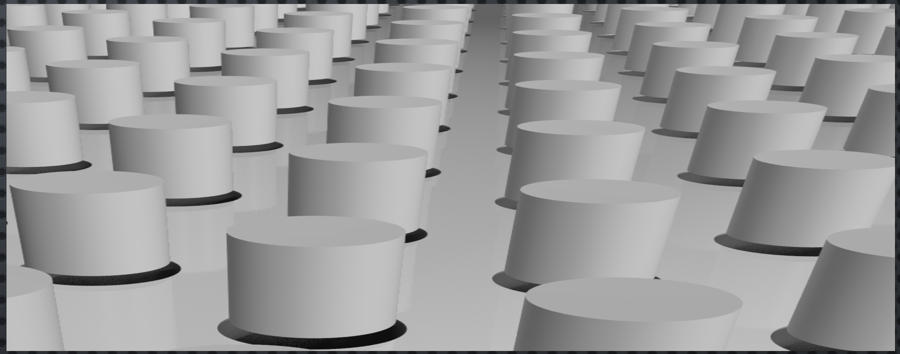
- n azimuthal variation (form of sin n and cos n)
- m denotes the field variation along the radial direction
- l along the z-axis

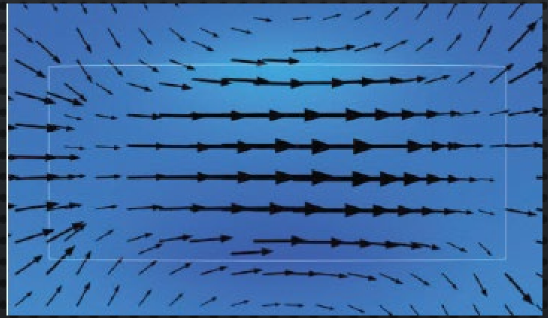
Y. Kobayashi et al., "Resonant Modes of a Dielectric Rod Resonator Short-Circuited at Both Ends by Parallel Conducting Plates," IEEE Trans. Microw. Theory Techn. 28, 1077–1085 (1980).

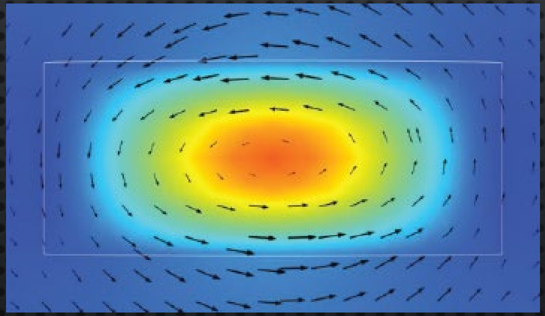
ELECTRIC AND MAGNETIC DIPOLE MODES











EH – Even Mode

HE – Odd Mode

Experimental realization of a terahertz all-dielectric metasurface absorber, Xinyu Liu, Kebin Fan, Ilya Shadrivov, and Willie J. Padilla, Optics Express **25**, 191 (2017)

THEORY OF DIELECTRIC METAMATERIAL ABSORBERS

$\underline{EH_{111}}$

$$J_1(k_r r) = 0$$

$$\tan\left(\frac{k_z h}{2}\right) = \frac{k_{z0}}{k_z}$$

$\underline{HE_{111}}$

$$k_z h = \pi$$

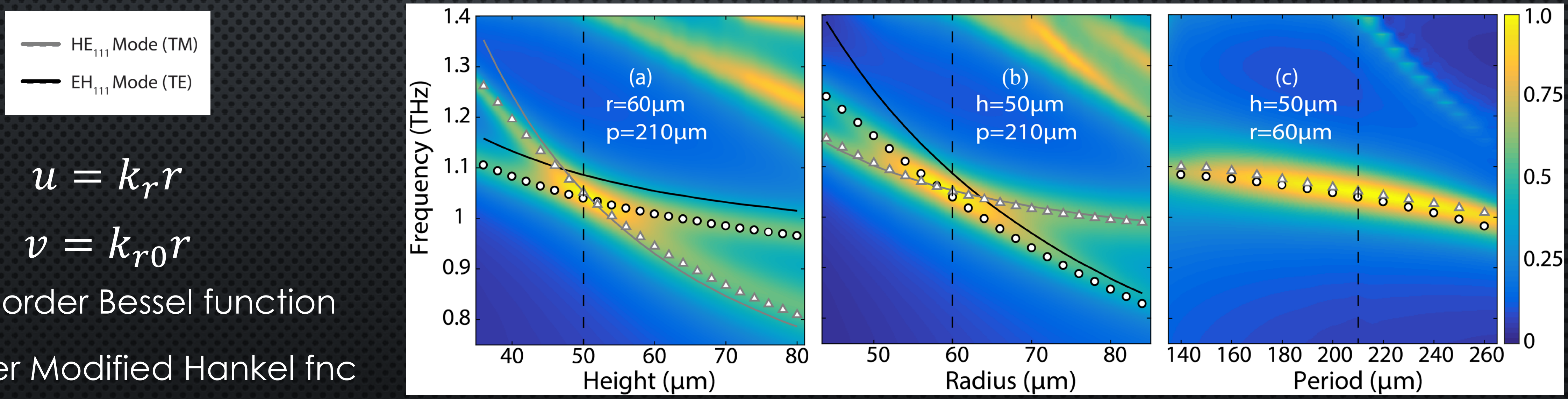
$$\left[\frac{J_1'(u)}{uJ_1(u)} + \frac{K_1'(v)}{vK_1(v)}\right]\left[k_0^2\varepsilon_{1r}\frac{J_1'(u)}{uJ_1(u)} + k_0^2\frac{K_1'(v)}{vK_1(v)}\right] = k_z^2\left(\frac{1}{u^2} + \frac{1}{v^2}\right)^2$$

$$u = k_r r$$

$$v = k_{r0} r$$

$J_1'(u)$ 1st order Bessel function

K_1' 1st order Modified Hankel fnc



Xianshun Ming, Xinyu Liu, Liqun Sun, and Willie J. Padilla, *Degenerate critical coupling in all-dielectric metasurface absorbers,* Optics Express 25, 24658 (2017)

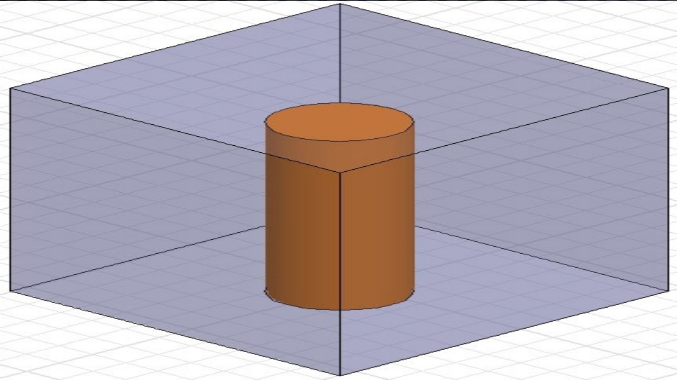
DEGENERATE CRITICAL COUPLED MODE THEORY

$$A(\omega) = \sum_{j=1}^{2} \frac{2\gamma_j\delta_j}{(\omega-\omega_{0,j})^2+(\gamma_j+\delta_j)^2}$$

δ Material loss rate

γ Radiative loss rate

ω_0 Resonant frequency



Degenerate $\omega_{0,1} = \omega_{0,2}$

Critical $\delta = \gamma$

$$\tilde{\omega} = \omega_1 - i\omega_2 = \omega_1 - i(\gamma + \delta)$$

$$A(\omega_0) \geq 49.0\% \quad \text{for} \quad \frac{3}{4} \leq \frac{\delta}{\gamma} \leq \frac{4}{3}.$$

Mode	Analytical ω_0 (THz)	Simulated ω_0 (THz)	γ ($\times 10^9$ 1/s)	δ ($\times 10^9$ 1/s)
EH_{111}	1.086	1.0440	21.7	22.1
HE_{111}	1.053	1.0512	28.1	26.1

- Jessica R. Piper, Victor Liu, and Shanhui Fan, *Total absorption by degenerate critical coupling*, Applied Physics Letters, **104**, 251110 (2014)
- Xianshun Ming, Xinyu Liu, Liqun Sun, and Willie J. Padilla, *Degenerate critical coupling in all-dielectric metasurface absorbers*, Optics Express 25, 24658 (2017)

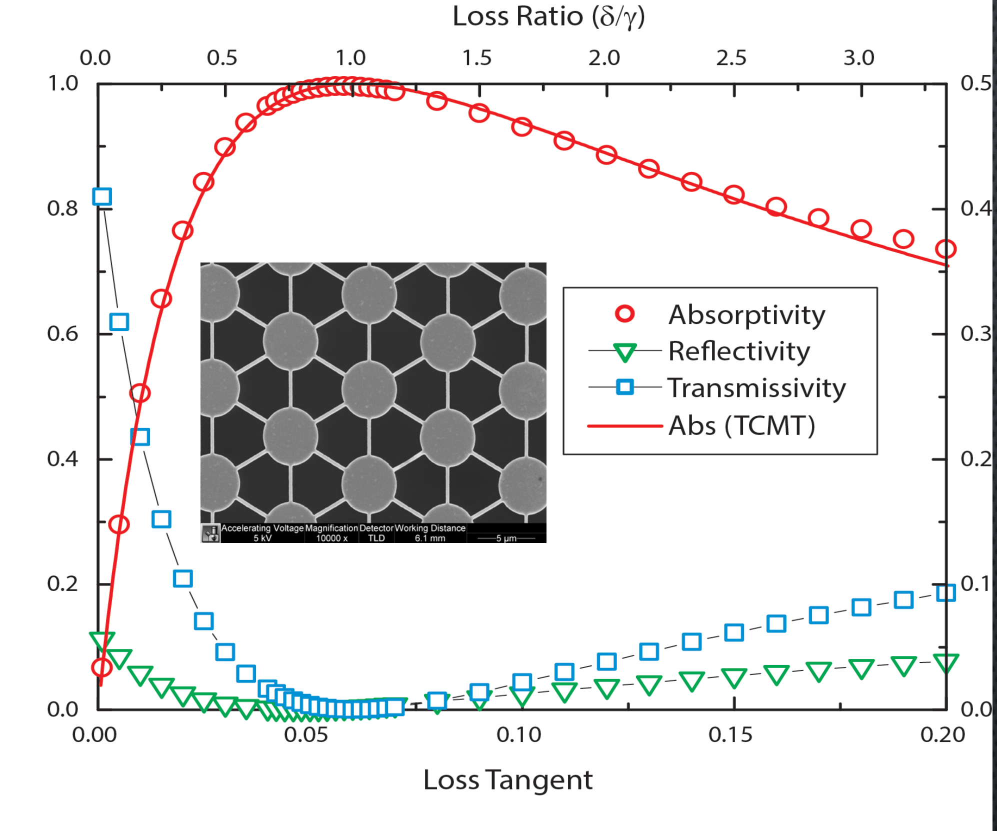
DESIGNER ALL-DIELECTRIC ABSORBERS

Absorber Design Rules

1. Operational wavelength λ_0
2. Use high index dielectric n
3. Geometry $\mathrm{r} = 0.61\frac{\lambda_0}{\sqrt{n^2-1}}$; $\mathrm{h} = \frac{\lambda_0}{2n}$
4. Periodicity $2\mathrm{r} < \mathrm{p} < \lambda \qquad r, h, p \longrightarrow \gamma$
5. Chose material loss $\delta = \gamma$

$$A(\delta/\gamma) = 4\frac{\delta/\gamma}{1 + (\delta/\gamma)^2 + 2\delta/\gamma}$$

$$\boxed{\frac{r}{h} = 1.22\frac{n}{\sqrt{n^2-1}} \approx 1.22}$$



Silicon Drude Model

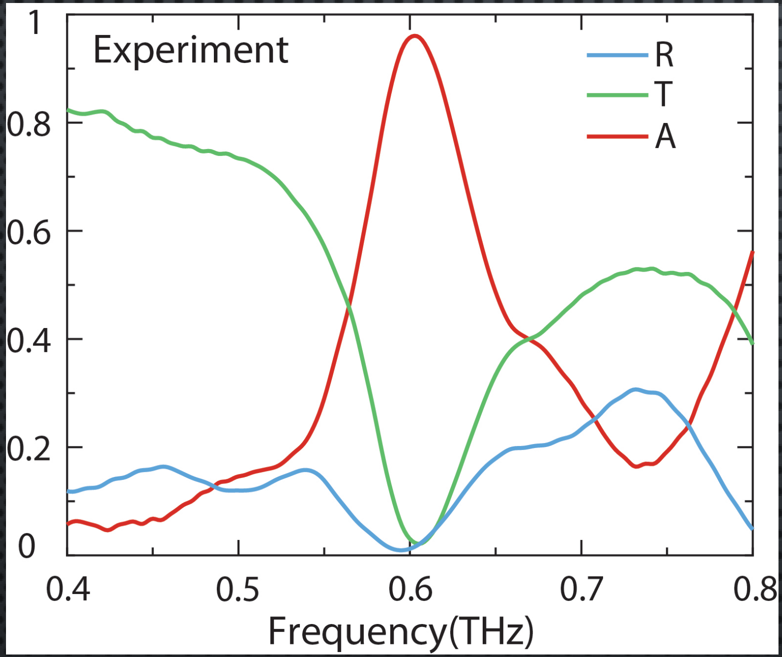
$\omega_p = 7.3 \times 10^{13}\ 2\pi \times$THz

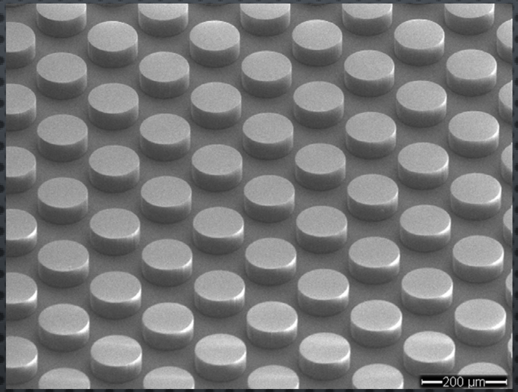
$\gamma = 1.0 \times 10^{13}\ 2\pi \times$THz

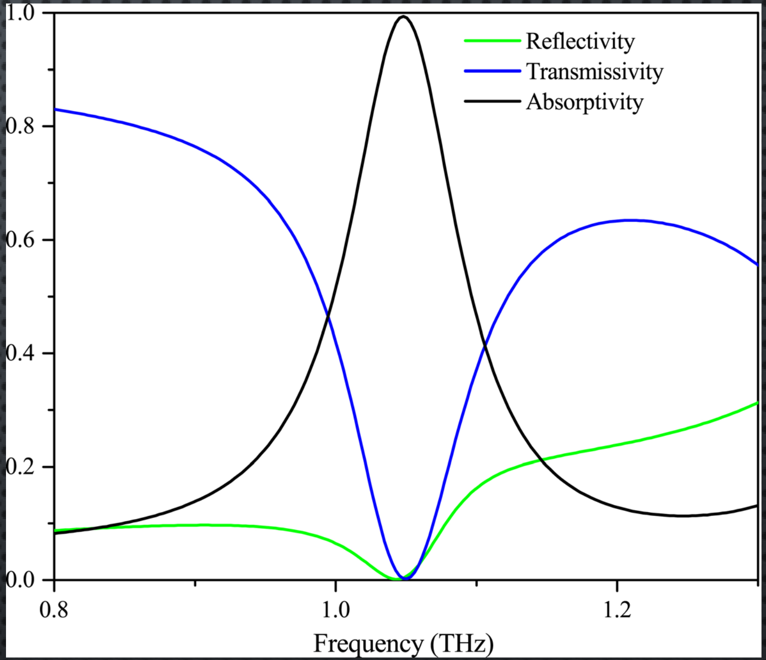
$\varepsilon_\infty = 11.7$

$\tan\delta = 0.06$

DIELECTRIC METAMATERIAL ABSORBERS







Experimental realization of a terahertz all-dielectric metasurface absorber, Xinyu Liu, Kebin Fan, Ilya Shadrivov, and Willie J. Padilla, Optics Express **25**, 191 (2017)

THZ ALL-DIELECTRIC ABSORBER

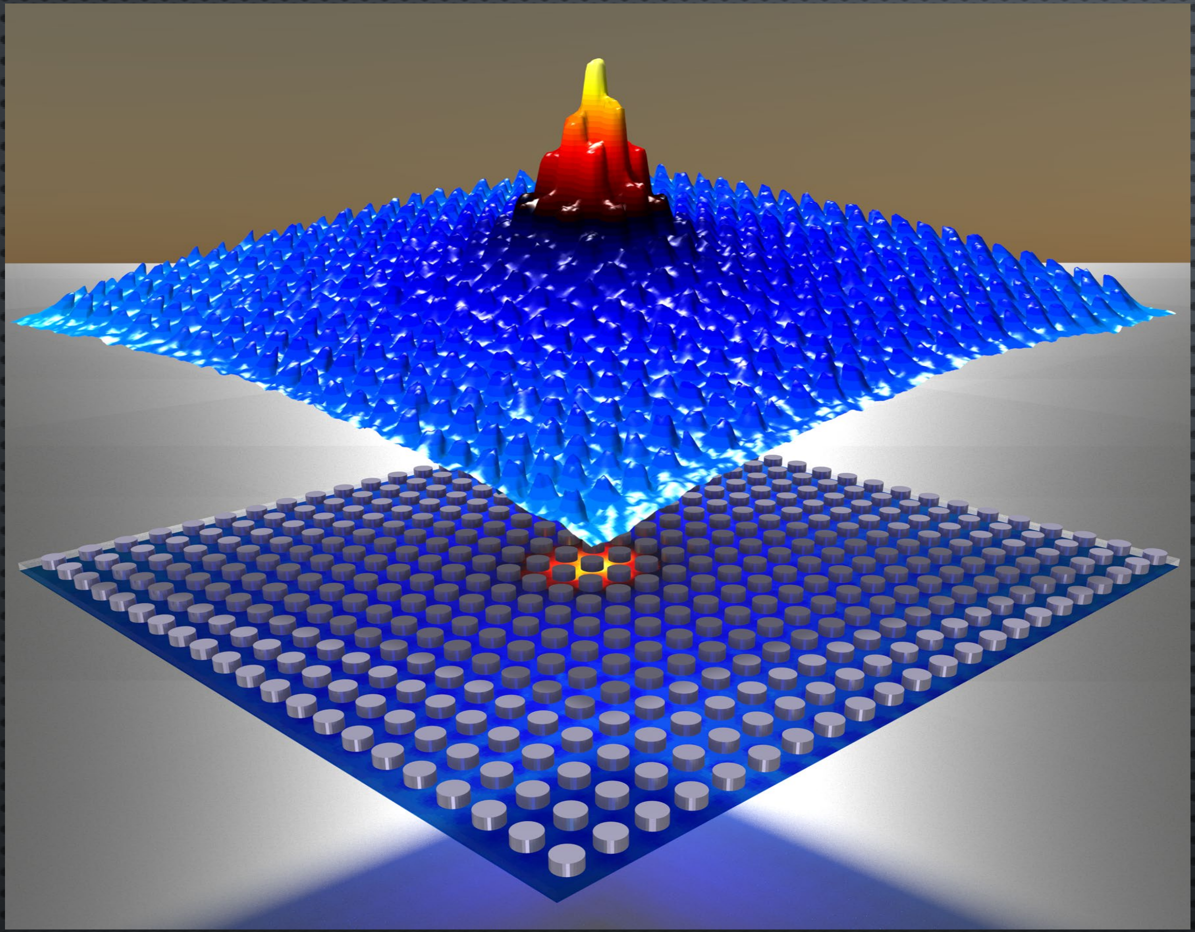
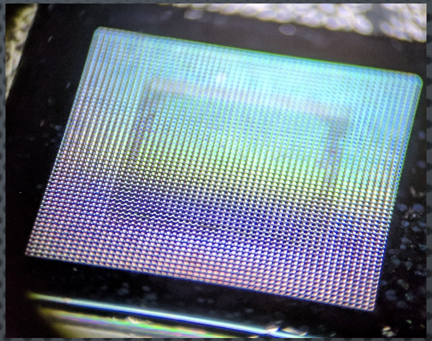
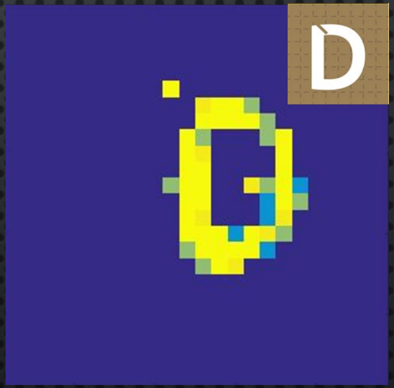
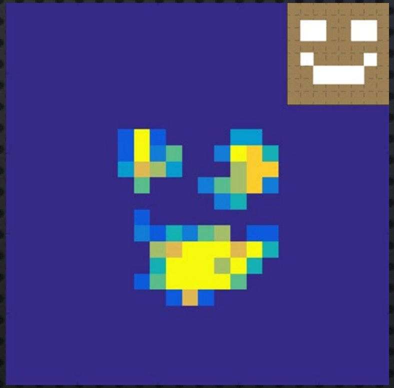


Image – Kebin Fan



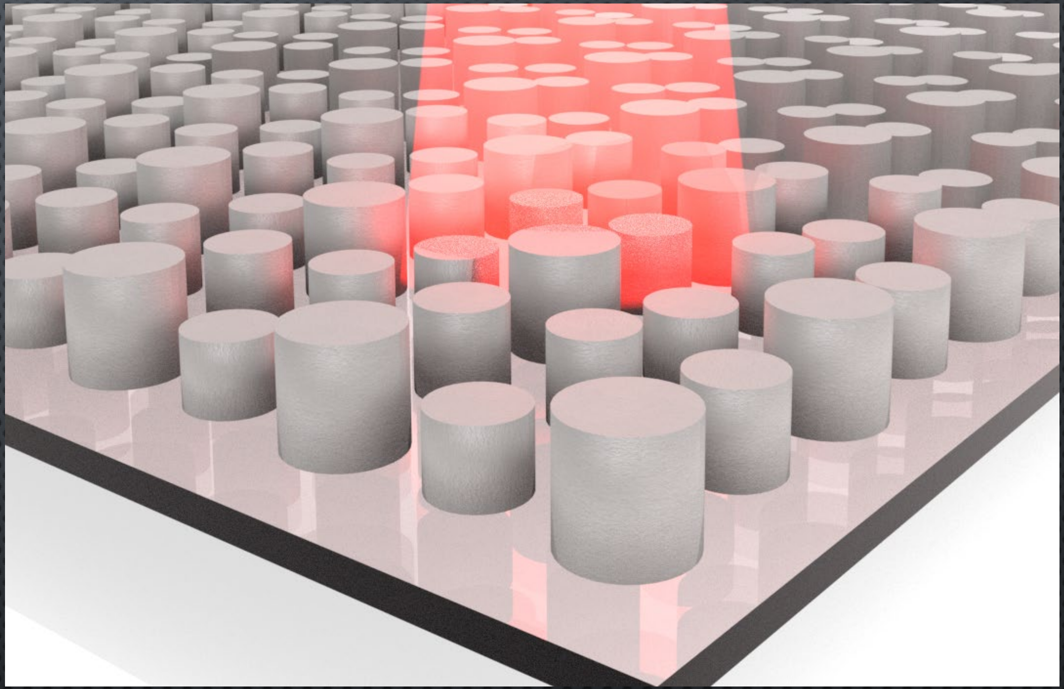




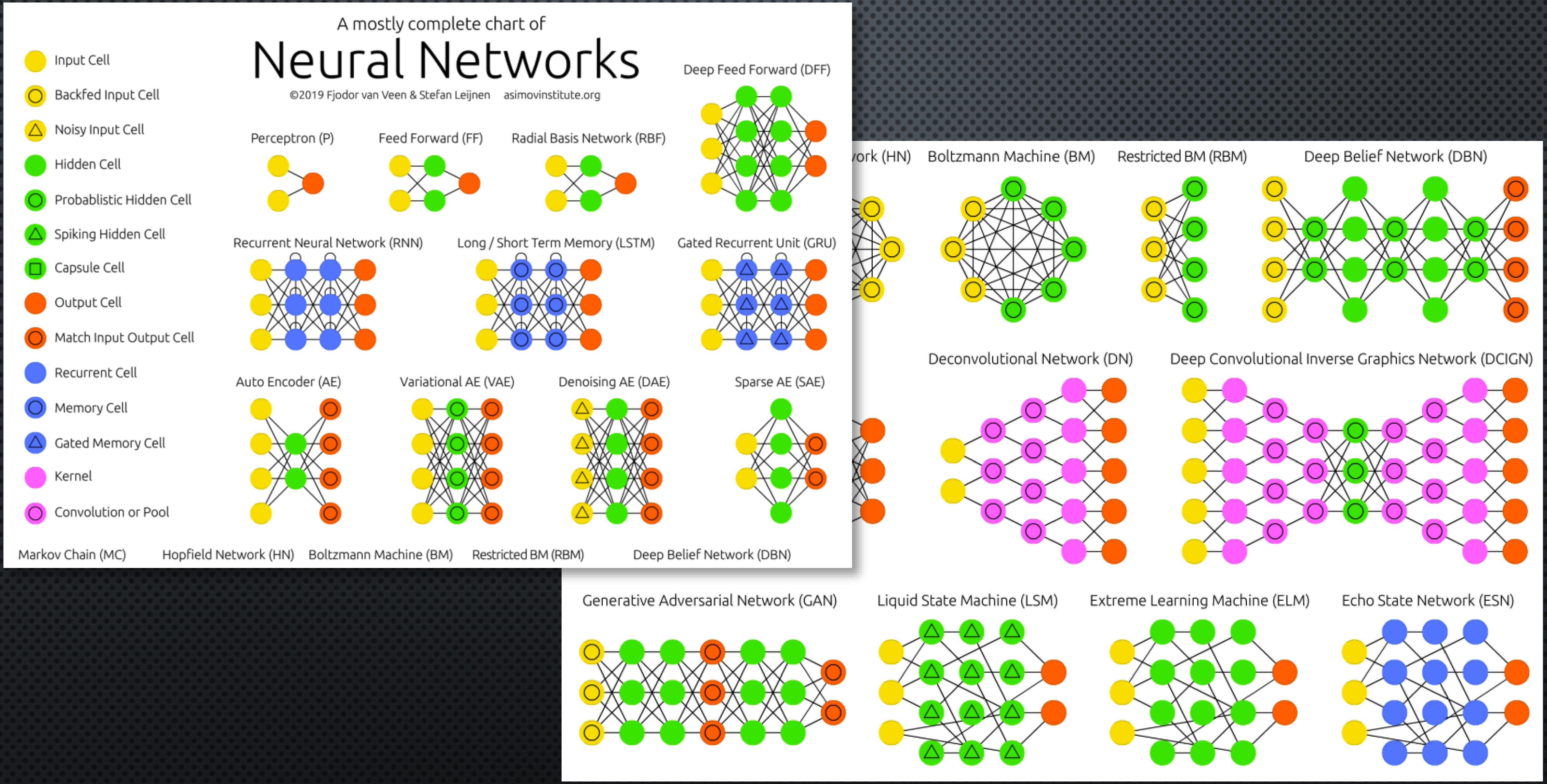
Kebin Fan, Jonathan Y. Suen, Xinyu Liu, and Willie J. Padilla, *All-dielectric metasurface absorbers for uncooled terahertz imaging*, Optica **4**, 601 (2017)

OUTLINE

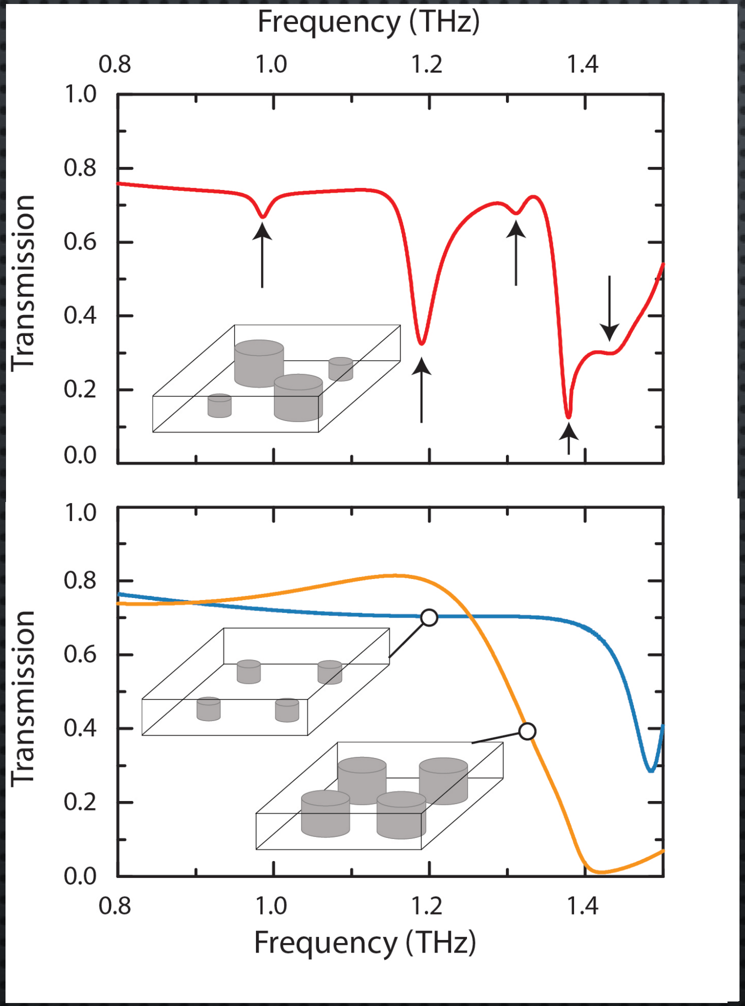
- All-Dielectric Metasurfaces
- **Machine Learning**
- Inverse Design
- Artificial "Intelligence"
- Conclusion

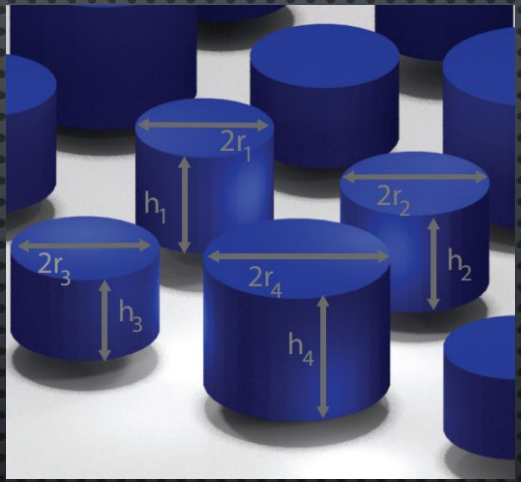


NEURAL NETWORK ARCHITECTURES



MACHINE LEARNING FOR ACCELERATED METASURFACE DESIGN





Drude Model

$$\omega_p = 7.3 \times 10^{13}\ 2\pi \times \text{THz}$$

$$\gamma = 1.0 \times 10^{13}\ 2\pi \times \text{THz}$$

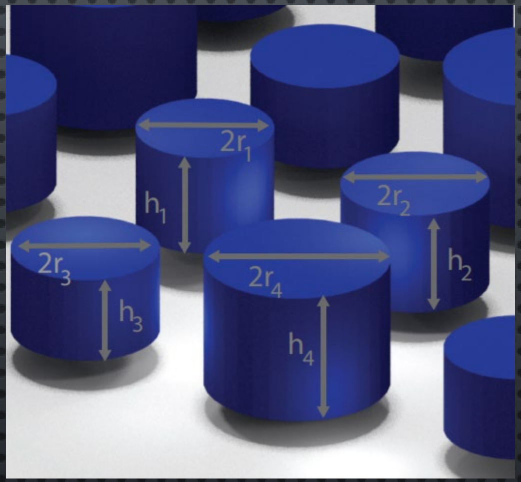
$$\varepsilon_\infty = 11.7$$

r (μm)	h (μm)
42.0	30.0
42.8	32.0
43.7	34.0
44.5	36.0
45.3	38.0
46.2	40.0
47.0	42.5
47.8	44.0
48.6	46.0
49.5	48.0
50.4	50.0
51.2	52.0
52.0	55.0

Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

MACHINE LEARNING FOR ACCELERATED METASURFACE DESIGN

- 13^8 total permutations ~ 816 million
- ~2200 years of compute time
- 18,000 electromagnetic simulations for the training set
- 3,000 electromagnetic simulations reserved for validation set



Drude Model

$$\omega_p = 7.3 \times 10^{13}\ 2\pi \times \text{THz}$$

$$\gamma = 1.0 \times 10^{13}\ 2\pi \times \text{THz}$$

$$\varepsilon_\infty = 11.7$$

r (μm)	h (μm)
42.0	30.0
42.8	32.0
43.7	34.0
44.5	36.0
45.3	38.0
46.2	40.0
47.0	42.5
47.8	44.0
48.6	46.0
49.5	48.0
50.4	50.0
51.2	52.0
52.0	55.0

Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

NEURAL NETWORK ARCHITECTURE

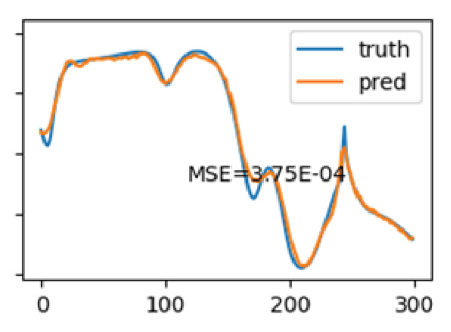
Input Geometry

$$\begin{Bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \\ r_1 \\ r_2 \\ r_3 \\ r_4 \end{Bmatrix}$$

Black Box

$$f\,(h_1, h_2, h_3, h_4, r_1, h_2, r_3, r_4)$$

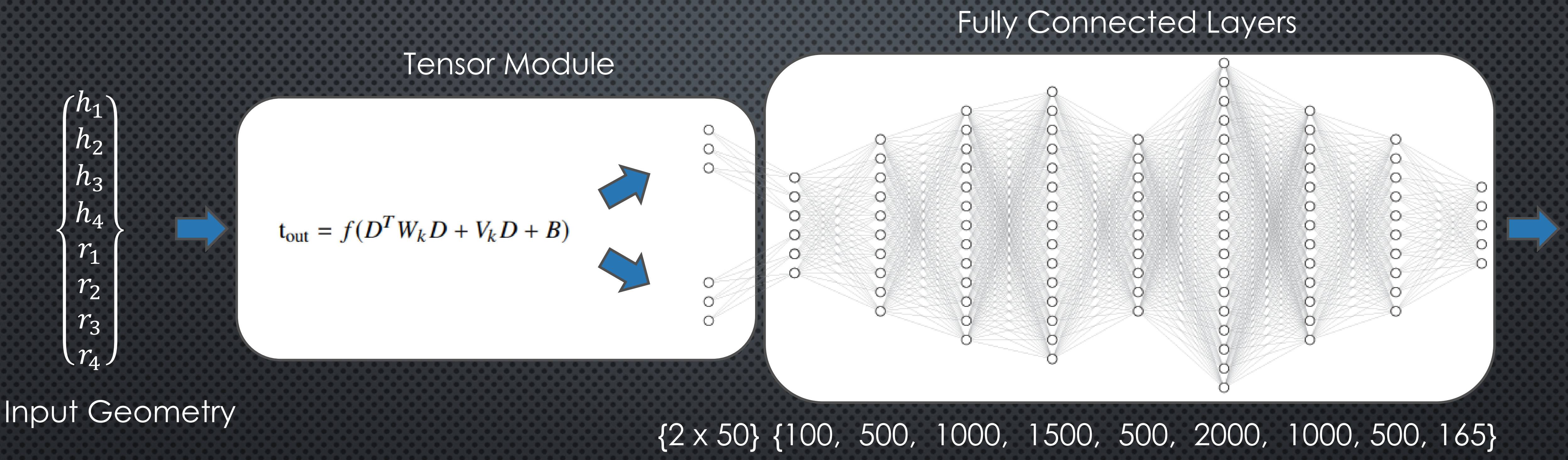
Predicted Spectra



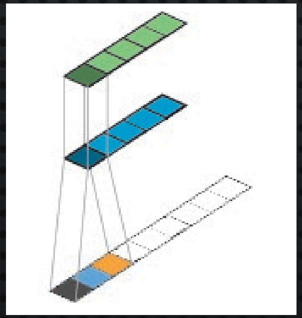
8 → 1000

Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

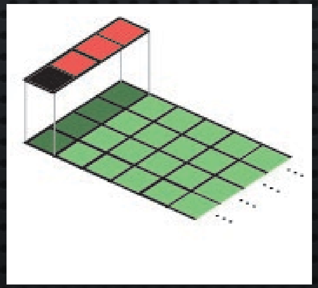
NEURAL NETWORK ARCHITECTURE – TENSOR LAYER



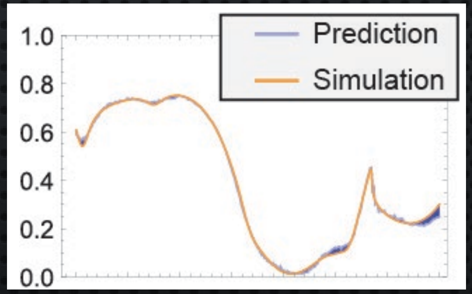
Transpose Convolution



Convolution



Predicted Spectra



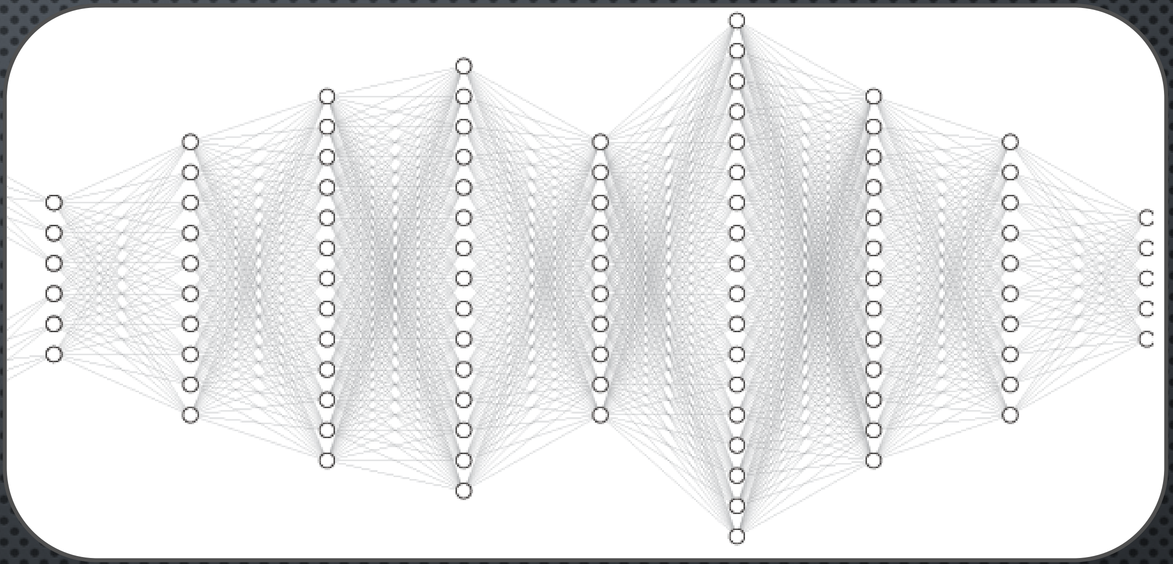
Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

NEURAL NETWORK ARCHITECTURE – RATIO INPUTS

$$\left\{ \begin{matrix} h_1 \\ h_2 \\ h_3 \\ h_4 \\ r_1 \\ r_2 \\ r_3 \\ r_4 \\ r_1/h_1 \\ r_1/h_2 \\ \vdots \end{matrix} \right\}$$

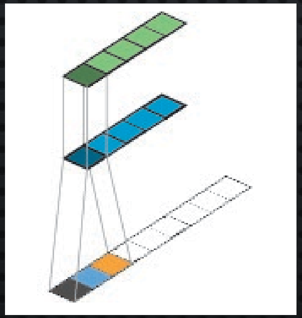
Input Geometry

Fully Connected Layers

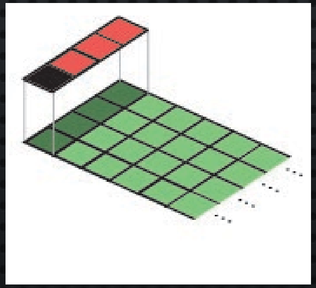


{100, 500, 1000, 1500, 500, 2000, 1000, 500, 165}

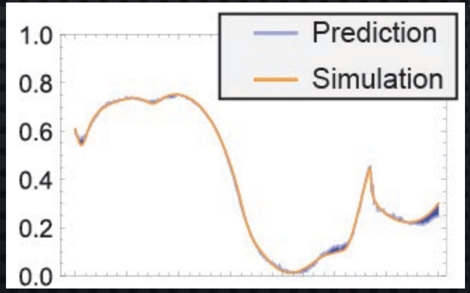
Transpose Convolution



Convolution

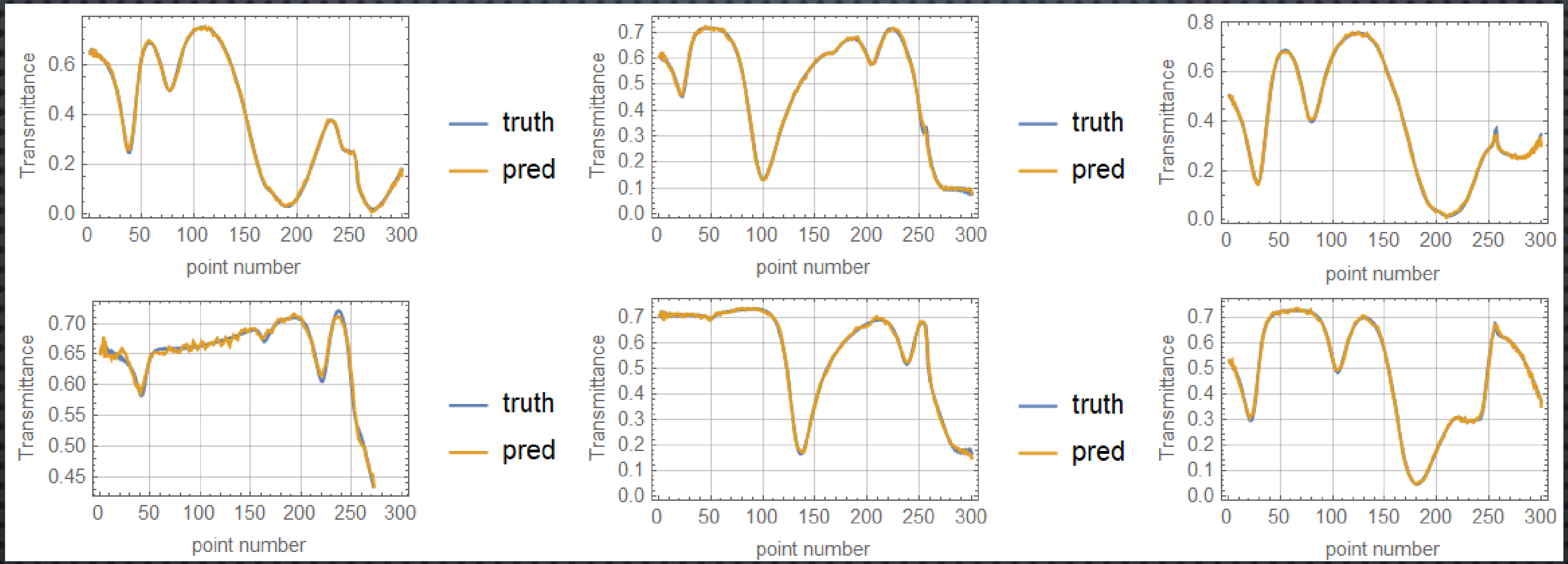


Predicted Spectra



Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

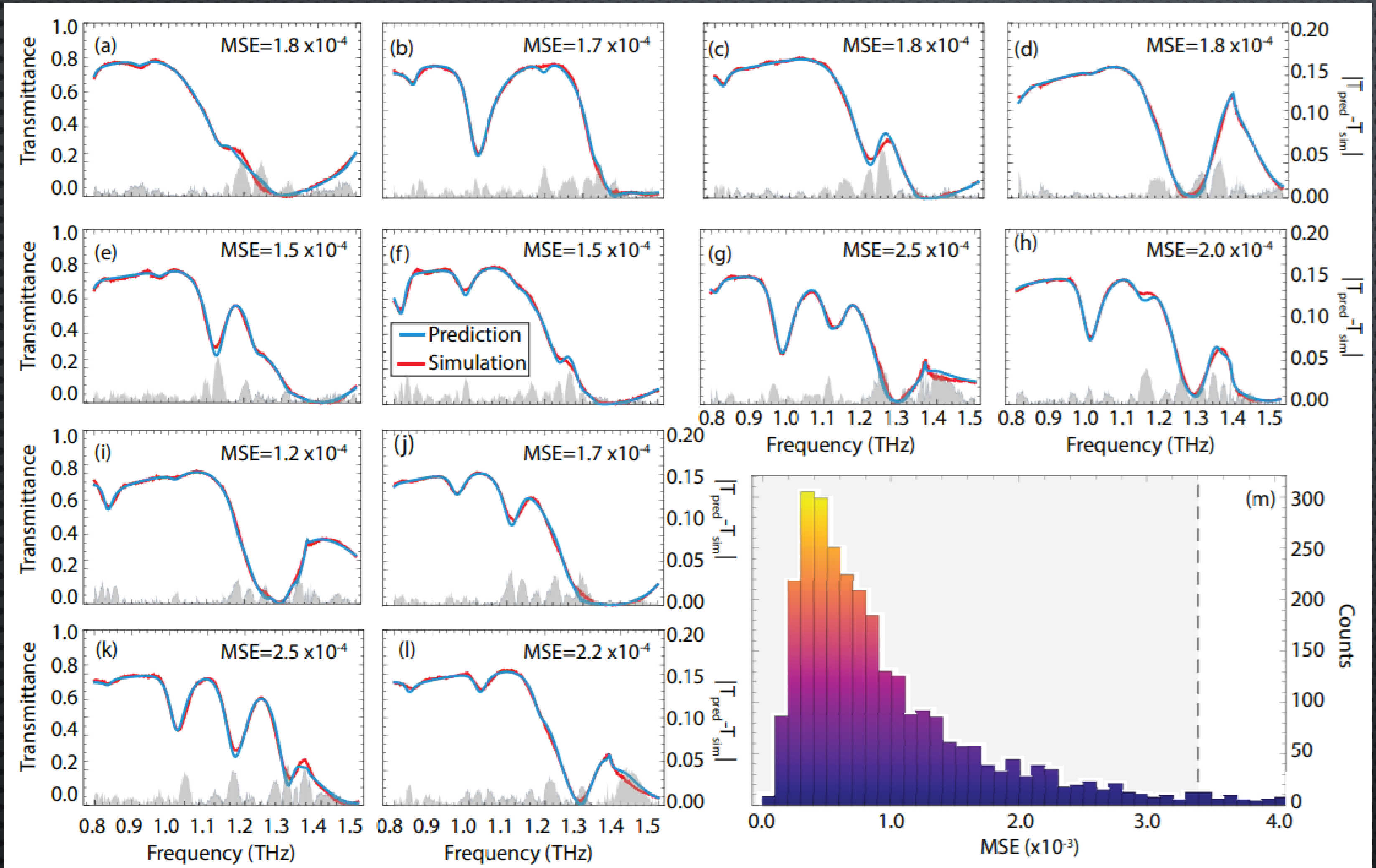
MACHINE LEARNING RESULTS – NN ARCHITECTURES



1. Tensor module (TM)
2. Geometrical ratios (GR)
3. Neither TM or GR
4. Both TM and GR

Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

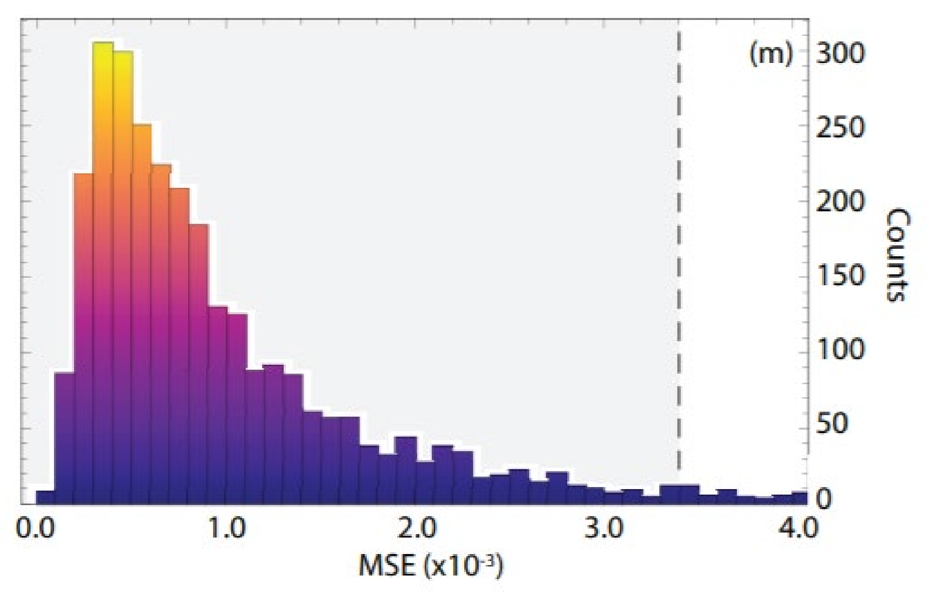
MACHINE LEARNING RESULTS



- $\text{MSE}_{\text{avg}} = 1.16 \times 10^{-3}$
- 95% have $\text{MSE} \lesssim 3.4 \times 10^{-3}$
- 99% have $\text{MSE} \lesssim 6.2 \times 10^{-3}$
- Sampled only 0.0022% of the hyperparameter space

Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

PERFORMANCE OF MACHINE LEARNING ARCHITECTURES



MSE	Tensor Module	Geometric Ratios
1.87×10^{-3}	yes	no
1.41×10^{-3}	no	no
1.32×10^{-3}	yes	yes
1.24×10^{-3}	no	yes

Tensor Module

$r_i \times r_j \qquad h_i \times h_j \qquad r_i \times h_j$

Geometric Ratios

r_i / h_j

Physics

$$\frac{r}{h} = 1.22 \frac{n}{\sqrt{n^2 - 1}}$$

Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

OUTLINE

- All-Dielectric Metasurfaces
- Machine Learning
- **Inverse Design**
- Artificial "Intelligence"
- Conclusions

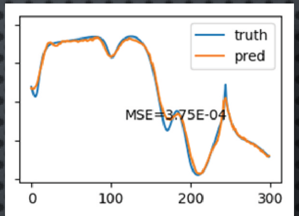
THE INVERSE MODEL

Input Geometry

Forward Model

$$\begin{Bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \\ r_1 \\ r_2 \\ r_3 \\ r_4 \end{Bmatrix} \rightarrow \underset{\text{Black Box}}{\boxed{f(h_1, h_2, h_3, h_4, r_1, h_2, r_3, r_4)}} \rightarrow$$

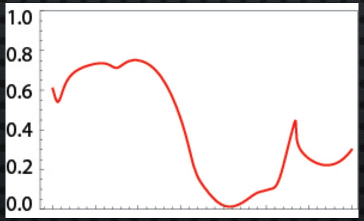
Predicted Spectra



Output Geometry

Inverse Model

Desired Spectra



$$\rightarrow \underset{\text{Black Box}}{\boxed{f(s_1, s_2, s_3, \cdots, s_n)}} \rightarrow \begin{Bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \\ r_1 \\ r_2 \\ r_3 \\ r_4 \end{Bmatrix}$$

Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

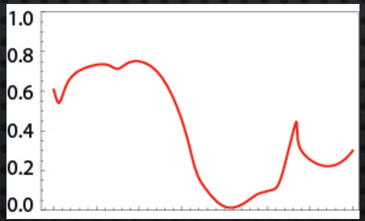
THE INVERSE MODEL

- There may be no geometry which realizes a desired spectra
- One-to-many mapping problem
- Does not indicate if a valid solution exists
- Does not provide a solution that *most closely* approximates desired spectra

Output Geometry

Inverse Model

Desired Spectra



Black Box

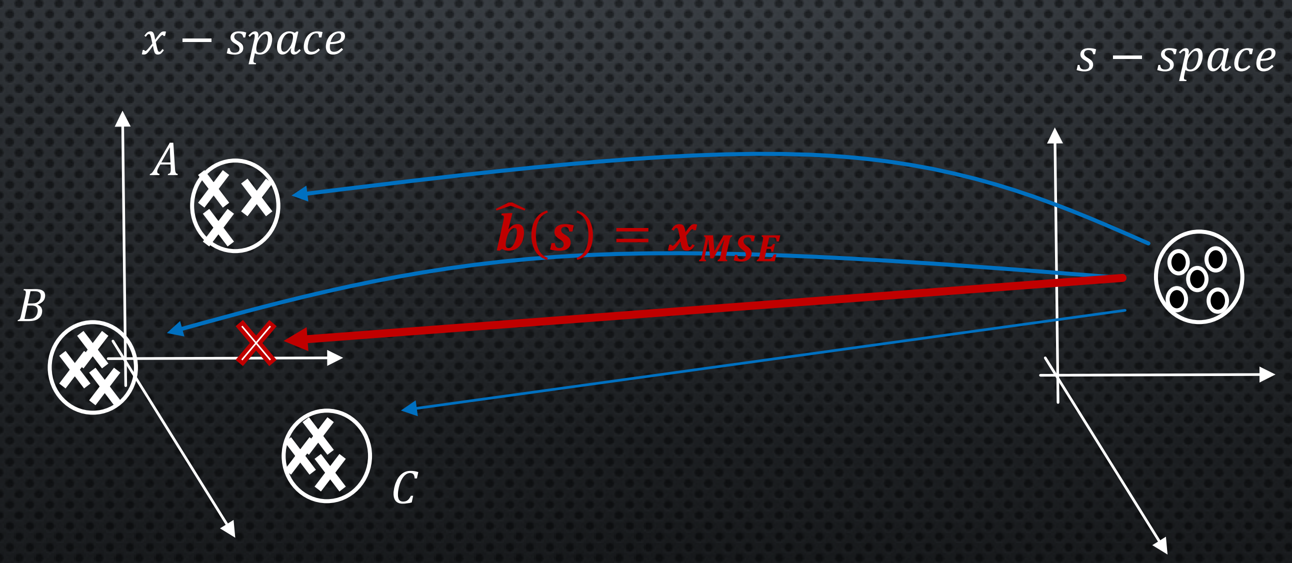
$$f(s_1, s_2, s_3, \cdots, s_n)$$

$$\begin{Bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \\ r_1 \\ r_2 \\ r_3 \\ r_4 \end{Bmatrix}$$

Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

THE INVERSE MODEL

- There may be no geometry which realizes a desired spectra
- One-to-many mapping problem
- Does not indicate if a valid solution exists
- Does not provide a solution that *most closely* approximates desired spectra



Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

THE INVERSE MODEL

$\times 8.2 \times 10^5 =$

2200 years
0.047 km/h

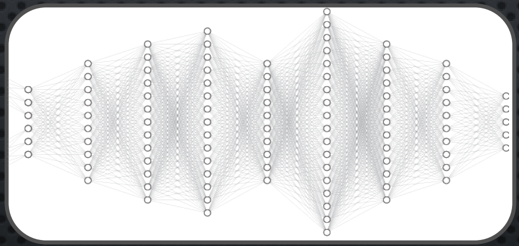
23 hours
113 km/h

Forward Model

Input Geometry

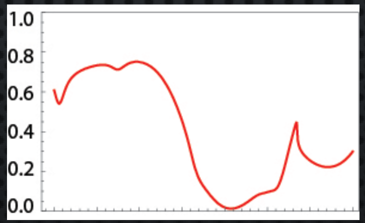
$$\begin{Bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \\ r_1 \\ r_2 \\ r_3 \\ r_4 \end{Bmatrix}$$

Trained ML Model



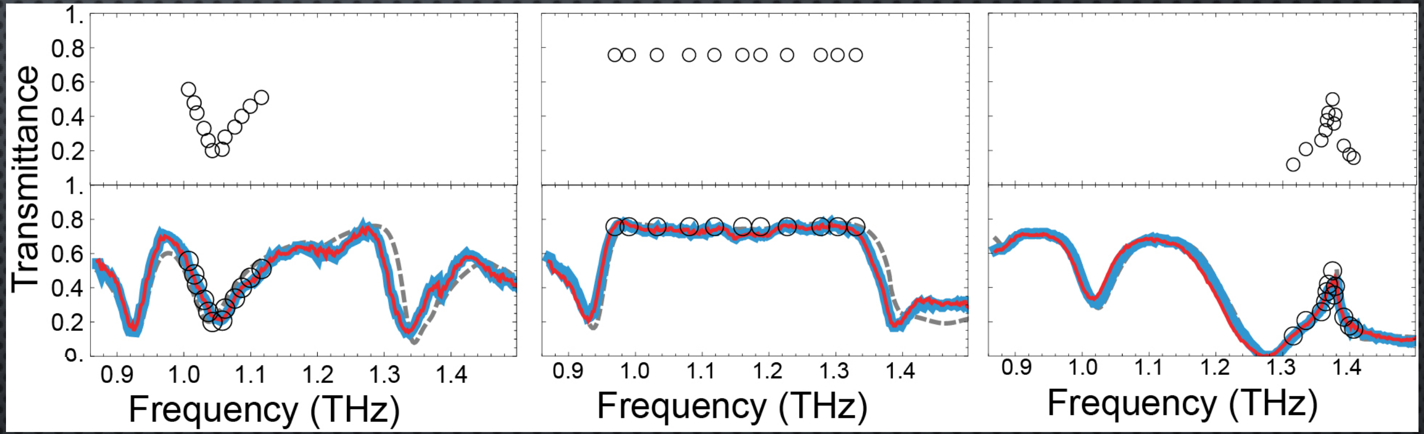
Simulation

Predicted Spectra



FAST FORWARD DICTIONARY SEARCH

- 13^8 total permutations ~ 816 million
- 2200 years of compute time
- 8.2×10^5 faster than conventional solver
- ML calculates in 23h – 9900 sp/s
- 2.6 Terabytes
- Search rate = 40 Msp/s
  - ~20 seconds for inverse solution



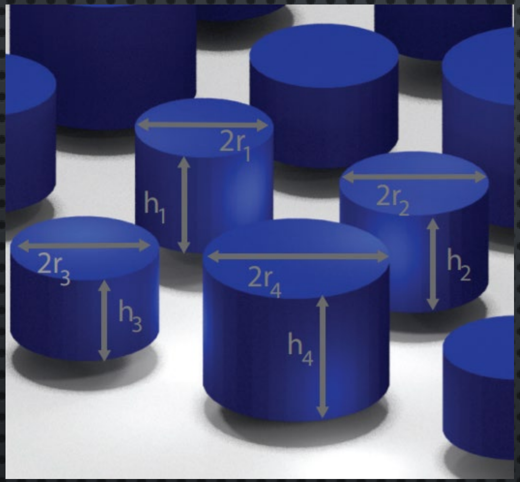
Global optimal solution
Second best solution
Simulated global optimal sol

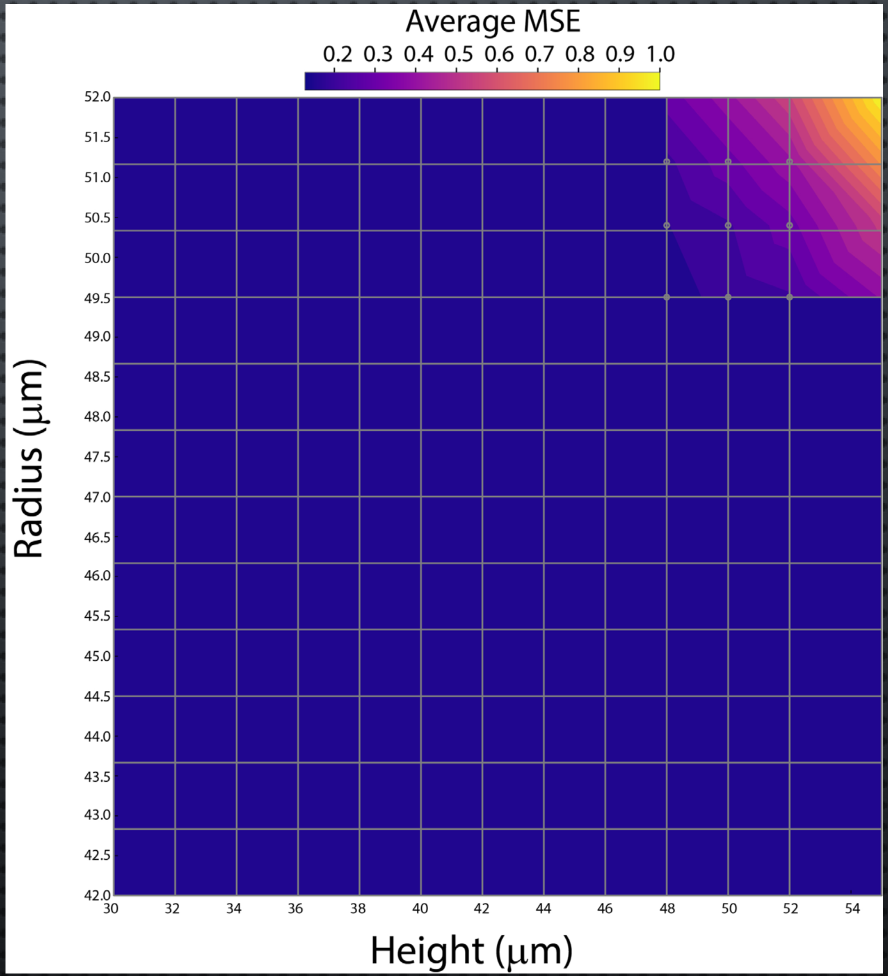
Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

OUTLINE

- All-Dielectric Metasurfaces
- Machine Learning
- Inverse Design
- **Artificial "Intelligence"**
- Conclusions

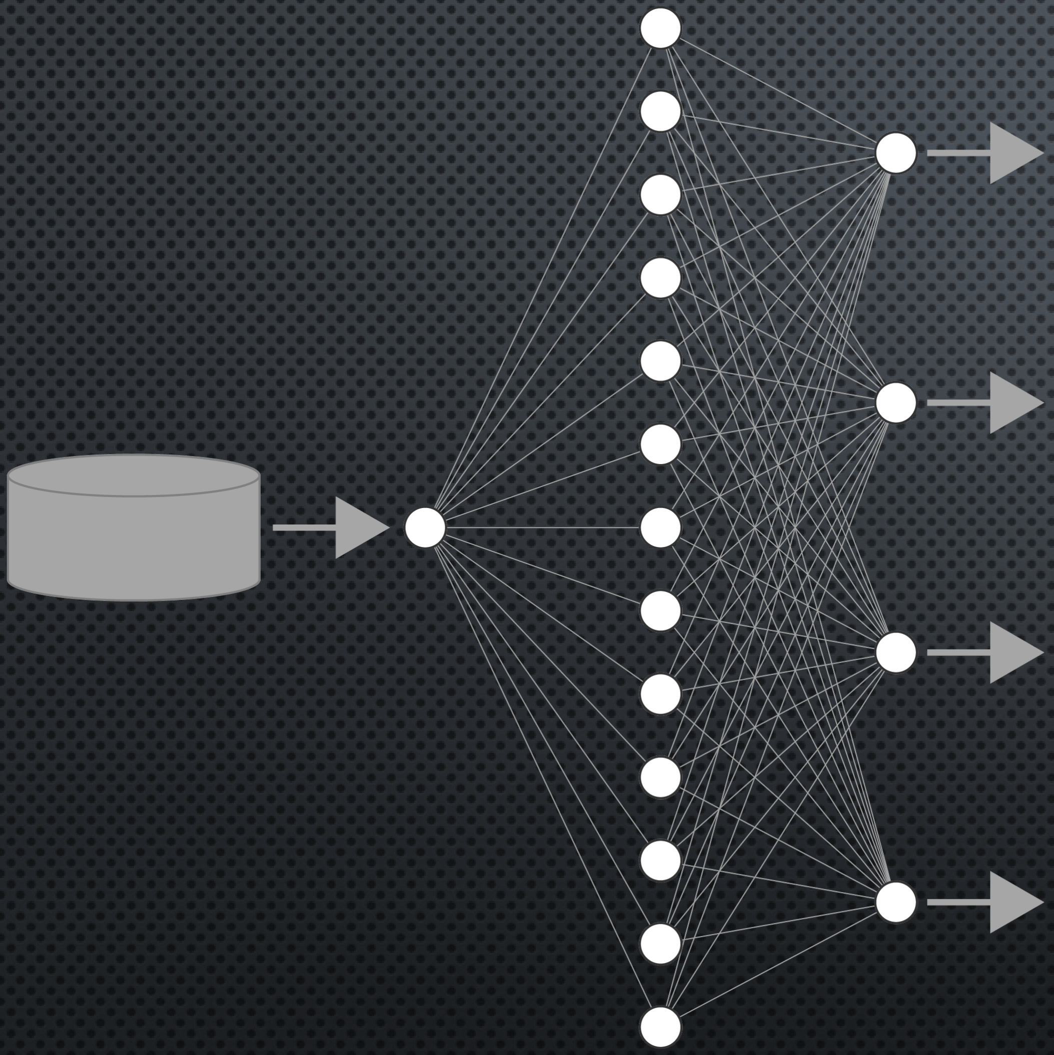
DID THE NEURAL NETWORK 'LEARN' SOME PHYSICS?





Christian C. Nadell, Bohao Huang, Jordan M. Malof, and Willie J. Padilla, *Deep learning for accelerated all-dielectric metasurface design*, Optics Express **27**, 27523 (2019).

CONCLUSIONS



Machine learning solves challenging problems

FFDS efficiently solves the inverse problem

ML is a great interpolator, but doesn’t “learn” physics

ML + Metamaterials can achieve more complex response than what has been achieved before


THANK YOU